The Dodd-Frank Act and Hedge Fund Operational Risk

William N. Goetzmann,[1] Bing Liang,[2] and Jue Wang[3*]

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Abstract

We examine the impact of the 2011 Dodd-Frank disclosure reform on hedge fund transparency. Newly added questions in the SEC's Form ADV significantly improve the prediction of adverse operational events relative to pre-reform disclosures. Using machine learning, we construct a unidimensional operational risk score from public regulatory data that predicts liquidation, leverage, performance, and net fund flows. Over the five years of the post-Dodd-Frank Act, fund flow response significantly increased following the amended Form ADV implementation, indicating greater use of disclosed information. Overall, mandatory regulatory disclosure outperforms voluntary vendor data in identifying operational risk and has meaningful economic effects.

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[1] Yale University, 165 Whitney Ave, New Haven, CT 06511, william.goetzmann@yale.edu.
[2] University of Massachusetts Amherst, 121 Presidents Drive, Amherst, MA 01003, bliang@isenberg.umass.edu
[3] Yale University, 165 Whitney Ave, New Haven, CT 06511, jue.wang@yale.edu;
University of Massachusetts Amherst, 121 Presidents Drive, Amherst, MA 01003, juewang@umass.edu.
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*"The importance and impact of conflicts of interest controls and the registration and reporting requirements are indisputable … **And by 'operational risk', I generally mean risk from inadequate or failed internal processes and systems.**"*[4]

Mary Jo White (Former SEC Chair)

1. Introduction

With the broad adoption of alternative investment strategies over the past three decades, the global hedge fund market has become an important asset class for both institutional and individual investors. According to an authoritative industry source, total hedge fund assets reached a record $5 trillion in the third quarter of 2025.[5] Hedge funds seek to generate risk-adjusted returns through active trading,[6] but competitive pressures lead them to maintain opacity over portfolio positions and proprietary strategies, limiting external assessment of risk. High-profile failures, such as the collapse of Bernard Madoff's fund in 2008, have underscored the importance of operational risk, defined as "the risk of loss resulting from inadequate or failed internal processes, people, and systems."[7] Industry evidence suggests that operational risk accounts for roughly half of hedge fund failures (Capco, 2003).

The Dodd-Frank Wall Street Reform and Consumer Protection Act, enacted in 2010 in response to the global financial crisis, aimed to reduce systemic risk. Among its provisions, it imposed new regulatory requirements on hedge funds, including mandatory Form ADV filings. In July 2011, the SEC substantially expanded the scope and content of Form ADV to enhance

[4] https://www.sec.gov/news/speech/2014-spch121114mjw
[5] https://www.hfr.com/media/market-commentary/global-hedge-fund-industry-capital-surges-nears-historic-5-trillion-milestone/.
[6] Cf. Cao, Liang, Lo, and Petrasek (2018), Cao, Chen, Goetzmann, and Liang (2018).
[7] Basel Committee on Banking Supervision (Basel Committee), International Convergence of Capital Measurement and Capital Standards (the revised Basel II framework), November 2005, Paragraph 644. www.bis.org/publ/bcbs118.htm.

transparency. As former SEC Chair Mary L. Schapiro noted, these rules closed a key regulatory gap by bringing previously opaque private fund managers into regulatory and public view.[8] The hedge fund industry has operated under this regime since 2011, providing over a decade of data to assess the effects of Dodd-Frank-mandated disclosure and the materiality of conflict of interest reporting.

In this paper, we examine several questions of interest to regulators, managers, and investors. First, we test whether new disclosure items in the post-Dodd-Frank Form ADV improve the prediction of adverse operational outcomes such as fund liquidation. We fit a model to predict operationally risky funds based on post-Dodd Form ADV data, using a regularization technique (LASSO) to identify the most salient predictor variables.[9] Most of the important variables in the estimation were not included in the pre-Dodd Form ADV. We then test whether the additionally disclosed items on the post-Dodd Form ADV added materially to the operational risk assessment. We find they do.

We construct a univariate measure – ADV-based Ω-score based on the ADV information from the SEC website. Brown, Goetzmann, Liang, and Schwarz (2008b) [BGLS] develop an operational risk metric, the ω-score, using the short-lived 2006 mandatory disclosure data linked to proprietary commercial databases such as TASS. Because this linkage requires matching across data sources, some observations are inevitably lost. Despite these limitations, the ω-score significantly predicts adverse fund outcomes such as liquidation. Our ADV-based Ω-score improves on this approach by using more advanced methods and updated, granular disciplinary

[8] As stated by former SEC Chair Mary L. Schapiro, "These rules will fill a key gap in the regulatory landscape… In particular, our proposal will give the Commission, and the public, insight into hedge fund and other private fund managers who previously conducted their work under the radar and outside the vision of regulators." (https://www.sec.gov/news/speech/2011/spch062211mls-items-1-2.htm).
[9] Problem funds are defined as those that have encountered past legal or regulatory issues. For a detailed explanation of our problem fund definition, please refer to Section 4.

data over an 11-year post-2011 panel following the Dodd-Frank Form ADV expansion. Using LASSO for weight assignment and only public SEC data, the *Ω*-score more accurately predicts adverse operational events, offering a transparent, replicable, and high-dimensional risk metric that outperforms prior costly approaches. In addition, our paper benefits from substantially expanded Form ADV content, including exact litigation types, decision dates, and more detailed conflict-of-interest disclosures, none of which were present in the 2006 filings examined in earlier papers.

We next ask whether investors and lenders respond to the provision of potentially material information about operational risk. In a post-Madoff industry white paper, Scharfman (2009) argued that hedge fund investors failed to adequately take operational risk into account in their investment decisions. Consistent with this argument, using data from 1994 to 2005, BGLS found little evidence of a relationship between operational risk and investor fund flows. They concluded that investors either lacked this information or regarded it as immaterial to their decision to invest.[10] In contrast, the current paper finds a strong and increasing investor response to operational risk post-Dodd, showing that enhanced disclosures changed behavior over time, including fund flows and credit access—implying both learning and information uptake by markets.

In particular, we test whether investor flow elasticity to operational risk increased in the post-Dodd-Frank period. We find that the post-Dodd ADV-based *Ω*-score derived solely from publicly disclosed and easily available information is significantly and negatively correlated with investor flows, controlling for the number of operational risk-related news items for public sentiment. This result is consistent with access to or attention to the disclosed information improving investor

[10] Cf. Brown et al. (2008b) for a TASS-based operational risk score, and Brown et al. (2008a, 2012) for due diligence (DD) operational risk scores.

decision-making.

Furthermore, we use an out-of-sample analysis to test whether investor response to operational risk, measured both by the BGLS ω-score and the post-Dodd LASSO-based Ω-score, has changed over time. We find that the LASSO-based Ω-score is a better predictor of investor flows, even though the BGLS metric incorporates information such as fund characteristics and performance information provided by a major private data vendor (TASS).

The fund flow results also indicate a significant change in investor response to operational risk measures. Flow elasticity in the second five years of the sample has significantly increased compared to the first five years. We interpret this as evidence of an increasing attention to operational risk over the period. Turning to hedge fund lenders, we find clear evidence that higher fund operational risk, as measured by the Ω-score, is associated with lower access to credit.

The paper also includes tests for the effect of operational risk metrics on performance outcomes of interest to investors, including risk-adjusted returns. High operational risk scores negatively predict future style-adjusted returns, implying that operational risk is a risk of loss and has no risk premium associated with it. This is consistent with the notion defined by the Basel Accord for banks.

Our results are also of potential interest to regulators. Operational risk is a significant factor in fund failure. Using the matched 2023 TASS-ADV sample, Figure 1 graphs two 'Value at Risk' measures for our hedge fund sample in 2023.[11] Figure 1A plots the cumulative AUM against the predicted firm liquidation probability within the next two years.[12] In our sample, 13% of the AUM, equivalent to approximately $25 billion, corresponds to firms with an estimated liquidation

[11] This additional analysis uses an independent 2023 sample and serves as a potential 'real' out-of-sample test of the increased materiality of the post-Dodd-Frank Form ADV.
[12] The two plots illustrate the estimated minimum dollar amount of fund AUM at risk of liquidation and the increase in litigation risk over the next two-year period.

probability exceeding 20%. Figure 1B highlights that 6% of the AUM, or roughly $13 billion, is allocated to funds with an estimated probability of future litigation above 5%.

Interestingly, a firm (referred to here as Firm A for anonymity) in our sample stands out in both charts with predicted ADV-based Ω-score probabilities of 16.36% for liquidation and 1.40% for increased litigation. Specifically, the firm's 2021 ADV filing showed several internal relationships linked to custody issues that were red flags in the model.[13] In 2024, the FBI investigated it as a suspected Ponzi scheme.

[Insert Figure 1]

In summary, our post-Dodd paper builds on and substantially extends the previous studies by using a longer, richer data panel; employing modern statistical tools; providing stronger evidence of market reactions; and connecting regulatory disclosure improvements with broader systemic implications for financial institutions and regulatory design. We show that mandatory, standardized regulatory disclosure, rather than voluntary vendor data, plays a critical role in identifying funds with elevated operational risk and demonstrates the meaningful economic consequences of the 2011 Dodd-Frank reporting expansion.

Beyond hedge funds, our findings have broader implications for banks, insurers, and other financial institutions engaged in due diligence and risk modeling. The increasing informativeness of Form ADV underscores how standardized public disclosures can improve credit decisions, counterparty assessment, and governance, consistent with the Basel Accord's emphasis on operational risk management and transparency.

This paper contributes to the literature in several ways. First, it advances hedge fund operational risk research by providing large sample, post-Dodd-Frank evidence on the

[13] Specifically, this firm's 2021 ADV filing revealed over 37% of internal relationships linked to custody issues, and later civil charges in May 2023 for mismanagement and fraud.

informational value of mandated regulatory disclosures and introducing a scalable methodological framework. Prior studies identify operational risk using either qualitative, top-down governance measures (BGLS, 2008, 2009) or bottom-up statistical flags (Liang, 2003; Bollen and Pool, 2009; Getmansky et al., 2004; Getmansky et al., 2005), while recent work shows limited Form ADV variables can detect fraud (Dimmock and Gerken, 2012; Dimmock et al., 2020). We show that the post-Dodd-Frank expansion of Form ADV significantly improves ex-ante prediction of operational risk events, reducing information asymmetry for investors and regulators. Methodologically, we extend BGLS (2008) using publicly available filings and machine-learning to synthesize high-dimensional disclosure data, extracting economically meaningful signals without relying on proprietary datasets, informing ongoing debates on data accessibility and regulatory design.

Second, our study contributes to the literature on regulation and disclosure by documenting the economic consequences of the 2011 Dodd–Frank reporting expansion for operational risk assessment. Prior work examines regulatory oversight on misreporting and enforcement (Dimmock and Gerken, 2016; Honigsberg, 2019), client complaints (Charoenwong et al., 2019), performance and risk (Cumming et al., 2020), and compliance costs (Restrepo, 2024). More broadly, disclosure and regulatory transparency influence market discipline, monitoring, and risk-taking (Agarwal et al., 2015; Edmans et al., 2017). In asset management, enhanced disclosure requirements, such as Form PF and post-crisis transparency reforms, aim to reduce opacity and improve oversight of systemic and operational risks (Agarwal et al., 2013; Aragon and Strahan, 2012; BGLS, 2012). Evidence on whether standardized disclosure improves prediction of adverse outcomes remains limited. We show that mandatory, uniform regulatory disclosure, rather than voluntary reporting or selective vendor data, is crucial for identifying funds with elevated operational risk, complementing existing findings on the trade-offs between regulation, transparency, performance, and risk.

Third, we contribute to the hedge fund performance literature. Prior studies identify multiple sources of “super performance,” including fee structures and managerial incentives (Agarwal et al., 2009), share restrictions and liquidity premia (Aragon, 2007), cross-jurisdictional differences (Aragon et al., 2014), and service-provider selection, such as prime brokers (Aragon et al., 2023). We show that, unlike market, liquidity, or credit risk, operational risk provides no compensation and exposes investors to downside losses, which can be mitigated by avoiding funds with high Ω-scores.

The remainder of the paper is organized as follows. Section 2 presents our research questions and hypotheses. Section 3 describes the data. Sections 4 and 5 describe the methodology and display the results. Section 6 concludes.

2. Background and research questions

Hedge funds were historically regarded as private investment vehicles serving a limited number of wealthy individuals and families. As such, they were not subject to the same regulatory oversight as retail investment products such as mutual funds. In 1985, the SEC broadened the definition of hedge fund clientele to allow pooled assets – effectively eliminating restrictions on the number of investors in a given fund. Among other events, such as the collapse of Long-Term Capital Management in 1998, this alerted the SEC and other regulators to the potential of broader effects of hedge funds on investors and capital markets.[14]

In May 2003, motivated in part by “…a growing number of enforcement cases in which hedge

[14, 15] *Registration Under the Advisers Act of Certain Hedge Fund Advisers* https://www.sec.gov/rules/final/ia-2333.htm#I

fund advisers defrauded hedge fund investors," the SEC organized a Hedge Fund Roundtable to discuss hedge fund structure and operations, as well as the assessment of the current regulatory scheme relating to the industry.[15] In December 2004, the Commission adopted new rules that required all hedge funds to register with the SEC and to submit Form ADV annually. These rules were successfully challenged, leading to the termination of mandatory hedge fund disclosure requirements in June 2006. However, in 2009, less than a year after the arrest of Bernard Madoff for running a Ponzi scheme through a hedge fund, the SEC established the *Custody of Funds or Securities of Clients by Investment Adviser Rule*.[16] The new rule required all qualified advisory companies to disclose custody information to the SEC.

Subsequently, in July 2011, in response to the Dodd-Frank Act, the SEC introduced an expanded version of Form ADV. This revision altered both the filing submission standards and the scope and depth of information required for disclosure. The SEC forms require most hedge funds to register as Registered Investment Advisors (RIAs). A limited subset of funds was granted reduced registration and reporting obligations. Exempt Reporting Advisors (ERAs) need only file an abbreviated version of the new Form ADV with state authorities.[17] Subsequently, in August 2016, RIAs utilizing an Umbrella Registration (UR) were required to adhere to a unified compliance policy and a single code of ethics, both overseen by a designated chief compliance officer. The SEC also greatly enhanced the scope of questions related to operational risk. Item 7, for example, pertains to *Financial Industry Affiliations and Private Fund Reporting*. It was expanded to include 17 types of external conflicts of interest, compared to seven types in the pre-Dodd form.[18] The new form also expanded disclosure of internal conflicts of interest, increasing

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[16] Rule 206(4)-2 under the Investment Advisers Act of 1940.
[17] A detailed ERA and RIA classification can be found in Figure A.2 of the Appendix (p.53).
[18] The structure of the amended Form ADV can be found in Figure A.3 of the Appendix (p.54).

the number of questions in Item 8: *Participation or Interest in Client Transactions* and creating two new categories: Item 9 *Custody*, and Item 10 *Control Person* (a detailed evolution of the history of Form ADV and related amendment rules can be found in Figure A.1 of Appendix (p.52).

The amended Form ADV thus provides market participants and regulators with more information potentially material for the assessment of operational risk. However, additional regulation requires a cost-benefit analysis. To test whether the expanded requirements have material benefits, it is necessary to address several questions. First, did the expansion of mandated information disclosure, along with its public availability, enhance the ability to predict future adverse operational events? Second, is there any indication that market participants based their investment decisions on the augmented information set, and is there evidence of any evolving learning behavior over time? Third, is there evidence to suggest that the private market for information (such as TASS data) has not already fulfilled investors' needs for data critical to assessing operational risk? We address each of these questions in the paper.

3. Data

3.1 TASS and Form ADV Data

Our study relies on two data sources. The first data source is the TASS database. TASS is one of the principal vendors of hedge fund data. It provides detailed information on fund characteristics and performance. We retrieve TASS live fund data from 2012 to 2022.[19] We also include defunct funds that were liquidated or became unresponsive in vendor attempts to contact them in the period 2013 to 2022. The performance and characteristics of the defunct fund sample are also included in

[19] We begin the sample in 2012 for consistency across funds. Form ADV was amended in July 2011, and funds typically file in April. Thus pre-2012 filings are mostly the pre-Dodd. In addition, while the TASS data performance data are monthly, most of the characteristics are updated annually as of December.

our analysis.

The second data source is the SEC's Office of Freedom of Information Act (FOIA) service website, which allows downloading of amended Form ADV filings for both Exempt Reporting Advisers (ERA) and Registered Investment Advisers (RIA) at a monthly frequency starting in July 2006.[20] We retrieve Part 1A filings from 2012 to 2022 for live funds and Part 1A filings for the year 2023 for liquidated or unable-to-contact funds (used for the analysis in Figure 1 only). Part 1A data has 12 Items and 3 Schedules. Items 7 to 10 provide self-reported conflicts of interest. Item 7 documents advisory firms' external conflicts of interest, and Items 8 to 10 document internal conflicts of interest. Item 11 reports prior legal and regulatory events.

These four items comprise 44 external and internal conflicts of interest variables, more than double the number available before 2011. In addition, Item 11 reports detailed information on the legal and disciplinary history of advisors and related person. We can link each filing with its Disclosure Reporting Page (DRP) for each advisory firm and year. The DRP page offers rich details about sanctions faced by advisory companies and their related parties, including sanction dates and textual descriptions of charges. Sanctions are categorized into financial regulatory charges, criminal offenses, and civil judicial matters according to Form ADV. [21] Figure 2 presents Word Clouds depicting the sanction details for these three types of disciplinary histories from 2012-2022.[22]

[20] https://www.sec.gov/help/foiadocsinvafoiahtm.html. BGLS use the SEC Investment Adviser Public Disclosure (IAPD) website as their Form ADV data source. The SEC FOIA service website used in our study contains nearly identical information but provides a more accessible format and a complete historical archive, whereas IAPD offers only recent filings.

[21] We include only unique cases based on textual sanction details (e.g., if firm X has multiple records with identical sanction details under the same category, we document it as a single event). Additionally, if a firm is charged by multiple authorities for the same violation, we count it as one event. We also exclude cases without a precise status or resolution date and drop cases with statuses of dismissed, vacated, or withdrawn.

[22] After matching with our TASS-ADV sample, we identify a total of 264 unique cases (233 regulatory, 23 civil judicial, and 8 criminal). The average rate of firms with negative operational risk litigation from 2012 to 2022 is 5.38%.

[Insert Figure 2]

For regulatory charges and civil judicial matters (Figures 2A and 2C), securities-related violations are the primary litigation reasons, with significant attention given to fund managers. Regulatory charges predominantly involve misconduct related to trading, client interactions, and commission issues, while civil judicial matters are often insurance related. For criminal cases (Figure 2B), charges are mainly related to conspiracy, fraud, defraud, and antitrust issues, with a notable number involving Libor and securities.

Furthermore, there is another difference between the original Form ADV and the amended Form. The ownership information in the amended Form ADV does not require precisely the same annual updates as the pre-Dodd form. Specifically, direct and indirect ownership information in Schedules A and B is now required only for the initial application, meaning the ownership details may not always be up to date. In summary, the amended Form ADV expands the disclosure of fund characteristics potentially relevant to the assessment of operational risk and makes it readily accessible to investors in a timely manner. In the analysis below, we are thus able to use the data that was available in most cases to investors in real-time to conduct our tests.

3.2 Descriptive Statistics

We identify 1,386 management companies in the SEC database out of 2,772 listed in TASS (50% of the TASS database).[23] These management companies represent 6,216 (52.76%) of the 11,782 live and dead funds according to the 11-year TASS and amended Form ADV filing samples. We identify 1,717 defunct funds liquidated or unable to be contacted within the prior 10-

[23] We match funds across the two databases using a two-step procedure. First, we identify exact matches between the TASS Company Name and the Legal Name in Form ADV Part 1A. For remaining observations, we search Form ADV firms using unique keywords from the TASS fund or parent company names and verify matches using domicile country, address, and website information. The same procedure is applied to defunct TASS funds.

year period, representing 27.62% of the matched TASS-ADV dataset.[24] Moreover, because only RIA funds' related companies are required to file the full amended Form ADV, the remainder of the analysis focuses primarily on RIA funds.

Table 1 reports descriptive statistics for the ADV and TASS live and dead funds. We compare the RIA-matched fund sample with the TASS live and dead fund sample. In general, RIA funds have a higher Sharpe ratio, appraisal ratio, alpha, margin usage, high-watermark provisions, longer lockup, subscription and redemption periods, and longer histories. When further comparing with Table 1, we find that ERA funds, which are exempt from full filing, exhibit significantly lower returns, Sharpe ratios, appraisal ratios, assets under management, high watermarks, and lockups/redemption frequency. This suggests that registration serves as a signal of fund quality.

[Insert Table 1]

Columns 1-3 and 4-6 in Table 1 further differentiate RIA funds into those with and without Umbrella Registration (UR and non-UR), while also comparing them to the TASS sample in the last two columns.[25] Specifically, UR funds have a higher average return, Sharpe ratio, appraisal ratio, alpha, incentive fee, more frequent use of margin and set with high watermark provisions, longer lockup and redemption/subscription frequency, as well as longer fund lifespans.[26] These differences caution against pooling UR funds with non-UR funds. Among all fund classes, RIA

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[24] We exclude TASS funds reporting quarterly or gross-of-fee returns, as well as funds with assets under management below $10 million. Annual returns are computed as the average of monthly returns within each year and winsorized at the top and bottom 1%. Observation counts for both matched and full TASS samples are based on the winsorized data. Assets under management and returns for foreign-domiciled funds are converted to U.S. dollars using annual OECD exchange rates (https://data.oecd.org/conversion/exchange-rates.htm). Among the 6,216 RIA and ERA funds, 4,819 remained RIA, 1,124 remained ERA, and 273 switched statuses during the sample period. Among the 1,717 defunct funds, 1,186 remained RIA, 258 remained ERA, and 273 experienced status changes. Details are reported in Appendix Table A.2 on p.55.

[25] Since August 25th, 2016, a single Form ADV can be submitted by one filing advisor with one or more relying advisors who only advise for private funds. (https://www.sec.gov/rules/proposed/2015/ia-4091-appendix-a.pdf).

[26] According to Table 1, we can also observe that the UR funds outperform the entire TASS live fund sample in terms of average return, Sharpe ratio, appraisal ratio, and alpha.

funds with the UR registration display the highest risk-adjusted performance and higher quality.

3.3 Problem Funds and Non-problem Funds

We next classify funds as having high or low operational risk using a method similar to BGLS but with a more refined and accurate standard.[27] We identify problematic firms based on the exact operational risk management failures. Specifically, we map responses from Item 11 – which includes "Reportable events include felonies and investment-related misdemeanors, regulatory disciplinary actions, court judgments related to violations of investment-related statutes and regulations by the investment advisor and its affiliated persons"[28] – to their corresponding DRP filings to find the unique events and exact charged dates. We document the sanction date and classify the associated firms as problem firms for the respective year. If a firm is deemed problematic in a given year, all related funds for that firm are labeled as problem funds (see Footnote 21 for details on how we identify non-duplicated events and determine resolution dates).

[Insert Table 2]

Table 2 separates the entire RIA sample (live and defunct funds) into Problem Funds and Non-Problem Funds. The last column presents the differences in outcomes from our univariate analysis of RIA funds. Consistent with BGLS's findings for the earlier sample period, problem funds had significantly lower alpha/appraisal ratio, incentive/management fees, personal capital, leverage, usage of margin, high watermark provisions, lockups/subscription/redemption

[27] BGLS define problem funds as those whose related companies answered "yes" to any Item 11 disclosure and show that Form ADV variables significantly predict this measure. However, because Item 11 covers disciplinary histories over the prior ten years, this legacy definition raises concerns about staleness. Accordingly, we define problem funds based on whether a fund's related company experienced any litigation events during the 2012–2022 sample period, capturing contemporaneous operational risk.

[28] RIA Compliance Associates "Form ADV Drafting Tips (n.d.) https://www.ria-compliance-consultants.com/compliance_tips/form_adv_drafting_tips_for_investment_advisor_compliance/

frequencies, as well as a shorter history.[29]

4. Test of the Materiality of Amended Form ADV

In this section, we evaluate whether the newly added items in the amended Form ADV significantly enhance the identification and prediction of litigation changes or shifts in Problem Firm status (from non-problem to problem).[30] Specifically, we aim to address the question: Can the amended Form ADV identify 'real' litigation events and potential fund failures caused by inadequate operational risk management?

To assess predictive power, we approximate the timing of 'real' operational risk events, assuming these occur one to four years before the first litigation settlement, given that SEC investigations typically span two to four years.[31] We conduct panel OLS, panel logit, and panel Cumulative Link Mixed Model (CLMM) regressions. The dependent variables are tested using two specifications: (1) the full post-2011 set of variables and (2) a subset representing only the pre-2011 variables. The null hypothesis is that the additional post-Dodd variables do not significantly improve predictions of the changes of violations or Problem Firm status, as assessed through error terms from these models.

Table 3 presents the results of the test of the added value of the new operational risk-related variables (Items 7, 8, 9, and 10) in the amended Form ADV in the post-Dodd (Post-2011) period. The specifications are:

$$Pos\Delta ProblemNum_{i,t} = \alpha_{i,t} + \boldsymbol{\beta_{ORV}} \boldsymbol{X_{ORV\ i,t-l}} + \sum_{j=1}^{N} \gamma_j FirmDummies_{ji} + \quad (1)$$

[29] In addition, in untabulated results, we find that both external and internal conflicts of interest were significant predictors of the Problem fund status.
[30] We perform firm-level analysis and estimation for the results in Sections 5.1 to address duplicate records in the Form ADV data, as each advisory firm files Form ADV annually.
[31] https://secwhistlebloweradvocate.com/sec-whistleblower-frequently-asked-questions/

$\sum_{q=1}^{9-l} \eta_q YearDummies_{qi} + \varepsilon_{i,t}$

$$\Delta ProblemNum_{i,t} = \alpha_{i,t} + \boldsymbol{\beta_{ORV} X_{ORV\,i,t-l}} + \sum_{j=1}^{N} \gamma_j FirmDummies_{ji} + \sum_{q=1}^{9-l} \eta_q YearDummies_{qi} + \varepsilon_{i,t} \tag{2}$$

$Pos\Delta ProblemNum_{i,t}$ is a binary variable representing if there is a positive change of the sum of the three Form ADV violation category dummies (ranging from 0 to 3) for a fund company i in year t. $\Delta ProblemNum_{i,t}$ is a variable representing the changes of the sum of the three Form ADV violation category dummies (ranging from 0 to 3) for a fund company i in year t. $\boldsymbol{X_{ORV\,i,t-l}}$ is the set of the operational risk-related variables in the pre-2011 Form ADV or the amended Form ADV after 2011 (this includes both pre-Dodd and additional post-Dodd variables) for fund i in year $t-l$, where l is the number of the lagged years that ranges from 0 to 4. Both the pre-Dodd and post-Dodd models include firm and year fixed effects, as well as the clustered standard errors for both.

[Insert Table 3]

Table 3 reports predictions for the likelihood and magnitude of increased litigation events. The first column analyzes the probability of litigation increases, the second column predicts the magnitude of changes, and the last column applies a CLMM to account for both the categorical nature and severity of litigation changes. According to the three sub-panels, the post-Dodd variables enhance forecasting power, especially in the two years leading up to the start of investigations, where both the *F*-statistics and χ^2 statistics reach their peak. These findings highlight the significance of the post-Dodd Form ADV in predicting operational risk-related failures even before regulatory actions occur, providing a valuable early warning tool for market participants to manage risks proactively.[32]

Figure 3 further displays the Principal Component Analysis (PCA) outcomes for the amended Form ADV filing variables of RIA funds. Over 11 dimensions are necessary to explain over 80% of the variance. This suggests that not only does the amended Form ADV filing provide improved power for regulatory problem identification, but the variables in the post-Dodd version of Form ADV are not spanned by the pre-Dodd set. Table 3 and Figure 3 thus demonstrate that not only has the number of operational risk variables increased in the amended Form ADV filings, but these newly added variables (along with the original variables) may capture latent variables not previously spanned by the pre-Dodd set.

[Insert Figure 3]

5. Reduced Form Operational Risk Assessment and Estimation

5.1 Operational Risk Indicators Selection

The variables in Items 7 to 10 comprise 44 potential operational risk–related variables. As described above, we group them into external and internal relationship categories: Item 7 variables capture external relationships, while Items 8, 9, and 10 capture internal relationships (see Figure IA.1 in the Internet Appendix, p.57, for variable structure and counts).[33]

Given the large number of variables (44) in the amended Form ADV, we use LASSO regression (Tibshirani, 1996) to select a parsimonious set of operational risk indicators. The dependent variable is the annual sum of regulatory, criminal, and civil judicial violation dummies

[32] Our untabulated results further show the results of using lagged operational risk variables to forecast the number of litigation events (level prediction; $ProblemNum_{i,t}$) and adverse liquidations for both pre-and post-2011 models. The two-lag specification again offers the strongest predictive power, consistent with the results in Table 3.

[33] Variables in Item 7 can be classified as external relationship and variables in Item 8 as internal relationship-related. Regarding the operational risk-related items added in the Amended Form ADV variables in Items 9 and 10 are treated as internal relationship variables, since they pertain to internal operational processes rather than external factors.

for each firm (Section 5). We estimate a linear regression with L1 regularization (LASSO) over the 44 variables; variables with non-zero coefficients are retained. The resulting coefficients define a unidimensional ADV-based operational risk measure, the *Ω*-score, constructed as a linear combination of the selected variables.

Table 4 presents the LASSO regression results for RIA funds. Among the 44 variables, 35 are selected as important for problem fund identification. This includes 16 external variables (out of 17 in total) and 19 internal variables (out of 27 in total). Panel A also reports whether the variables are in the pre-Dodd Form ADV, the variable importance, and the importance rank for the top 10 important variables (5 internal and 5 externals; 70% of them are new variables).

[Insert Table 4]

Panel A's variable coefficients provide valuable insights into operational risk. Seven of the top 10 variables are newly added; negative coefficients indicate a lower likelihood of being a Problem Firm. All external variables show a positive relationship with increased violation types. Specifically, the presence of a Future Commission Merchant (*FuturesCommission*) and Swap Dealer (*SwapDealer*) relationships increase operational risk due to pricing opacity. Other external variables, such as *Insurance*, *Trust*, and *BankingThrifting,* also significantly impact the likelihood of problems, by adding transactional complexity through their intricate relationships with hedge funds.

Internal relationships account for half of the top 10 variables and generally load positively on violations. Custody and conflict-of-interest variables are particularly salient: *RelatedQualifiedCustodian* and *AdvisorQualifiedCustodian* capture custody risks, while *AgencyCrossTransaction* reflects conflicts that can facilitate front-running or preferential treatment. Ownership variables such as *OtherControlCompany* and *OtherControlPerson*, show opposing effects on operational risk due to the SEC's ADV glossary[34] and our sample examination: *OtherControlCompany* is associated with lower risk, consistent with stronger oversight, whereas *OtherControlPerson* is associated with higher risk, reflecting agency problems when control lacks substantial ownership or voting power.

Panel B summarizes counts, ranks, and percentages by group. Among the 35 selected variables, 65.71% are post-Dodd variables, which also exhibit higher median importance ranks, consistent with improved identification from amended disclosures. Although more internal variables are selected, external variables have a higher median rank (13.50 vs. 21.00), underscoring the greater risk impact of external affiliations. Increased external relationships can add complexity and reduce transparency, making it more challenging for investors and regulators to assess risk, as evidenced by the Madoff scandal.[35]

Panel C reports the result of a Kruskal-Wallis Test of the differences in medians. The results in Panels B and C suggest that external relationships and post-Dodd variables are more important in association with the Problem Firm events than internal relations and pre-Dodd variables.

5.2. ADV-based Ω-score Construction for Predicting Adverse Events and Performance

BGLS (2008) develop an ω-score that is based on fund performance, risk, and characteristic variables from the data vendor TASS to indirectly (through mapping between TASS data and ADV data) evaluate operational risk due to the unavailability of the Form ADV at that time. As discussed previously, since their sample period, the expanded post-Dodd Form ADV was made mandatory and became entirely accessible to the public.

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[34] https://iard.com/sites/iard/files/glossary.pdf.

[35] For instance, Bernie Madoff orchestrated his Ponzi scheme through affiliations with a broker-dealer, which was also involved in executing and clearing trades.

In this section, we use a reduced form and univariate specification, a new Ω-score based only on publicly available information to predict adverse operational risk events. The ADV-based Ω-score is a weighted score based on the LASSO regression estimated above. Equations (3) and (4) present those testing strategies.[36]

$$h_{i,t}(T) = h_{0i,t}(T) \times \exp\Big(\beta_1 ADV - Based\ \Omega\ score_{i,t-1} + C_{t-1}^{\prime\delta_C} + \delta_U Umbrella_{i,t-1} + \sum_{j=1}^{13} \gamma_j StyleDummies_{ji} + \sum_{q=1}^{9} \eta_q YearDummies_{qi}\Big) \quad (3)$$

$$Appraisal\ ratio_{i,t}\ or\ Alpha_{i,t}\ or\ Leverage_{i,t} = \alpha_{i,t} + \beta_1 ADV - Based\ \Omega\ score_{i,t-1} + C_{t-1}^{\prime\delta_C} + \delta_U Umbrella_{i,t-1} + \sum_{j=1}^{13} \gamma_j StyleDummies_{ji} + \sum_{q=1}^{9} \eta_q YearDummies_{qi} + \varepsilon_{i,t} \quad (4)$$

Table 5 reports the adverse outcomes prediction results for the ADV-based Ω-score. In Panel A, models 1 and 2 indicate that an increase in the ADV-based Ω-score by one unit results in a decrease of 26% and 56% in a fund's future alpha and appraisal ratio. Models 3 and 4 suggest that funds with a higher ADV-based Ω-score are less likely to be leveraged and are more likely to be liquidated in the future. Furthermore, consistent with Table 1, Umbrella funds are positively associated with increased leverage and better performance. This suggests that SEC's revised registration categorization – Umbrella Registration – may add a useful variable for separating funds by quality and risk.

[Insert Table 5]

Panel B presents the results of predicting future litigations (regulatory, criminal, and civil

[36] C_{t-1} is a vector of variables, including average and standard deviation of monthly returns, leveraged or not, onshore, and high-water mark indicators, log of assets, and fund management fee in year $t-1$. Furthermore, for performance prediction in the second equation, average return in year $t-1$ will not be included. Similarly, for leveraged or not prediction, leveraged or not indicator in year $t-1$ will not be included as well.
Moreover, a fund i will be considered as adversely impacted at year t with age T if it is liquidated or unable to contact according to TASS, with a negative average return in the previous 6 months, as well as decreased AUM in the previous 12 months (Liang and Park, 2010).

judicial charges) using our constructed ADV-based Ω-score, according to the logit regression(s) specified in equation (5). The dependent variables, $Regulatory_{i,t}$, $Criminal_{i,t}$, and $Civil\ Judicial_{i,t}$, are binary indicators representing whether the fund's associated companies will face related charges in the next period. All three models demonstrate that funds with higher prior operational risk are more likely to face future charges, particularly criminal cases. Overall, the findings from both Panels A and B indicate that the ADV-based Ω-score, constructed based on the post-Dodd-Frank Form ADV, has predictive power for fund-specific adverse outcomes, including performance, leverage, liquidation, and litigation-related charges.

$$Regulatory_{i,t}\ or\ Criminal_{i,t}\ or\ Civil\ Judicial_{i,t} = \alpha_{i,t} + \beta_1 ADV - Based\ \Omega\ score_{i,t-1} + C_{t-1}^{\prime\delta_C} + \delta_U Umbrella_{i,t-1} + \sum_{j=1}^{13} \gamma_j StyleDummies_{ji} + \sum_{q=1}^{9} \eta_q YearDummies_{qi} + \varepsilon_{i,t} \quad (5)$$

5.3 Operational Risk Forecasting Future Fund Flows

Thus far we report evidence that the ADV-based Ω-score negatively predicts future performance and adverse events (survival and performance) for hedge funds in the post-Dodd (and post-BGLS) period. Next, we investigate whether mandated disclosure affects the behavior of investors. Scharfman (2009) argues that investors are aware of the negative relationship between a fund's operational risk management skills and hedge fund failures. BGLS used investor flows to test investor awareness of operational risk and found little evidence of it. In this section, we similarly estimate fund flow response to the ADV-based Ω-score in the post-Dodd period. Equation (6) specifies a predictive panel model of net fund flows, controlling for past performance, volatility, size, fees, style umbrella status, and year.

$$Flow_{i,t} = \alpha_{i,t} + \beta_1\, ADV - Based\, \Omega\, score_{i,t-1} + \delta_1\, High\, rank_{i,t-1} + \delta_2 Mid\, rank_{i,t-1} + \delta_3 Low\, rank_{i,t-1} + \delta_4 Log\, assets_{i,t-1} + \delta_5 Stdev_{i,t-1} + \delta_6 Management\, fee_{i,t-1} + \delta_U Umbrella_{i,t-1} + \sum_{j=1}^{13} \gamma_j StyleDummies_{ji} + \sum_{q=1}^{9} \eta_q YearDummies_{qi} + \varepsilon_{i,t} \quad (6)$$

Table 6 presents the results. Models 1 to 3 present the fund flow analysis for the full sample. Clustered standard errors are used for style, years, and funds' advisory companies in the two models. A potential concern is that the relationship between funds' operational risk and flows is driven by increased operational risk attention after Dodd-Frank rather than actual operational risk levels. Consequently, for each model, we control news-based operational risk attention. *Log (OR attention*) is calculated as the log number of media articles mentioning 'Madoff,' 'operational risk,' or 'hedge fund failure' from the previous year, using the RavenPack database as a media attention proxy.[37] Model 1 clearly indicates that funds with higher operational risk exposure in the past are viewed less favorably by investors. Specifically, a one-unit increase in the ADV-based *Ω*-score leads to a 27% decrease in future fund flows. Interaction terms in Model 2 suggest investors in funds in the mid-and low-performance ranks are more responsive to the operational risk metric.

[Insert Table 6]

The outcomes in this section collectively imply that, unlike the flow findings of BGLS that suggested that investors either overlooked operational risk or lacked sufficient information to assess it, in the post-Dodd-Frank era, investors exhibited increased responsiveness to even a reduced-form predictive measure of hedge fund operational risk. This heightened awareness may reflect the more comprehensive post-Dodd-Frank Form ADV disclosures and investors' learning behavior,

[37] Following RavenPack platform recommendations, we select articles with the previously mentioned keywords and event relevance scores of 70 or higher for each year's news article calculation. Event relevance is a 0-100 score indicating how strongly the mentioned company relates to the underlying news story, with higher values indicating greater relevance.

even after controlling for operational risk attention.

Model 3 examines how ADV-based Ω-scores, funds' previous performance, and media operational risk attention jointly affect future fund flows. Funds with weaker past performance and higher operational risk experience greater outflows, especially following years of elevated media focus on operational risk. These findings highlight the Omega score's robustness and the amended Form ADV's added value in enhancing operational risk assessment materiality.[38]

5.4 Out-of-Sample Operational Risk Predicting Adverse Outcomes and Fund Flows

The ADV-based Ω-score used in Tables 5 and 6 is constructed using in-sample LASSO weights. To evaluate its predictive performance out of sample, Figure 4 presents annual cross-sectional results from 2013–2022 for fund flows, adverse liquidation, leverage, and performance outcomes using dynamically estimated weights. Each year, we re-estimate the LASSO model described in Section 5.1 using backward-looking data on post-Dodd Form ADV variables.[39]

For comparison, we also report results based on the Canonical Correlation Analysis (CCA) approach of BGLS in Table IA.2 (p.59).[40] The two approaches differ along three dimensions. First, the CCA score relies only on 15 pre-Dodd Form ADV variables, whereas the LASSO score

[38] In untabulated results, fund flow predictions using the same specifications as Models 1 and 2 remain robust when operational risk attention measures are excluded. In addition, all results in Sections 5.2 and 5.3 are robust when using the combined sample of RIA and ERA funds.

[39] To construct the dynamic score, we first apply the LASSO regression process (Section 5.1) to select variables and determine weights. The dependent variable is the sum of dummy variables for regulatory, criminal, and civil violations for firm i in year $t + 1$. The independent variables are the 44 binary indicators from firm i's Form ADV filings in year t. We use the LASSO coefficients as weights, applying them to the binary variables for firm i to calculate the ADV-based Ω-score of the funds under this firm for year t.

[40] Specifically, we implement CCA method on the 15 pre-Dodd variables (*BrokerDealer*, *InvestmentAdvisor*, *CommodBroker*, *Banking*, *Insurance*, *LimitedPartnership*, *ManagingMember*, *BuySellYourOwnSecurity*, *BuySellYourselfClientSecurity*, *RecommendSecurityYourOwn*, *AgencyCrossTransaction*, *RecommendUnderwriter*, *RecommendSalesInterest*, *RecommendBrokers*, and *OtherResearch*) from Form ADV and a set of fund performance and characteristic variables (*Return*, *Stdev.*, *Age*, *High water mark*, *Minimum investment*, *Log assets*, *Personal capital*, *Onshore*, *Open to public*, and *Accepts management account*) from TASS. Raw coefficients for the pre-Dodd Form ADV variables each year are used as the weight for the CCA-constructed Ω-score.

incorporates both pre- and post-Dodd disclosures (44 variables), allowing us to assess whether expanded regulatory disclosure improves predictive power. Second, because the CCA approach requires overlap between TASS and Form ADV, its sample size is approximately 80% of that available for the LASSO score. Third, and most importantly, the CCA score is indirectly constructed through a rotation between TASS variables and Form ADV variables, while the LASSO-based Ω-score directly aggregates litigation-related indicators from Form ADV. Because TASS is a proprietary data source primarily accessible to large institutional investors, these differences allow us to test whether government-mandated disclosures have become more informative relative to private-sector data.

We also report results using a LASSO-based *Ω*-score constructed solely from pre-Dodd variables, providing an intermediate benchmark that separates methodological differences from disclosure enhancement effects.

Figures 4A to 4E report results for fund flows, adverse liquidation, leverage, appraisal ratio, and alpha.[41] Higher *Ω*-scores generally predict fund outflows (yellow solid lines). Figure 4A shows that flow sensitivity to *Ω*-scores increases over time, particularly after 2017, and is strongest for the LASSO-based score using amended Form ADV disclosures. Interaction tests reported in Internet Appendix Table IA.2 (p.59) confirm that coefficients are significantly larger in the post-2016 period for the LASSO-based *Ω*-score.

[Insert Figure 4]

The blue dashed lines in Figure 4 represent predictions using the LASSO score based only on pre-Dodd variables. Before 2017, the pre-Dodd LASSO score outperforms the CCA metric, while the post-Dodd *Ω*-score dominates thereafter. Overall, both LASSO-based scores exhibit larger

[41] Detailed coefficients, *t/z* statistics, goodness-of-fit measures, and sample sizes can be found in Table IA.2 in the Internet Appendix (p.59).

elasticities and better fit than the CCA score. Moreover, the two LASSO measures display complementary strengths across the two five-year subsamples, particularly for fund flows and adverse liquidation, suggesting increasing investor use of expanded Form ADV disclosures in the later period.

[Insert Figure 5]

Figure 5 helps explain sharp increases in fund flow sensitivity observed in 2016 and 2020 (coefficient of -0.78 compared to -0.09 in 2015) and in 2020 (coefficient of -1.45 compared to -0.71 in 2019). Panel A of Table IA.2 (p.59) shows large jumps in the *Ω*-score coefficients in these years. Figure 5 documents spikes in litigation activity among advisory firms, which appear to precede heightened flow sensitivity by approximately one year. This pattern suggests that litigation waves may increase investor attention to operational risk, amplifying the impact of disclosed risk signals.

Results for adverse liquidation in Figure 4B and Table IA.2 (p.59) reveal a stark contrast. The CCA metric is significant only early in the sample and becomes insignificant thereafter, whereas the LASSO-based *Ω*-score is consistently significant in the second half of the period. This reverses the findings of BGLS and indicates a structural shift in how operational risk is assessed.

Leverage results in Figure 4C show a similar transition. The CCA metric performs better early on, while the LASSO metric dominates later, consistent with creditors and prime brokers increasingly incorporating post-Dodd disclosures into risk assessments. Figures 4D and 4E and Panel C of Table IA.2 (p.59) show that the LASSO-based *Ω*-score significantly predicts appraisal ratios and alpha from 2016 onward, with consistently larger and more significant coefficients than alternative measures. The *Ω*-score explains cross-sectional return differences beyond standard style and firm controls.

Finally, Internet Appendix Table IA.1 (p.58) reports summary statistics of out-of-sample Ω-scores by investment style. Dedicated short bias funds exhibit the lowest operational risk, while Undefined, Fixed Income Arbitrage, and Other Strategies show the highest scores, consistent with greater leverage and opacity.[42] Panel B documents a general decline in average operational risk after 2019, suggesting increased market awareness of operational risk management.

5.5 Litigation Charges Forecasting Future Adverse Outcomes and Fund Flows

Our previously developed LASSO metric is based on the correlation between the litigation records of funds' related firms and their submitted Form ADV variable filings. This raises a pertinent question: Does our ADV-based Ω Score provide better performance than using the litigation records alone? Specifically, is the LASSO score construction redundant compared to just using Item 11? In this section, we address this question.

Table 7 presents in-sample predictions for adverse outcomes and fund flows using a similar regression setup as in Sections 5.2 and 5.3, with the main difference being the replacement of the LASSO-based Ω-score with three types of litigation dummies as the key predictors. The variables $Regulatory_{i,t-1}$, $Criminal_{i,t-1}$, and $Civil\ Judicial_{i,t-1}$ are binary indicators (0 or 1) for violations by fund i 's related firm in the previous year.

[Insert Table 7]

Panel A reports forecasting results for performance, leverage accessibility, and adverse liquidation outcomes. The predictive power of the three dummies seems most effective in terms

[42] Cumming et al. (2020) document style-based heterogeneity in post–Dodd-Frank fund flows. We account for these differences by including style fixed effects and clustering standard errors by style in all panel regressions. In addition to acknowledging cross-style heterogeneity, our analysis focuses on industry-wide effects of enhanced operational risk disclosure following Dodd–Frank. Importantly, our fund flow predictions rely on direct, post–Dodd-Frank operational risk measures rather than a generic regulatory dummy. Our results suggest that the amended Form ADV provides more material operational risk information, which investors and creditors increasingly incorporate over time.

of performance. The previous regulatory indicator can predict alpha effectively, while previous criminal indicators are more aligned with predicting the appraisal ratio. However, none of the three indicators plays a significant role in predicting leverage or adverse liquidation. Panel B presents fund flow prediction results, showing that almost none of the three types of dummies can effectively predict flows.

In summary, compared to the results in Tables 5 and 6, we demonstrate that using the LASSO method to select variables and determine their related weights for a unidimensional but comprehensive operational risk metric is necessary. The litigation indicators reflect outcomes for cases and firms that have been caught, whereas our ADV-based Omega score assesses and attributes variables 'one step ahead', potentially leading to failure due to the nature of poor operational risk management.

6. Discussion

The post-Dodd-Frank Form ADV is especially valuable because of its expanded scope and richer operational risk disclosures, including precise litigation dates and detailed descriptions of sanctions involving advisors and related parties. Our results show that SEC-mandated disclosures alone can still support effective prediction of fund failure and related outcomes. More importantly, they reveal a dynamic interaction among funds, regulators, lenders, and investors. The Dodd-Frank Act enabled regulators to refine Form ADV based on lessons from the pre-Dodd regime, and these enhancements provide materially improved information for assessing risk and returns.

A key finding is that, for outcomes such as liquidation, the predictive value of pre-Dodd Form ADV variables declines over time, while the expanded post-Dodd disclosures gain importance. This pattern is consistent with strategic adaptation by funds under a previously stable disclosure regime and highlights the need for dynamic regulatory design alongside predictable rules.

Lenders, another strategic group in hedge fund markets, have strong incentives to avoid high-risk funds. Consistent with this, access to leverage is negatively related to operational risk, while disclosed credit relationships signal quality to other investors. Hedge fund investors also respond to SEC-mandated disclosures: non-investment information such as conflicts of interest and governance characteristics appears to be material to fund flows, even if the information is processed indirectly through intermediaries.

Investor sensitivity to operational risk strengthens over time rather than immediately following the 2008 crisis, suggesting a learning process regarding the informational content of post-Dodd Form ADV disclosures. Overall, the post-Dodd enhancements to Form ADV represent a clear success for the SEC, improving transparency and enabling meaningful market discipline without replacing private information channels. Relative to prior work, our contribution lies in broader data coverage, methodological innovation, a richer regulatory setting, stronger market responses, and superior predictive performance of the operational risk score.

Beyond hedge funds, our findings have broader implications for banks, insurers, and other financial intermediaries that rely on due diligence and risk modeling. The evolving informativeness of Form ADV illustrates how standardized public disclosures can complement proprietary assessments in credit allocation, counterparty evaluation, and governance, underscoring the value of regulatory adaptability in managing operational risk across the financial system.

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Figure 1 Predicted Increased in Litigation Cases and Firm Death Against Accumulative AUM in 2023

This figure illustrates the 'Value at Risk' analysis for predicted increase in litigation and firm liquidation probability against real accumulative assets under management (AUM) in the 2023 TASS-ADV matched live fund sample.[43] The analysis uses data from the TASS-ADV matched fund-firm sample for 2023, leveraging ADV filing records from 2021 to estimate probabilities using a two-lag model (post-2011) with 44 variables.

Figure 1A shows the predicted adverse liquidation probability against the accumulative AUM. The liquidation probability is estimated by using a Cox proportional hazards model:

$$\hat{h}_{i,2023}(T) = \hat{h}_{0i}(T) \times \exp\left(\widehat{\boldsymbol{\beta}}_{\boldsymbol{ORV}} \boldsymbol{X}_{\boldsymbol{ORV\ i,2021}} + C_{2021}^{'}\hat{\delta}_{C} + \hat{\delta}_{U} Umbrella_{i,2021} + \sum_{f=1}^{353} \hat{\theta}_f FirmDummies_{fi}\right)$$

Where $\hat{h}_{i,2023}(T)$ is the predicted adverse liquidation probability with age T for fund i in 2023. $\boldsymbol{X}_{\boldsymbol{ORV\ i,t-2}}$ represents operational risk-related variables from the post-2011 (amended) Form ADV for the fund company i in year 2021.[44] The chart includes a yellow dashed line representing the total accumulative AUM in the sample ($188.86 billion). Labeled points indicate unaffected asset values (Total AUM minus the cumulative AUM) at 5.24%, 10.05%, 16.36%, 20.09%, and 50.05% predicted death probabilities.

Figure 1B presents the predicted increase in litigation cases using a logit model:

$$Pos\Delta\widehat{ProblemNum}_{i,2023} = \hat{\alpha}_i + \widehat{\boldsymbol{\beta}}_{\boldsymbol{ORV}} \boldsymbol{X}_{\boldsymbol{ORV\ i,t-2}} + \sum_{j=1}^{353} \hat{\theta}_f FirmDummies_{ji}$$

Where $Pos\Delta\widehat{ProblemNum}_{i,t}$ is the predicted positive litigation change probability, representing whether there will be a positive change of the sum of the three Form ADV violation category dummies for a fund company i in year 2023.[45] The chart includes a yellow dashed line representing the total accumulative AUM in the sample ($213.82 billion). Labeled points indicate unaffected asset values at predicted probabilities of 0.38%, 1.00%, 1.22%, 1.40%, and 5.00%.

[43] Specifically, it is the estimated minimum dollar amount of estimated fund AUM at risk of liquidation within the next two years period (starting from 2021). We only include the firms that with AUM reported in the TASS database in 2023.

[44] C_{2021} represents a vector of variables, including average and standard deviation of monthly returns, leveraged, onshore, and high-water mark indicators, log of assets, and fund management fee in year 2021. $\hat{h}_{0i}(T)$, $\widehat{\boldsymbol{\beta}}_{\boldsymbol{ORV}}$, $\hat{\delta}_C$, and $\hat{\theta}_f$ are derived from the two-lag model presented in Appendix Table A.3 (p.56).

[45] $\hat{\alpha}_i$, $\widehat{\boldsymbol{\beta}}_{\boldsymbol{ORV}}$ and $\hat{\theta}_f$ are estimated from the two-lag model presented in Table 3. The decreased total AUM for the death prediction sample compared to the increased litigation change sample is attributed to the exclusion of certain firms due to missing firm characteristics (C_{2021}) in the TASS database.

Figure 1A Predicted Adverse Liquidation Probability and Accumulative AUM in 2023

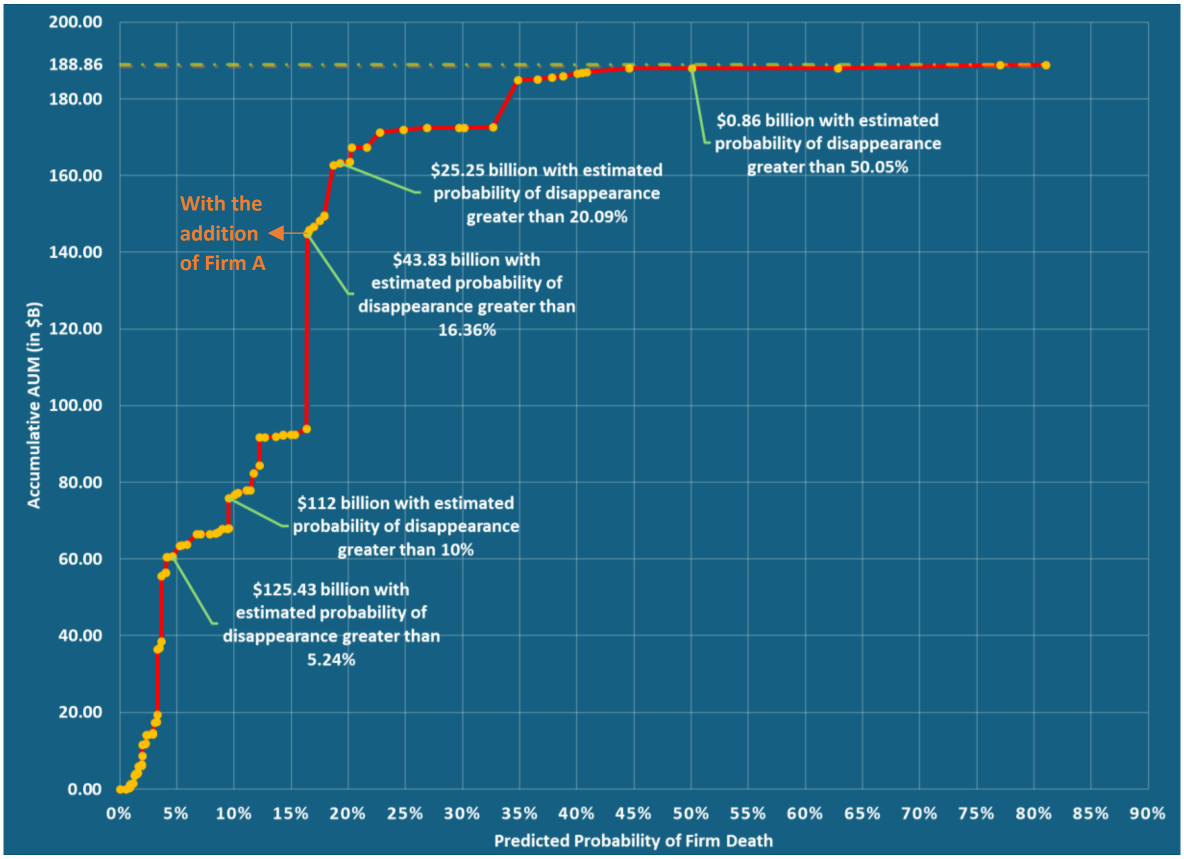

Figure 1B Predicted Increased Litigation Changes and Accumulative AUM in 2023

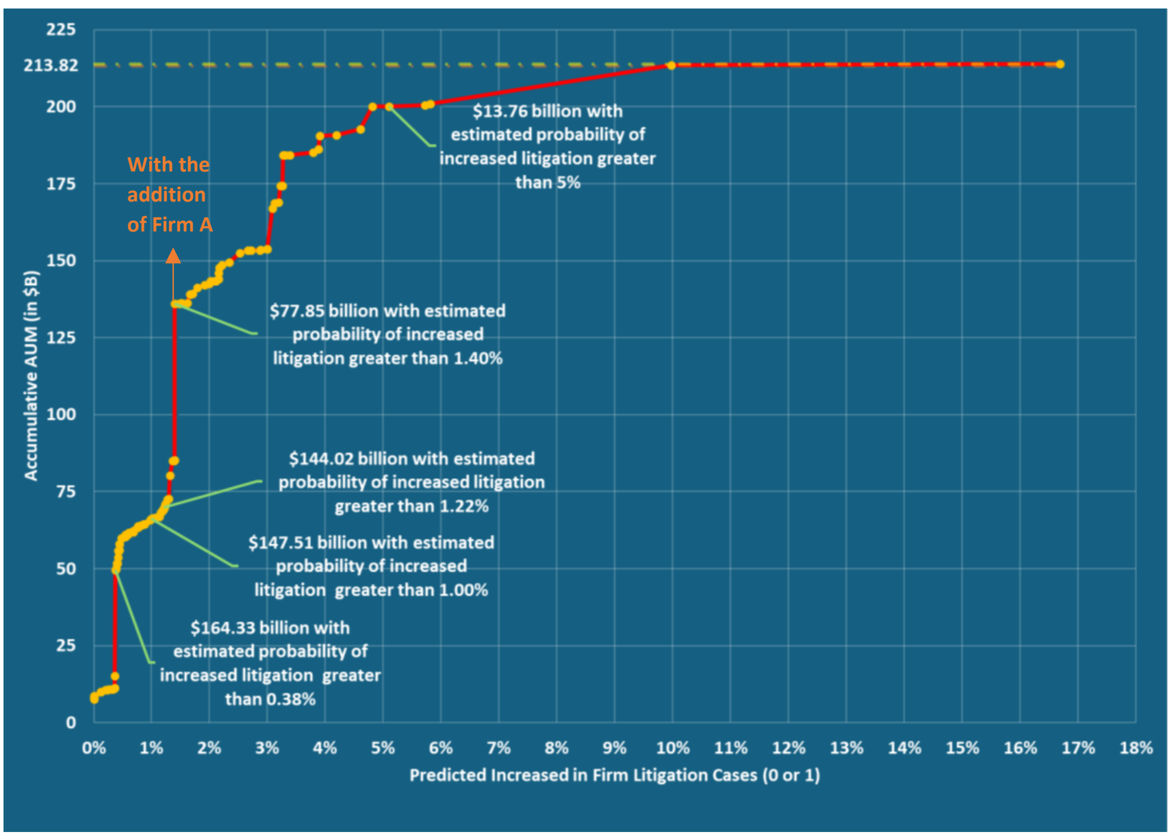

Figure 2 Word Clouds for Sanction Descriptions

This set of figures shows Word Clouds for the sanction descriptions of problem advisory companies involved in regulatory charges, criminal offenses, and civil judicial matters according to Form ADV and the related Disclosure Reporting Page (DRP). Words with larger sizes indicate higher mention frequencies.

Figure 2A Word Cloud for Regulatory Sanctions

Figure 2B Word Cloud for Criminal Sanctions

Figure 2C Word Cloud for Civil Judicial Sanctions

Figure 3 PCA Explained Variance Plot for Amended Form ADV Filings Variables

This figure presents the explained variance for the 44 orthogonal dimensions according to the amended Form ADV Filings from January 2012 to December 2022 panel sample of RIA funds.

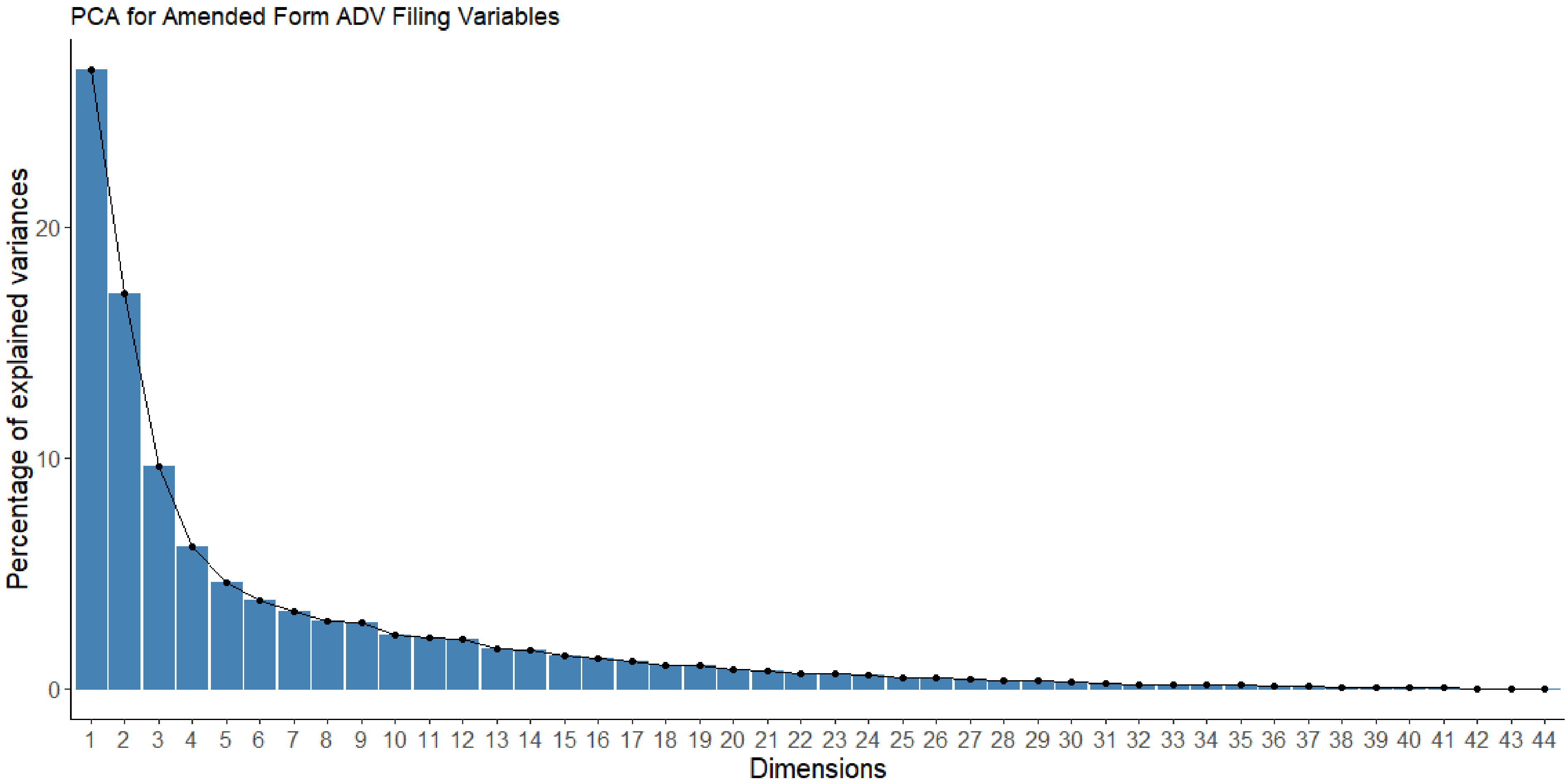

Figure 4 Operational Risk Scores Predicting Flows, Adverse Liquidation, Leverage, and Performance (OOS)

This set of figures presents the adverse outcomes out-of-sample (OOS) prediction by using the Canonical Correlation Analysis (CCA; pre-Dodd), and LASSO-constructed *Ω*-scores (pre- and post-Dodd variables) for RIA funds (Operational risk score). Figures 4A, 4B, 4C, 4D, and 4E present the fund flows, adverse liquidation, leveraged or not, appraisal ratio, and alpha cross-sectional predictions according to the equation:

$$Flow_{i,t} = \alpha_{i,t} + \beta_1\ Operational\ risk\ score_{i,t-1} + \delta_1\ High\ trank_{i,t-1} + \delta_2 Mid\ trank_{i,t-1} + \delta_3 Low\ trank_{i,t-1} + \delta_4 Log\ assets_{i,t-1} + \delta_5 Stdev_{i,t-1} + \delta_6 Management\ fee_{i,t-1} + \delta_U Umbrella_{i,t-1} + \sum_{j=1}^{13} \gamma_j StyleDummies_{ji} + \sum_{q=1}^{9} \eta_q YearDummies_{qi} + \varepsilon_{i,t}$$

$$Leverage_{i,t}\ or\ Appraisal\ ratio_{i,t}\ or\ Alpha_{i,t} = \alpha_{i,t} + \beta_1 Operational\ risk\ score_{i,t-1} + C_{t-1}^{'}\delta_C + \delta_U Umbrella_{i,t-1} + \sum_{j=1}^{13} \gamma_j StyleDummies_{ji} + \sum_{q=1}^{9} \eta_q YearDummies_{qi} + \varepsilon_{i,t}$$

$$h_{i,t}(T) = h_{0i,t}(T) \times \exp\left(\beta_1 Operational\ risk\ score_{i,t-1} + C_{t-1}^{'}\delta_C + \delta_U Umbrella_{i,t-1} + \sum_{j=1}^{13} \gamma_j StyleDummies_{ji} + \sum_{q=1}^{9} \eta_q YearDummies_{qi}\right)$$

Each line (except the red dot with square markers) shows β_1 coefficients for each year. The blue dashed line with diamond markers represents CCA-constructed scores (pre-Dodd), the pink dashed line with circles, and the yellow solid line with triangles represent LASSO-constructed scores (pre- and post-Dodd). These scores predict fund flows, adverse liquidations, leverage, and performance. The red dotted line with square markers in Figure 4A indicates the annual number of news mentions of 'Madoff,' 'Operational Risk,' or 'Hedge Fund Failure' from the RavenPack database. Table IA.2 (p.59) in the Internet Appendix presents detailed coefficients, *t*/*z* statistics, goodness-of-fit measures, and sample sizes.

Figure 4A Out-of-Sample Fund Flow Elasticities and Operational Risk News Frequency

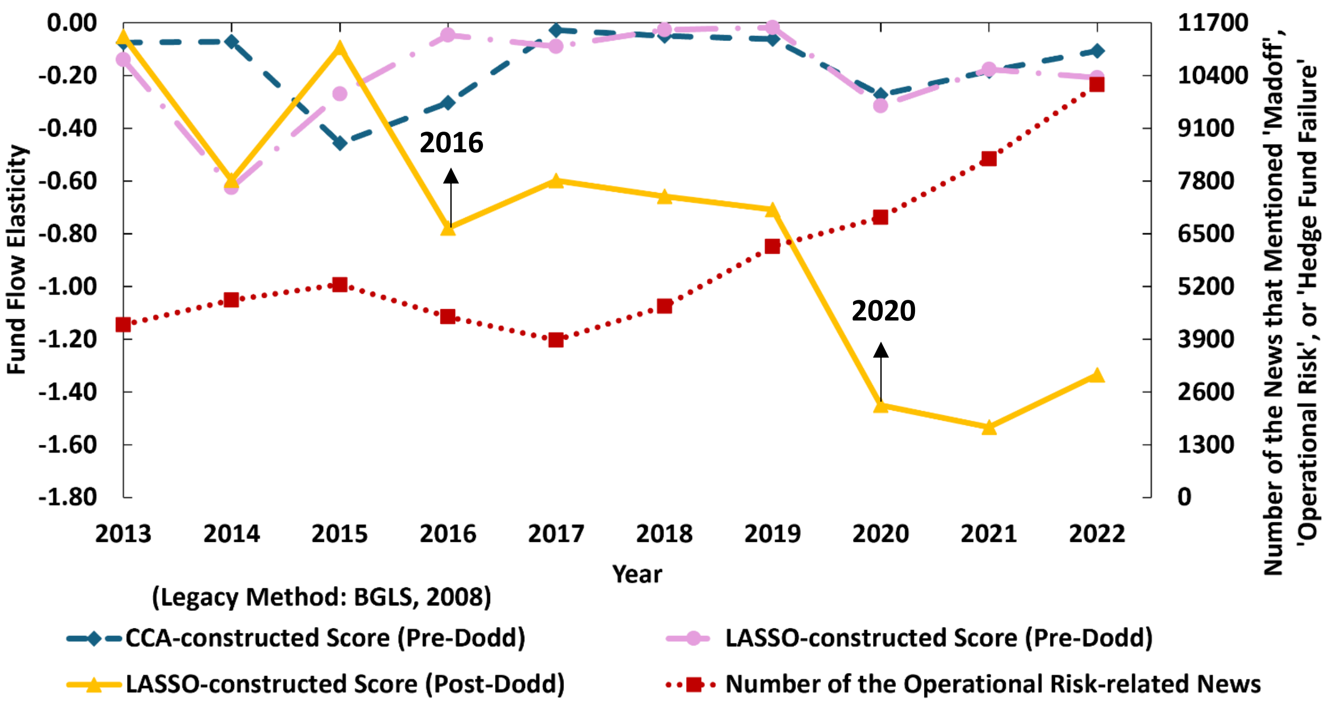

Figure 4B Out-of-Sample Adverse Liquidation Elasticities

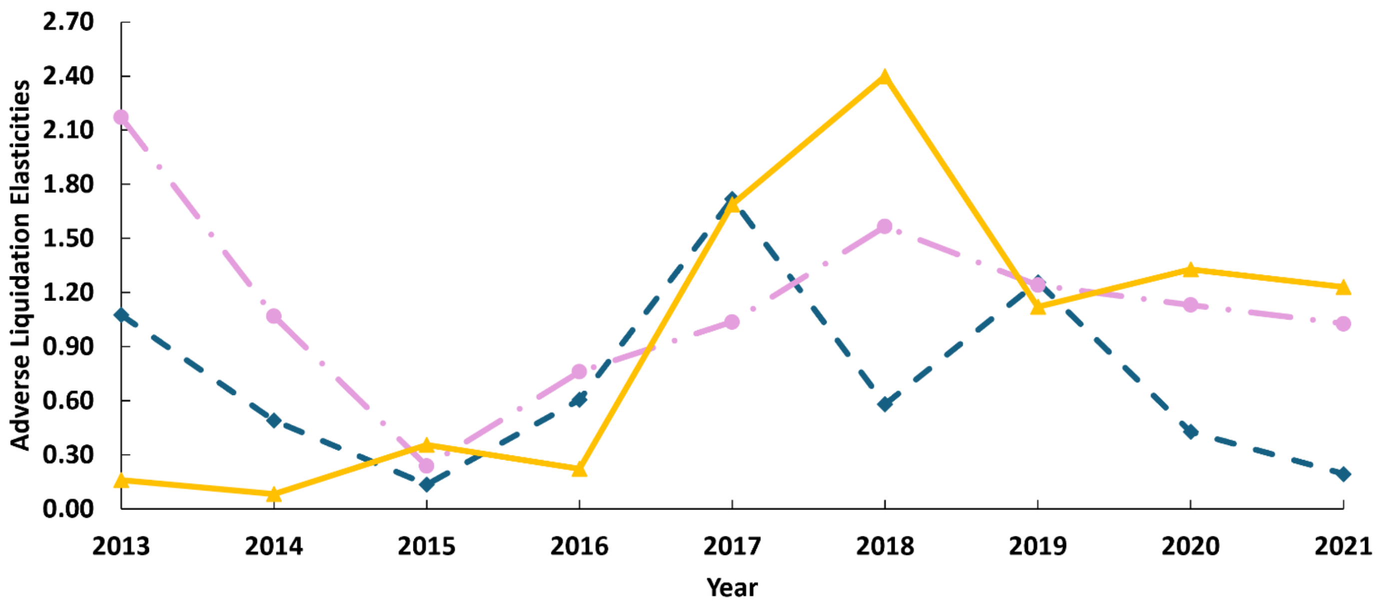

Figure 4C Out-of-Sample Leveraged Elasticities

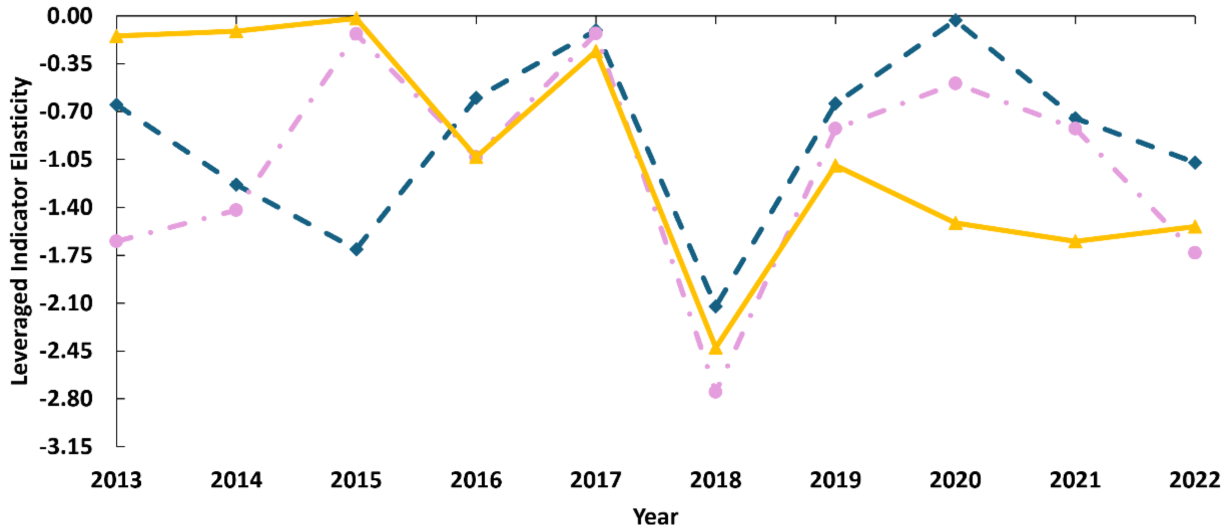

Figure 4D Out-of-Sample Appraisal Ratio Elasticities

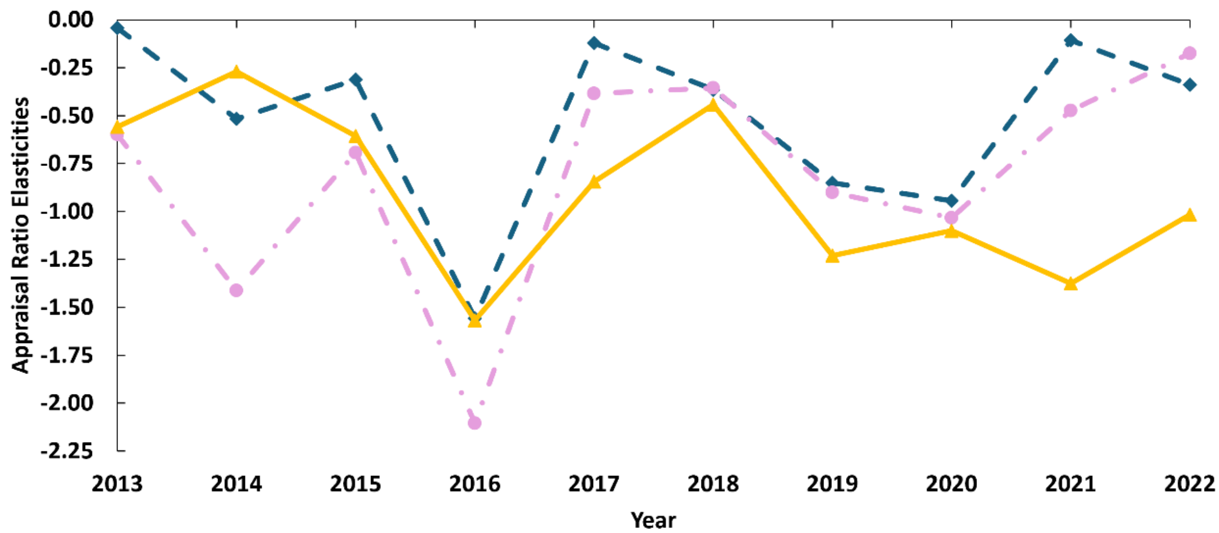

Figure 4E Out-of-Sample Alpha Elasticities

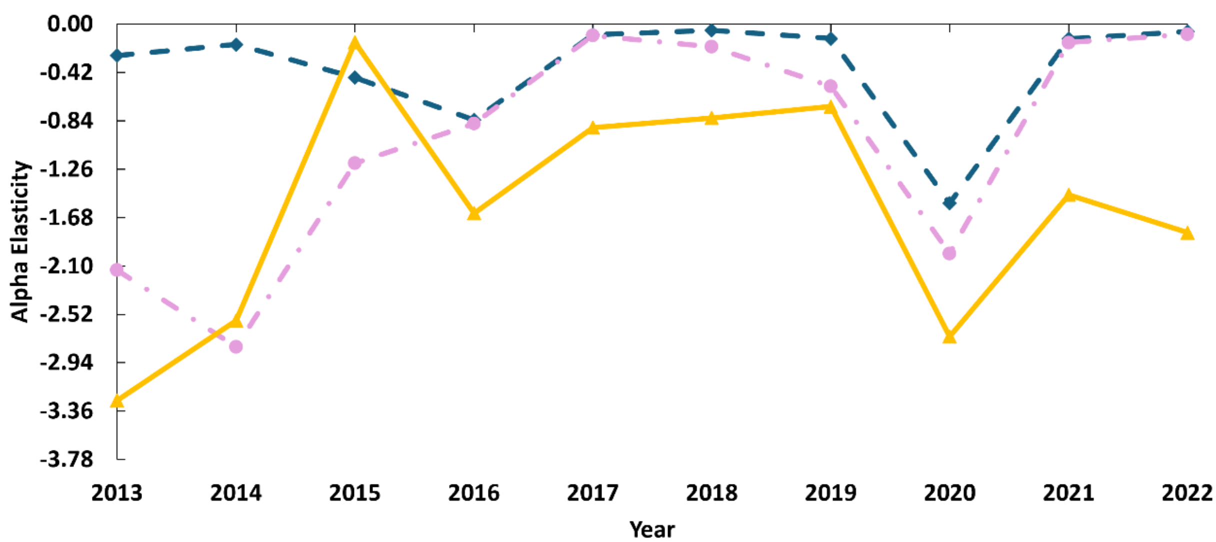

Figure 5 Number of Charges Violated by Advisory Firms and Affiliates

This figure illustrates the number of charges received by advisory firms and their affiliates from 2012 to 2022. The orange solid line (corresponding to the right y-axis) represents the violations committed by affiliates of the funds' related firms, while the green dashed line (corresponding to the left y-axis) represents the violations committed solely by the funds' related firms.

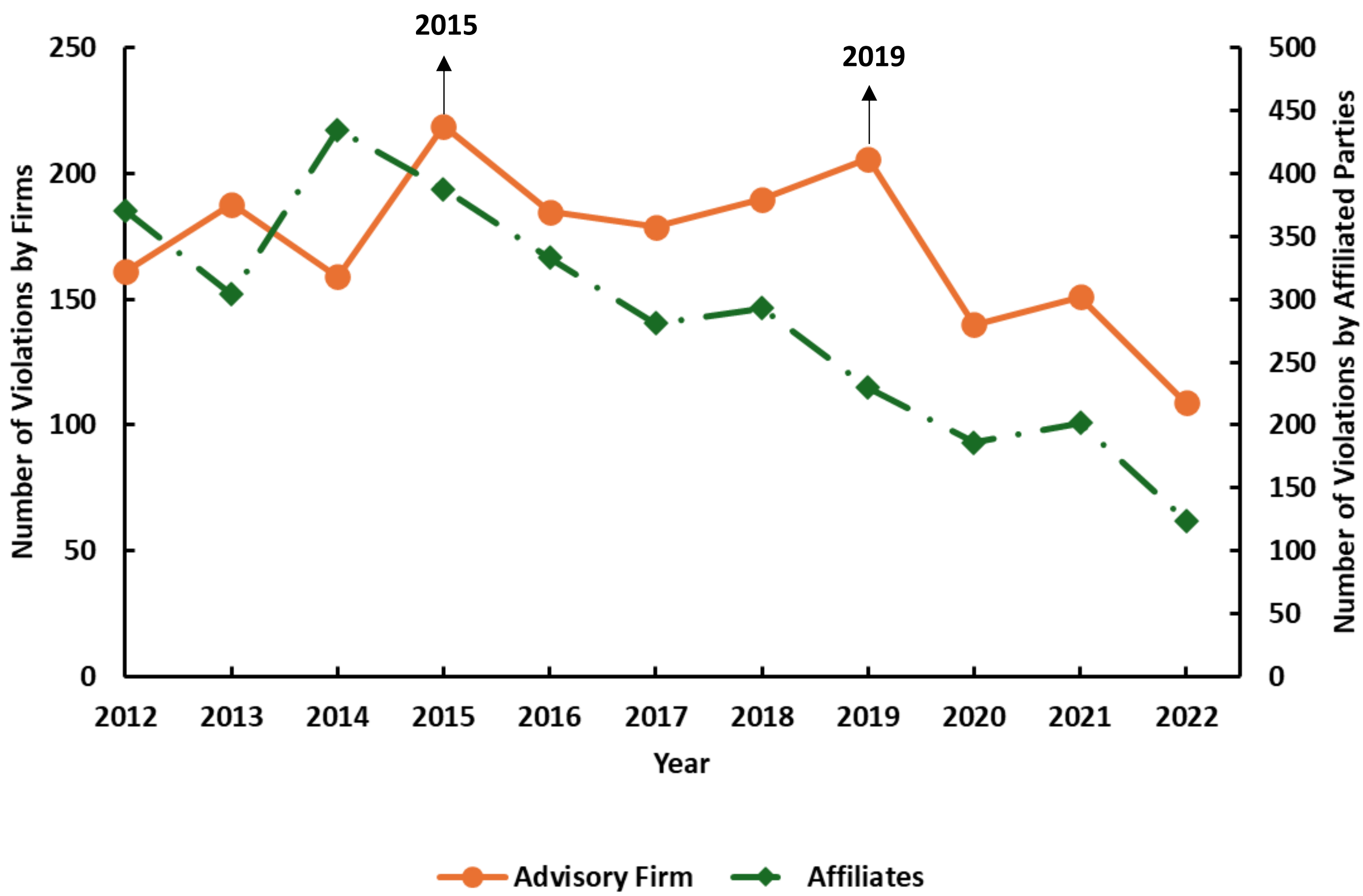

Table 1 Descriptive Statistics of TASS and Matched RIA Funds Panel Sample

This table reports descriptive statistics for RIA funds in the TASS database that have Form ADV filed by their advisory companies. The TASS live and dead (all TASS) funds include those in TASS with at least one month of return data for a given year. Within the RIA funds, we differentiate between Umbrella Registration (UR) and non-UR RIA funds.[46] Columns 13 and 14 show the *t*-test between UR-RIA funds and all TASS funds. Columns 15 and 16 compare non-UR RIA funds with all TASS funds. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively.

	UR RIA			Non-UR RIA			All TASS Live and Dead Funds			UR RIA vs TASS		Non-UR RIA vs TASS	
	N	Mean	Median	N	Mean	Median	N	Mean	Median	Diff		Diff	
Return	929	0.55	0.51	5,037	0.26	0.26	11,782	0.32	0.29	0.22	***	-0.06	
Stdev.	926	1.67	1.16	5,034	2.05	1.55	11,776	2.62	1.61	-0.95	***	-0.58	***
Skewness	926	-0.10	-0.11	4,966	0.00	0.02	11,752	-0.11	-0.11	0.00		0.10	***
Kurtosis	926	-0.64	-0.86	4,966	-0.71	-0.83	11,752	-0.67	-0.81	0.02		-0.04	***
1st-order AC	926	-0.06	-0.06	4,966	-0.02	-0.03	11,752	-0.04	-0.04	-0.03	***	0.02	***
Sharpe ratio	575	0.42	0.31	4,736	0.44	0.20	11,752	0.26	0.20	0.16	***	0.19	***
Appraisal ratio	405	0.84	0.41	3,598	0.72	0.54	11,782	0.21	0.13	0.63	***	0.51	***
Alpha	581	0.23	0.22	4,839	-0.02	0.04	11,782	0.08	0.13	0.16	**	-0.09	**
Management fee	905	1.41	1.50	4,928	1.36	1.50	11,430	1.41	1.50	0.00		-0.05	***
Incentive fee	732	13.86	20.00	4,490	13.27	20.00	10,259	12.64	15.00	1.22	***	0.63	
Min. Invt. ($M)	894	2.23	0.50	4,987	2.46	0.12	11,677	2.22	0.10	0.01		0.24	
Asset ($M)	635	1,761.35	77.35	3,088	211.03	57.23	7,293	288.95	45.22	1472.40		-77.92	
Fund age	929	12.29	11.00	5,037	9.11	8.00	11,782	8.32	7.50	3.97	***	0.80	***
Leveraged	929	0.46	0.00	5,037	0.43	0.00	11,782	0.45	0.00	0.01		-0.02	
Margin	546	0.27	0.00	2,735	0.26	0.00	6,135	0.24	0.00	0.03	***	0.02	
High water mark	926	0.53	1.00	5,011	0.52	1.00	11,630	0.50	0.33	0.04	**	0.02	***
Lockup period	929	2.96	0.00	5,037	2.03	0.00	11,782	1.69	0.00	1.28	***	0.34	***
Sub. Freq.	929	17.15	21.00	5,037	16.91	21.00	11,782	15.72	21.00	1.42	***	1.18	***
Red. Freq.	929	39.49	21.00	5,037	31.19	21.00	11,782	26.77	21.00	12.72	***	4.43	***

[46] The 929 UR RIA funds include 52 consistently UR RIA, 783 with changing UR status, and 94 with changes in both RIA ERA and UR Non-UR status. The 5,037 non-UR RIA funds comprise 3,984 consistently Non-UR RIA, 176 with changing UR status, and 94 with changes in both RIA ERA and UR Non-UR status.

Table 2 Univariate Analysis: Comparison of Problem and Nonproblem RIA Funds

This table reports fund-level performance and characteristics univariate analysis for Problem and Non-problem RIA funds.[47] 'Problem Funds' are defined as those managed by advisory companies that, at any point during our 11-year sample period, reported regulatory violations, criminal offenses, or civil judicial matters in Item 11 or the Disclosure Reporting Page (DRP) of Form ADV. The last two columns present the *t*-test for Problem and Nonproblem funds. ***, **, * indicate the statistically significant at the 1%, 5%, and 10% levels, respectively.

	Problem			Non-problem				
	N	Mean	Median	N	Mean	Median	Diff	
Return	896	0.27	0.27	4,196	0.29	0.30	-0.02	
Stdev.	896	2.14	1.61	4,193	1.58	1.26	0.56	***
Skewness	894	-0.08	-0.09	4,128	-0.19	-0.19	0.10	***
Kurtosis	894	-0.72	-0.86	4,128	-0.70	-0.83	-0.02	
1st-order AC	894	0.01	-0.01	4,128	-0.03	-0.04	0.03	***
Sharpe ratio	856	0.39	0.27	3,915	0.46	0.18	-0.07	
Appraisal ratio	719	0.80	0.41	2,929	1.04	0.44	-0.24	*
Alpha	860	-0.03	0.04	4,014	0.08	0.09	-0.10	***
Management fee	865	1.29	1.50	4,113	1.42	1.50	-0.13	***
Incentive fee	745	11.96	15.00	3,781	13.50	20.00	-1.55	***
Min. Invt. ($M)	876	1.35	0.08	4,166	2.67	0.17	-1.33	
Asset ($M)	557	181.49	58.46	2,581	566.12	57.19	-384.63	
Personal Capital ($M)	792	0.41	0.00	3,643	3.06	0.00	-2.65	***
Fund age	896	8.69	7.50	4,196	9.32	8.00	-0.63	***
Leveraged	896	0.40	0.00	4,196	0.47	0.00	-0.08	***
Margin	389	0.21	0.00	2,424	0.27	0.00	-0.06	***
High water mark	890	0.43	0.00	4,182	0.54	1.00	-0.11	***
Lockup period	896	0.71	0.00	4,196	2.35	0.00	-1.64	***
Sub. Freq.	896	14.99	21.00	4,196	17.32	21.00	-2.33	***
Red. Freq.	896	25.75	21.00	4,196	32.74	21.00	-6.99	***

[47] Among the 896 problem RIA funds, 881 are consistently problem RIA funds, while 15 experienced changes in RIA ERA status but had problem records during their time as RIA funds. Of the 4,196 non-problem funds, 3,938 are consistently non-problem RIA funds, and 258 experienced RIA ERA status changes but remained non-problematic during their time as RIA funds.

Table 3 Changes of Disciplinary History Predictions Using Lagged Operational Risk Variable

This table reports the result of tests on whether the additional operational risk-related variables (Items 7-10) in the amended Form ADV in the post-Dodd (Post-2011) period improve the Problem Firm (disciplinary history) identification and predictions for the RIA sample, using contemporary and lagged operational risk variables, in the pre-Dodd (Pre-2011) period.[48] The presented panel reports changes in the predictive power for disciplinary history. Logit specifications are compared using likelihood ratio tests (LRTs), while OLS and cumulative link mixed model (CLMM) specifications are evaluated using F-tests and LRTs,[49] respectively, based on the following specification:

$$PosΔProblemNum_{i,t} \text{ or } ΔProblemNum_{i,t} = \alpha_{i,t} + \boldsymbol{\beta_{ORV}} \boldsymbol{X_{ORV\ i,t-l}} + \sum_{j=1}^{N} \gamma_j FirmDummies_{ji} + \sum_{q=1}^{9-l} \eta_q YearDummies_{qi} + \varepsilon_{i,t}$$

Where $\Delta ProblemNum_{i,t}$ is a variable representing the changes of the sum of the three Form ADV violation category dummies (ranging from 0 to 3) for a fund company i in year t. $Pos\Delta ProblemNum_{i,t} = \mathbf{1}(\ \Delta ProblemNum_{i,t} > 0)$ is a binary variable representing if there is a positive change of the sum of the three Form ADV violation category dummies for a fund company i in year t. $\boldsymbol{X_{ORV\ i,t}}$ represents operational risk-related variables from the pre-2011 or post-2011 (amended) Form ADV for the fund company i in year t. N is the total number of firms during the regression period, and l is the number of lags (ranges from 0 to 4). Both the pre-Dodd and post-Dodd models include the firm and year dummies. ***, **, * indicate the statistically significant at the 1%, 5%, and 10% levels, respectively.

		LRT (Logit)			*F*-test (OLS)			LRT (CLMM)		
Lag(s)	Model	*Deviance*	*p*-value		*F*	*p*-value		χ^2	*p*-value	
0	Pre-2011									
	Post-2011	40.84	0.09	*	2.93	0.00	***	42.77	0.06	*
1	Pre-2011									
	Post-2011	62.13	0.00	***	5.19	0.00	***	46.81	0.03	**
2	Pre-2011									
	Post-2011	70.76	0.00	***	5.66	0.00	***	63.65	0.00	***
3	Pre-2011									
	Post-2011	37.71	0.16		0.93	0.57		41.42	0.08	*
4	Pre-2011									
	Post-2011	37.71	0.16		0.68	0.91		17.26	0.97	

[48] Since Form ADV is submitted annually by advisory companies, we conduct firm-level tests for the analyses in this table.
[49] Partial F test: $(SSR_R - SSR_F/p)/(SSR_F/n-k)$, where SSR_R and SSR_F represent the sum of squared residuals for the reduced model (pre-2011) and the full model (post-2011), respectively. p is the number of the variables removed from the post-2011 model, n is the total observations in our panel sample, and k is the number of the coefficients (including the intercept) in the post-2011 model. Likelihood-ratio test (LRT): $-2log_e(\mathcal{L}_R(\hat{\theta})/\mathcal{L}_F(\hat{\theta})) = Deviance_R - Deviance_F$. Where R and F represent reduced (pre-2011) and the full model (post-2011), respectively.

Table 4 LASSO Regression and Relative Importance

This table presents the results for estimating the following equation using a LASSO regression model (Tibshirani, 1996):

$$\min_{\beta_j} \sum_{i=1}^{n}\left(ProblemNum_{i,t} - \sum_{j=1}^{p} \boldsymbol{X}_{\boldsymbol{ORV\ i,t,j}}\boldsymbol{\beta}_{\boldsymbol{ORV\ i,t,j}}\right)^2 + \lambda \sum_{j=1}^{p}|\beta_j|$$

Where n is the total number of observations for RIA firms. $ProblemNum_{i,t}$ represents the sum of problem dummies reported for the company i in year t (regulatory issues, criminal offenses, and civil judicial matters). $\boldsymbol{X}_{\boldsymbol{ORV\ i,t,j}}$ is the set of the 44 operational risk-related variables in the amended Form ADV filed by fund i's related advisory company in year t, plus one intercept term ($p = 45$), and λ is the tuning parameter.[50]

Panel A shows LASSO coefficients for the top 10 variables, with external versus internal (E/I) classification, pre-/post-Dodd-Frank status (O/N; pre-2011/post-2011), and importance ranks based on absolute coefficient values. Panel B summarizes selected variables by period and category, reporting counts, percentages, and ranks. Panel C presents Kruskal–Wallis tests[51] comparing variable importance.

Panel A: LASSO Regression Result for RIA Funds (Top 10 Important Variables)

Variable	Coef.	External vs. Internal	Old vs. New	Importance	Rank
FuturesCommission	0.22	E	N	0.22	1
SwapDealer	0.19	E	N	0.19	2
OtherControlCompany	-0.19	I	N	0.19	3
Insurance	0.09	E	O	0.09	4
RelatedQualifiedCustodian	0.09	I	N	0.09	5
Trust	0.08	E	N	0.08	6
OtherControlPerson	0.08	I	N	0.08	7
AgencyCrossTransaction	0.07	I	O	0.07	8
AdvisorQualifiedCustodian	0.07	I	N	0.07	9
BankingThrifting	0.07	E	O	0.07	10

Panel B: Summary Statistics for the LASSO-selected Operational Risk-related Variables

		Num. of the Selected Variables	% of selected O/N or E/I variables	Median Rank	Sum Rank
Old vs New	Post-2011	23.00	65.71%	15.00	361.00
	Pre-2011	12.00	34.29%	23.50	269.00
External vs Internal	External	16.00	45.71%	13.50	256.00
	Internal	19.00	54.29%	21.00	374.00

Panel C: Relative Importance Comparison–Kruskal-Wallis Test

	Pre-2011 vs. Post-2011	External vs. Internal
H	136,347.83	133,567.44
p-value	0.00	0.00
Decision	**Post-2011**	**External**

[50] λ is the tunning parameter, which is optimally found by choosing the value that returns us the smallest MSE according to the 10-fold cross-validation for the LASSO regression.

[51] The H Statistic is calculated by $H = \left[12/\left(n(n+1)\right)\sum_{j=1}^{c} T_j^2/n_j\right] - 3(n+1)$. Where n is the total sample size for all groups, c is the number of the groups (in our case, it equals to 2), T_j is the sum of the ranks in the jth group, and n_j is the size of the jth group.

Table 5 ADV-based Ω-score and Future Adverse Outcomes

This table presents the result of estimating a prediction model for adverse outcomes. Panel A presents fund performance, characteristics, and survival analysis using a unidimensional operational risk score. Panel B reports predictions of problem charges using the same score. Panel A reports Models 1 to 3, estimating the effects of the ADV-based Ω-score on fund alpha, appraisal ratio, and the leveraged indicator. Panel B reports Models 1 to 3 using the same specification, with dependent variables given by indicators for regulatory, criminal, and civil judicial charges,[52] respectively, as defined in the equation below ($ADV - Based\ \Omega\ score_{i,t}$ is the LASSO-based score described in section 5):

$$Appraisal\ ratio_{i,t}\ or\ Alpha_{i,t}\ or\ Leverage_{i,t}\ or\ Regulatory_{i,t}\ or\ Criminal_{i,t}\ or\ Civil\ Judicial_{i,t} = \alpha_{i,t} + \beta_1 ADV - Based\ \Omega\ score_{i,t-1} + C_{t-1}^{'\delta_C} + \delta_U Umbrella_{i,t-1} + \sum_{j=1}^{13} \gamma_j StyleDummies_{ji} + \sum_{q=1}^{9} \eta_q YearDummies_{qi} + \varepsilon_{i,t}$$

Model 4 in Panel A presents the liquidation event prediction using the ADV-based Ω-score according to the equation below:

$$h_{i,t}(T) = h_{0i,t}(T) \times \exp\left(\beta_1 ADV - Based\ \Omega\ score_{i,t-1} + C_{t-1}^{'\delta_C} + \delta_U Umbrella_{i,t-1} + \sum_{j=1}^{13} \gamma_j StyleDummies_{ji} + \sum_{q=1}^{9} \eta_q YearDummies_{qi}\right)$$

The alpha and appraisal ratio prediction results in Panel A are reported with the clustered standard error for TASS style and year. All models in both Panels control the TASS-style and year dummies for predictions. ***, **, * indicate the statistically significant at the 1%, 5%, and 10% levels, respectively.

Panel A: ADV-based Ω Score predicts fund performance, leverage, and liquidation												
	Model 1			Model 2			Model 3			Model 4		
	Alpha			Appraisal Ratio			Leveraged			Adverse Liquidation Events		
	Coef.	*t*-Value		Coef.	*t*-Value		Coef.	*z*-Value		Coef.	*z*-Value	
ADV-based Ω Score	-0.26	-4.21	***	-0.56	-3.22	***	-0.30	-2.89	***	1.38	3.90	***
Return							0.06	2.04	**	-0.48	-6.64	***
Stdev.	-0.07	-5.25	***	-0.22	-9.38	***	0.02	1.67	*	-0.02	-0.65	
Management fee	0.02	1.61		0.36	9.00	***	0.20	5.22	***	-0.07	-0.73	
Log(Asset)	0.02	3.00	***	0.01	0.65		0.00	0.18		-0.36	-7.79	***
Leveraged	0.02	0.75		0.02	0.33					-0.14	-1.24	
Onshore	0.08	2.78	***	0.18	4.65	***	0.41	7.60	***	-0.49	-3.65	***
High water mark	0.07	2.40	**	0.37	7.26	***	0.29	5.42	***	-0.16	-1.31	
Umbrella	0.17	2.18	**	0.38	4.34	***	0.45	2.87	***	-0.43	-1.06	
Style	Y			Y			Y			Y		
Year	Y			Y			Y			Y		
Num. of Obs.	6,261			3,786			7,267			7,267		
Adj. R^2	4.97%			17.20%								
Pseudo R^2							14.98%					
Concordance										79.10%		

[52] $Regulatory_{i,t}$, $Criminal_{i,t}$, and $Civil\ Judicial_{i,t}$ are binary variables (0 or 1) that represent if a fund i's related company has any regulatory charges, criminal offenses, or civil judicial matters in year t.

Table 5 Continued

Panel B: ADV-based Ω Score predicts Regulatory, Criminal, and Civil Judicial Charges

	Model 1			Model 2			Model 3		
	Regulatory			Criminal			Civil Judicial		
	Coef.	z-Value		Coef.	z-Value		Coef.	z-Value	
ADV-based Ω Score	9.02	8.61	***	14.19	5.65	***	3.18	3.22	***
Return	-0.18	-1.90	*	1.48	2.01	**	-0.02	-0.08	
Stdev.	0.00	-0.03		-2.50	-2.50	**	-0.70	-1.84	*
Management fee	0.02	0.54		0.40	1.77	*	0.16	1.14	
Log(Asset)	-0.01	-0.22		-0.46	-0.94		-0.23	-0.87	
Leveraged	0.08	1.85	*	-1.28	-3.11	***	0.28	2.24	**
Onshore	-0.70	-4.77	***	-1.44	-1.13		-0.79	-1.77	*
High water mark	-0.43	-3.09	***	-1.41	-1.76	*	-1.39	-2.84	***
Umbrella	-2.54	-4.49	***	-11.71	0.00		-9.07	-0.01	
Style	Y			Y			Y		
Year	Y			Y			Y		
Num. of Obs.	7,267			7,267			7,267		
Pseudo R^2	41.74%			63.69%			27.67%		

Table 6 ADV-based *Ω*-score Predicting Fund Flows

This table presents the result of estimating the following model of RIA fund flow as a function of the LASSO-constructed ADV-based *Ω*-score:

$$Flow_{i,t} = \alpha_{i,t} + \beta_1\, ADV - Based\ \Omega\ score_{i,t-1} + \delta_1\, High\ trank_{i,t-1} + \delta_2 Mid\ trank_{i,t-1} + \delta_3 Low\ trank_{i,t-1} + \delta_4 Log\ assets_{i,t-1} + \delta_5 Stdev_{i,t-1} + \delta_6 Management\ fee_{i,t-1} + \delta_U Umbrella_{i,t-1} + \delta_{ORA} Log(OR\ attention)_{i,t-1} + \delta_U Umbrella_{i,t-1} + \sum_{j=1}^{13} \gamma_j StyleDummies_{ji} + \sum_{q=1}^{9} \eta_q YearDummies_{qi} + \varepsilon_{i,t}$$

Model 2 includes interaction terms between the *ADV-based Ω-score* and three average monthly return ranks in the previous year. Log(OR attention) is the logarithm of the annual number of news mentions of 'Madoff,' 'Operational Risk,' or 'Hedge Fund Failure' from the RavenPack database. All models control for TASS style, year, and firm fixed effects. All results are reported with the clustered standard error for TASS style, firm, and year. ***, **, * indicate the statistically significant at the 1%, 5%, and 10% levels, respectively.

	Model 1			Model 2			Model 3		
	Coef.	*t*-Value		Coef.	*t*-Value		Coef.	*t*-Value	
ADV-based *Ω* Score	-0.27	-3.13	***	-2.30	-9.67	***	-2.73	-3.83	***
ADV-based *Ω* Score*High trank				0.38	0.68		0.67	0.79	
ADV-based *Ω* Score*Mid trank				-0.97	-3.52	***	-0.71	-1.86	*
ADV-based *Ω* Score*Low trank				-5.46	-9.64	***	-8.14	-2.92	***
ADV-based *Ω* Score*High trank* Log(OR attention)							1.13	0.71	
ADV-based *Ω* Score*Mid trank* Log(OR attention)							-8.68	-1.98	**
ADV-based *Ω* Score*Low trank* Log(OR attention)							-9.18	-3.08	***
ADV-based *Ω* Score*Log(OR attention)							-3.46	-2.30	**
High trank*Log(OR attention)							0.50	1.36	
Mid trank*Log(OR attention)							-2.18	-3.11	***
Low trank*Log(OR attention)							-2.24	-4.07	***
High trank	3.44	9.98	***	3.79	9.06	***	3.80	2.49	**
Mid trank	-0.70	-7.91	***	-0.92	-7.29	***	-5.21	-1.67	*
Low trank	-3.27	-9.70	***	-3.88	-9.46	***	-5.27	-3.24	***
Log(OR attention)	-0.06	-2.22	**	-0.04	-1.50		-0.75	-3.36	***
Stdev.	-0.01	-2.08	**	-0.01	-2.09	**	-0.01	-1.70	*
Management fee	0.00	0.55		0.00	0.57		0.00	-0.41	
Log(Asset)	0.02	4.41	***	0.02	4.10	***	0.02	4.13	***
High water mark	0.02	0.82		0.02	1.12		0.02	1.00	
Onshore	0.01	0.41		0.01	0.55		0.01	0.41	
Umbrella	0.01	0.24		0.00	0.02		0.01	0.35	
Style	Y			Y			Y		
Firm	Y			Y			Y		
Year	Y			Y			Y		
Num. of Obs.	7,267			7,267			7,267		
Adj. R^2	71.18%			72.83%			73.12%		

Table 7 Regulatory, Civil Judicial, and Criminal Charges Predicting Performance, Leverage, Adverse Liquidation, and Fund Flows

This table uses previous regulatory, civil judicial, and criminal charges indicators to predict adverse outcomes for funds. In Panel A, Models 1 to 3 present results for predicting alpha and appraisal ratio as well as the leveraged indicator according to the equation below:

$$Appraisal\ ratio_{i,t}\ or\ Alpha_{i,t}\ or\ Leverage_{i,t} = \alpha_{i,t} + \varphi_1 Regulatory_{i,t-1} + \varphi_2 Criminal_{i,t-1} + \varphi_3 Civil\ Judicial_{i,t-1} + C_{t-1}^{'}\delta_C + \delta_U Umbrella_{i,t-1} + \sum_{j=1}^{13}\gamma_j StyleDummies_{ji} + \sum_{q=1}^{9}\eta_q YearDummies_{qi} + \varepsilon_{i,t}$$

Model 4 presents the liquidation event prediction according to the equation below:

$$h_{i,t}(T) = h_{0i,t}(T) \times \exp\Big(\varphi_1 Regulatory_{i,t-1} + \varphi_2 Criminal_{i,t-1} + \varphi_3 Civil\ Judicial_{i,t-1} + C_{t-1}^{'}\delta_C + \delta_U Umbrella_{i,t-1} + \sum_{j=1}^{13}\gamma_j StyleDummies_{ji} + \sum_{q=1}^{9}\eta_q YearDummies_{qi}\Big)$$

Panel B reports fund flow predictions by using previous problem charges indicators according to the equation below:

$$Flow_{i,t} = \alpha_{i,t} + \varphi_1 Regulatory_{i,t-1} + \varphi_2 Criminal_{i,t-1} + \varphi_3 Civil\ Judicial_{i,t-1} + \delta_1\ High\ trank_{i,t-1} + \delta_2 Mid\ trank_{i,t-1} + \delta_3 Low\ trank_{i,t-1} + \delta_4 Log\ assets_{i,t-1} + \delta_5 Stdev_{i,t-1} + \delta_6 Management\ fee_{i,t-1} + \delta_U Umbrella_{i,t-1} + \ \delta_U Umbrella_{i,t-1} + \sum_{j=1}^{13}\gamma_j StyleDummies_{ji} + \sum_{q=1}^{9}\eta_q YearDummies_{qi} + \varepsilon_{i,t}$$

$Flow_{i,t}$ is the annual net fund flow in year *t* for fund *i*. Model 1 shows prediction results using all three types of problem indicators, while Models 2-5 present results with each type of indicator separately. The alpha and appraisal ratio prediction results in Panel A are reported with the clustered standard error for TASS-style and year. All models in both Panels control the TASS-style and year dummies for predictions. ***, **, * indicate significance at the 1%, 5%, and 10% levels respectively.

Panel A: Previous Charges Predicting Fund Performance and Characteristics												
	Model 1			Model 2			Model 3			Model 4		
	Alpha			Appraisal Ratio			Leveraged			Adverse Liquidation Events		
	Coef.	*t*-Value		Coef.	*t*-Value		Coef.	*z*-Value		Coef.	*z*-Value	
Regulatory	-0.05	-2.22	**	-0.04	-0.49		-0.06	-0.65		0.39	1.86	*
Criminal	-0.26	-1.19		-0.68	-3.01	***	-1.11	-1.87	*	0.31	0.31	
Civil Judicial	-0.01	-0.08		-0.26	-2.72	***	-0.48	-1.17		0.01	0.00	
Return							0.04	1.26		-0.46	-5.34	***
Stdev.	-0.07	-5.29	***	-0.22	-9.68	***	-0.02	-1.44		0.05	1.24	
Management fee	0.03	1.88	*	0.37	9.17	***	0.17	3.96	***	-0.11	-0.95	
Log(Asset)	0.02	2.9	***	0.01	0.78		0.01	0.57		-0.31	-5.99	***
Leveraged	0.02	0.75		0.01	0.25					-0.09	-0.66	
Onshore	0.08	2.78	***	0.19	4.77	***	0.46	7.66	***	-0.55	-3.5	***
High water mark	0.07	2.4	**	0.39	7.83	***	0.36	5.86	***	-0.28	-1.86	
Umbrella	0.17	2.19	**	0.35	3.95	***	0.44	2.81	***	-0.44	-1.08	
Style	Y			Y			Y			Y		
Year	Y			Y			Y			Y		
Num. of Obs.	6,261			3,786			7,267			7,267		
Adj. R^2	4.81%			17.00%								
Pseudo R^2							14.98%					
Concordance										77.00%		

Panel B: Previous Charges Predicting Fund Flows												
	Model 1			Model 2			Model 3			Model 4		
	Coef.	*t*-Value		Coef.	*t*-Value		Coef.	*t*-Value		Coef.	*t*-Value	
Regulatory	-0.01	-0.59		-0.01	-0.29							
Criminal	-0.09	-0.60					-0.08	-0.54				
Civil Judicial	-0.16	-1.89	*							-0.16	-1.87	*
High trank	3.44	9.15	***	3.44	9.10	***	3.44	9.08	***	3.44	9.08	***
Mid trank	-0.70	-7.88	***	-0.70	-7.87	***	-0.70	-7.86	***	-0.70	-7.96	***
Low trank	-3.26	-9.63	***	-3.26	-9.60	***	-3.26	-9.59	***	-3.27	-9.72	***
Stdev.	-0.01	-2.03	**	-0.01	-2.03	**	-0.01	-2.05	**	-0.01	-2.02	**
Management fee	0.00	0.59		0.00	-0.57		0.00	0.51		0.00	0.57	
Log(Asset)	0.02	4.43	***	0.02	4.40	***	0.02	4.47	***	0.02	4.39	***
High water mark	0.02	0.83		0.02	0.84		0.02	0.85		0.02	0.80	
Onshore	0.01	0.47		0.01	0.49		0.01	0.44		0.01	0.43	
Umbrella	0.01	0.19		0.01	0.34		0.01	0.26		0.01	0.18	
Style	Y			Y			Y			Y		
Firm	Y			Y			Y			Y		
Year	Y			Y			Y			Y		
Num. of Obs.	7,267			7,267			7,267			7,267		
Adj. R^2	69.00%			68.15%			68.12%			68.20%		

Table of Contents for Appendix and the Internet Appendix (IA)

Appendix

This section provides explanations of the variables used in the paper, the history of the evolution of Form ADV, the classification definition for the ERA and RIA funds, the structure of the amended (post-Dodd) Form ADV, and sample composition.

Table A.1 Variable Explanation

This table details the external and internal conflict-related variables from Form ADV Part 1A and the variables used in our empirical analysis. Panel A reports variables and definitions from Item 7 (Financial Industry Affiliations and Private Fund Reporting). Panel B reports variables from Items 8 (Participation or Interest in Client Transactions), 9 (Custody), and 10 (Control Persons). Panel C reports fund performance and characteristics from TASS, along with the additional dependent/control variables.

Panel A: External Relationships (Item 7)	
Variables	Explanations
Banking	Whether a fund has a related person that is a banking or thrift institution.
SwapDealer	Whether a fund has a related person that is a registered security-based swap dealer.
FuturesCommission	Whether a fund has a related person that is a futures commission merchant.
Trust	Whether a fund has a related person that is in a trust company.
Insurance	Whether a fund has a related person that is in an insurance company or agency.
Panel B: Internal Relationships	
Variables	Explanations
Item 8	
AgencyCrossTransaction	Whether a fund has a related person that is a broker-dealer or registered representative of a broker-dealer, execute securities trades for brokerage customers in which advisory client securities are sold to or bought from the brokerage customer.
Item 9	
AdvisorQualifiedCustodian	Whether an advisor of a fund that acts as a qualified custodian for clients during the advisory services.
RelatedQualifiedCustodian	Whether a fund has a related person that acts as a qualified custodian for clients during the advisory services.
Item 10	
OtherControlCompany	Whether a fund has other unreported companies that directly or indirectly control the management or policies.
OtherControlPerson	Whether a fund has other unreported people that directly or indirectly, control the management or policies.

Panel C: Variables used in the Empirical analysis	
Variable	Definition
1^{st}-order AC	The first order autocorrelation for the monthly return of a fund of the relative year.
Accepts managed acct.	Whether a fund accepts a managed account.
Asset	The average monthly asset of a fund in the relative year.
ADV-based Ω-score	The Ω-score that constructed from the amended Form ADV variables in the previous year.
Alpha	Alpha of a fund according to the performance for the relative year.

Appraisal ratio	Regressing the 12-month excess return of fund i on the excess return of the fund's TASS-style index j within the same year (BGLS, 2008). Specifically, $r_{it} - R_{ft} = \alpha_i + \beta_i(r_{jt} - R_{ft}) + \varepsilon_{it}$, where R_{ft} is the 3-month US Treasury Bill return.
Log (Asset)	Log of the average monthly asset of a fund in the previous year.
Fund age	The age of a fund started from its inception date in the previous year.
Fund flow	Fund flow for fund i in year t is calculated by $Flow_{i,t} = Assets_{i,t} - Assets_{i,t-1} * \left(1 + Return_{i,t}\right)/Assets_{i,t-1}$.
High trank	Calculated by $Min\left(\frac{1}{3}, Frank\right)$, where $Frank$ is the fractional rank for funds from 0 to 1, according to their average historical return in the relative year.
High water mark	Whether a fund has a high-water mark in the relative year.
Incentive fee	Incentive fee of a fund in the relative year.
Kurtosis	Kurtosis for the monthly return of a fund of the relative year.
Leveraged	Whether a fund uses leverage or not for the relative year.
Lockup period	The lockup period of a fund (measured in months) in the relative year.
Low trank	Calculated by $Min\left(\frac{1}{3}, Frank - High\ trank - Mid\ trank\right)$.
Management fee	Management fee of a fund.
Margin	Whether a fund leverage using margin for borrowing.
Mid trank	Calculated by $Min\left(\frac{1}{3}, Frank - High\ trank\right)$.
Min. Investment	Minimum investment of a fund.
Onshore	Whether a fund is domiciled in the US in the previous year.
$Pos\Delta ProblemNum_{i,t}$	$\mathbf{1}(ProblemNum_{i,t}$- $ProblemNum_{i,t-1} > 0)$, where $ProblemNum_{i,t}$ is a continuous variable calculated as the sum of the three Form ADV classified violation category dummies (ranges from 0 to 3) for fund company i in year t.
$\Delta ProblemNum_{i,t}$	$ProblemNum_{i,t}$- $ProblemNum_{i,t-1}$. Where $ProblemNum_{i,t}$ is a continuous variable calculated as the sum of the three Form ADV classified violation category dummies (ranges from 0 to 3) for fund company i in year t. For instance, if firm i has regulatory or criminal charges, but no civil judicial charges in year t, its $ProblemNum$ will be 2.
Return	The average monthly return of a fund according to the performance on TASS in the relative year or previous year.
Red. Freq.	Redemption frequency of a fund, measured in days.
Sharpe ratio	Sharpe ratio of a fund according to the monthly return in the relative year.
Skewness	Skewness for the monthly return of a fund in the relative year.
Stdev.	The standard deviation of the return for a fund in the relative year or previous year.
Sub. Freq.	Subscription frequency of a fund, measured in days.
Umbrella	Whether a fund is with Umbrella Registration in the previous year.
High water mark	Whether a fund has a high watermark in the previous year.
Leveraged	Whether a fund uses leverage in the previous year.
Lockup period	The lockup period for a fund in the relative year (measured in months).

Figure A.1 History of Form ADV
This figure provides a detailed explanation of the timeline for the history of Form ADV.

Year 1979
- ***Rule 204-3 under Advisors Act:*** Form ADV is mandatorily for SEC registerd advisors

May 14 and May 15, 2003
- **The SEC Hedge Fund Roundtable:**
  - **The structure and operation**, marketing issues, investor protection issues, trading strategies and market participation, as well as **an assessment of the current regulatory scheme** relating to hedge fund industry.

Dec. 2, 2004
- ***A new rule and rule amendements under the Investment Advisers Act of 1940:*** all managers in hedge fund advisory firms with $25 million AUM and at least 14 clients need to submit Form ADV annually.

Jun. 23, 2006
- The **U.S. Court of Appeals for the District of Columbia Circuit** vacated the rule changes that had required many newly registered hedge fund managers to register as investment advisers under the Investment Advisers Act.

Dec. 30, 2009
- ***Custody of Funds or Securities of Clients by Investment Adviser Rule:* required each adviser to report all related persons** who are broker-dealers and to identify which, if any, serve as qualified custodians with respect to the adviser's clients' funds or securities.

Jul. 28, 2010
- ***Rule Amendments to Form ADV***: all Part 2 need to presented as a brochure and brochure supplements written in plain English in Form ADV Part 2.

Jul. 19, 2011
- ***Rules Implementing Amendments to the Investment Advisers Act of 1940 according to Dodd-Frank Act:***
  - ERA and RIA.
  - Expanded 6.A. and 7.A. to total 14 (6.A.) and 16 (7.A.) types of financial service business and added 7.B..
  - Expanded Item 8 with providing **discretionary authority to determine the brokers or dealers for client transactions**, **"soft dollar benefits"** and **direct or indirect compensation for client referrals information.**
  - Item 9: added the disclosure of **custody and custodial practice** information for client assets.
  - Item 10: added the disclosure of **Control person (directly and indirectly)** information.

Aug. 25, 2016
- ***Form ADV and Investment Advisers Act Rules*:** Umbrella Registration.

Jan. 2, 2018
- **An organized format (mainly in CSV format) for historical Form ADV data was available to public**.
- Time range and frequency: **2006-present (updated monthly)**

Figure A.2 Definition of the ERA and RIA Funds' Classification

This figure presents the definition of the ERA and RIA funds' classification according to the SEC. For the advisory companies (for relative funds) that with an Asset Under Management (AUM) smaller than or equal to $100 million, or the companies (for relative funds) that only advise private funds and with an AUM smaller than or equal to $150 million are considered as Exempt Advisors (ERA). The rest of the companies (and relative funds) are considered Registered Advisors (RIA).

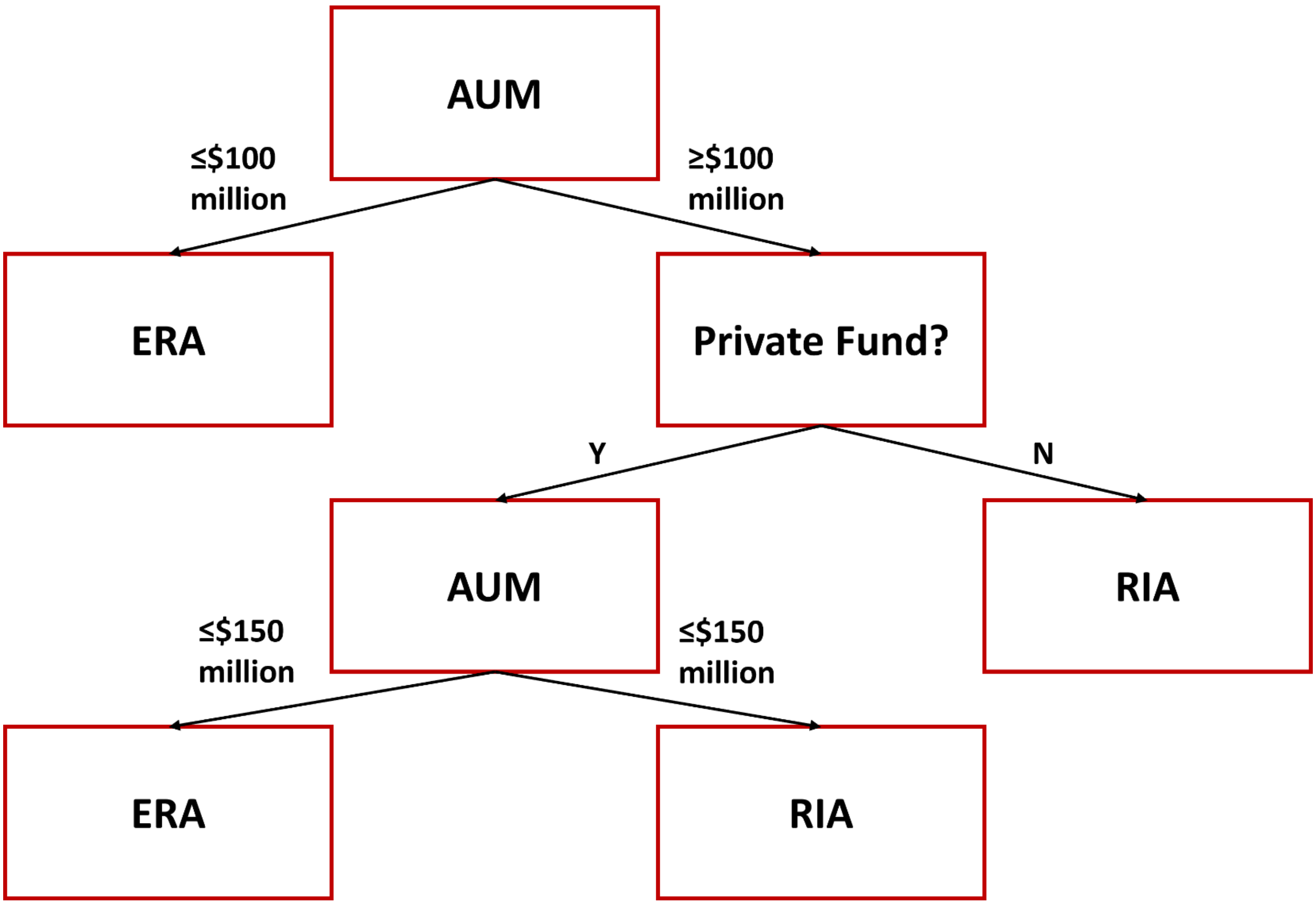

Figure A.3 Form ADV Structure

The figure below presents the general structure for Form ADV data that is disclosed to the public.

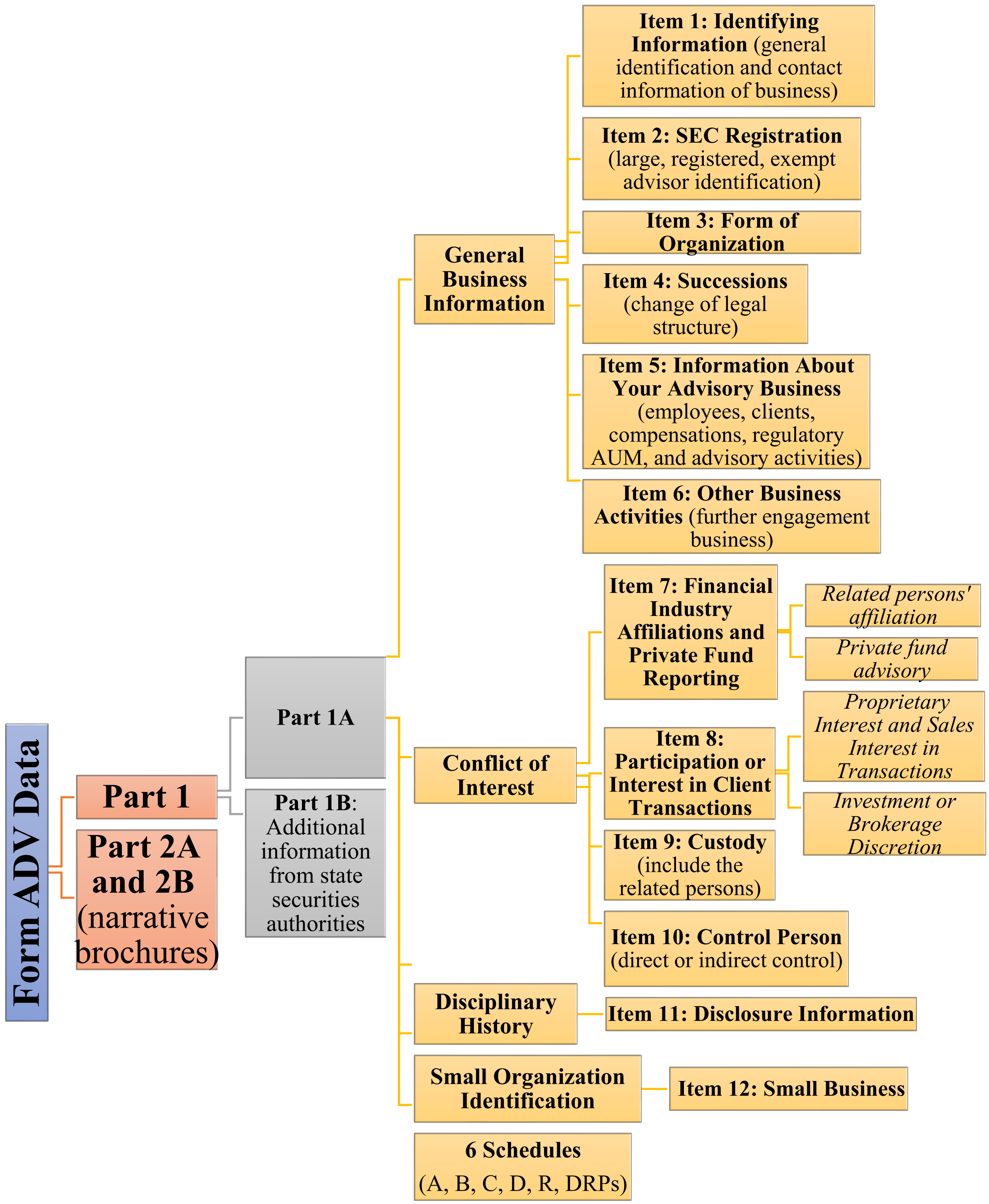

Table A.2 Sample and Subgroups Composition

This table details our sample construction and final observations for the RIA and ERA subgroups. Panels A and B show observation changes from data filtering. Panels C and D analyze sample composition by Umbrella Registration and problem funds within the RIA and ERA subgroups.

Panel A: Data Filtering Process – Characteristics

	Matched RIA and ERA		All TASS Live and Dead	
	Funds	Firms	Funds	Firms
Original	7,926	1,527	16,569	3,204
Monthly tracking & net of fee	7,602	1,502	15,902	3,171
Assets bigger than 10 million	6,287	1,393	12,616	2,865

Panel B: Data Filtering Process – Performance

	RIA		ERA		All TASS Live and Dead	
	Funds	Firms	Funds	Firms	Funds	Firms
Remaining samples	5,144	1,116	1,418	348	12,616	2,865
Winsorize top & bottom 1% Return	5,092	1,109	1,397	348	11,782	2,772

Panel C: Detailed Structures for Matched Samples − With vs. Without Umbrella Registration

	UR		Non-UR		With Changing UR Status		Total	
	Funds	Firms	Funds	Firms	Funds	Firms	Funds	Firms
Always RIA	52	25	3,984	906	783	282	4,819	1,213
Switching between RIA and ERA	0	0	1,303	328	94	33	1,397	361
Total	52	25	5,287	1,234	877	315		

Panel D: Detailed Structures for Matched Samples − Problem vs. Non-problem

	Problem		Non-problem		Total	
	Funds	Firms	Funds	Firms	Funds	Firms
Always RIA	881	124	3,938	989	4,819	1,113
Always ERA	0	0	1,124	291	1,124	291
Switching between RIA and ERA	21	4	252	68	273	72
Total	902	128	5,314	1,348		

Table A.3 Disciplinary History and Adverse Liquidation Predictions Using Lagged Operational Risk Variables

This table presents the results of forecasting disciplinary history and adverse liquidations using lagged operational risk variables, with a comparison between pre-2011 and post-2011 models. The left panel reports the F-test using the following equation:

$$ProblemNum_{i,t} = \alpha_{i,t} + \boldsymbol{\beta_{ORV}} \boldsymbol{X_{ORV\ i,t-l}} + \sum_{f=1}^{N} \theta_f FirmDummies_{fi} + \sum_{q=1}^{9-l} \eta_q YearDummies_{qi} + \varepsilon_{i,t}$$

Where $ProblemNum_{i,t}$ is a continuous variable representing the sum of the three Form ADV violation category dummies (ranging from 0 to 3) for a fund company i in year t. $\boldsymbol{X_{ORV\ i,t}}$ represents operational risk-related variables from the pre-2011 or post-2011 Form ADV for the fund company i in year t. N is the total number of firms during the regression period, and l is the number of lags (ranges from 0 to 4).

The right panel presents a comparison of adverse liquidation identification and predictions using an LRT with the Cox Proportional-Hazard model:

$$h_{i,t}(T) = h_{0i,t}(T) \times \exp\left(\boldsymbol{\beta_{ORV}} \boldsymbol{X_{ORV\ i,t-l}} + C_{t-2}^{\prime\delta_C} + \delta_U Umbrella_{i,t-2} + \sum_{f=1}^{N} \theta_f FirmDummies_{fi} + \sum_{q=1}^{9-l} \eta_q YearDummies_{qi}\right)$$

C_{t-2} represents a vector of variables, including average and standard deviation of monthly returns, leveraged or not, onshore, and high-water mark indicators, log of assets, and fund management fee in year $t-2$. Both pre-Dodd and post-Dodd models include the firm and year dummies. ***, **, * indicate the statistically significant at the 1%, 5%, and 10% levels, respectively.

F-test and LRT							
		F-test			LRT		
Lag(s)	Model (Pre- or Post-2011)	F	p-value		χ^2	p-value	
0	Pre-						
	Post-	2.34	0.00	***	61.03	0.00	***
1	Pre-						
	Post-	5.09	0.00	***	320.31	0.00	***
2	Pre-						
	Post-	7.47	0.00	***	615.00	0.00	***
3	Pre-						
	Post-	5.55	0.00	***	21.27	0.88	
4	Pre-						
	Post-	3.81	0.00	***	18.23	0.95	

Internet Appendix for

"The Dodd-Frank Act and Hedge Fund Operational Risk"

William N. Goetzmann, Bing Liang, and Jue Wang

January 2026

Abstract

This document provides supplementary materials to the paper "The Dodd-Frank Act and Hedge Fund Operational Risk". This section first presents the structure of the operational risk variables selection pool that is based on external/internal classification and related structures' information (Figure IA.1). Table IA.1 presents the summary statistics for ADV-based Ω-Score for different TASS-styles. Table IA.2 reports detailed out-of-sample prediction results for performance, leverage, adverse liquidation, and fund flows using the operational risk measure illustrated in Figure 4 of the main text.

Figure IA.1 Operational Risk Variable Selection Pool

This figure presents the construction of the variables for our operational risk variable selection pool. Among our total 44 variables. 17 of the variables belong to the external relationship category that is collected from Item 7 of Form ADV Part 1A filing. 27 of the variables belong to the internal relationship category that is collected from Item 8 (15 variables), Item 9 (10 variables), and Item 10 (2 variables).

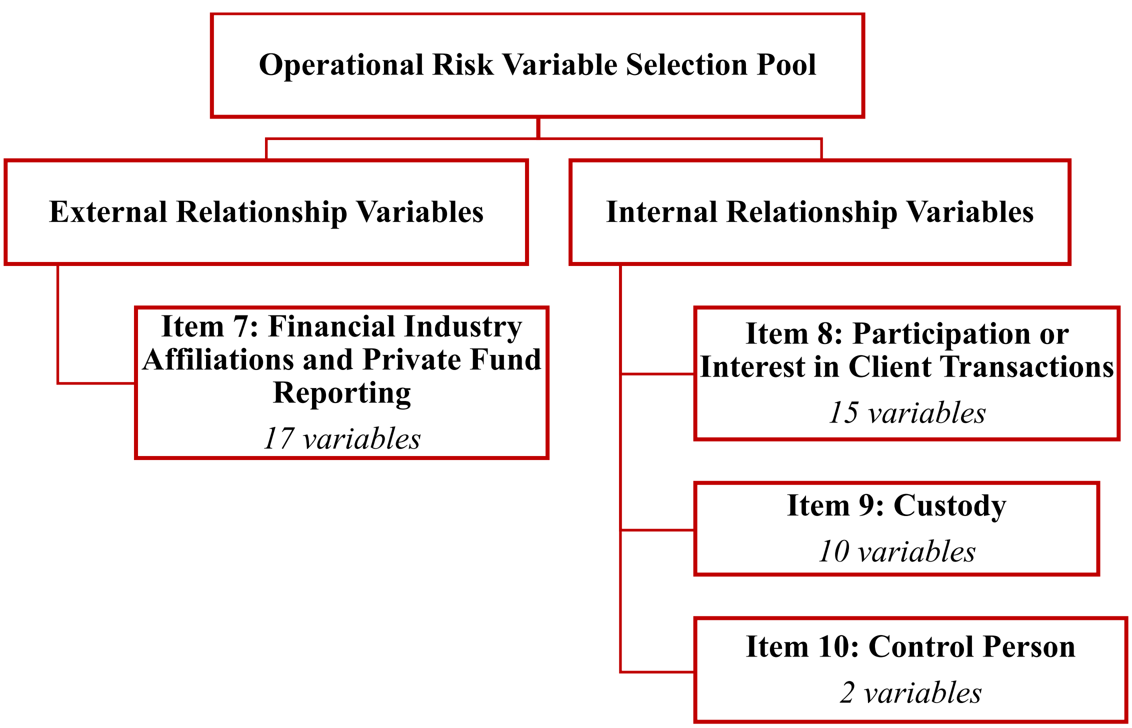

Table IA.1 Summary Statistics for Dynamic ADV-based *Ω*-Score Within Different Styles and Years

This table presents the mean and median for RIA funds ADV-based *Ω*-Score (dynamic) within different TASS-style and across different years.

Panel A: Dynamic ADV-based *Ω*-Score by Fund Style		
TASS Style	Mean	Median
Convertible Arbitrage	7.40%	6.42%
Dedicated Short Bias	-0.34%	-4.85%
Emerging Markets	8.95%	5.23%
Equity Market Neutral	8.93%	6.03%
Event Driven	9.12%	7.28%
Fixed Income Arbitrage	14.88%	9.76%
Fund of Funds	14.35%	7.39%
Global Macro	6.86%	5.87%
Long/Short Equity Hedge	7.65%	5.38%
Managed Futures	14.62%	8.74%
Multi-Strategy	13.32%	8.17%
Options Strategy	4.02%	4.70%
Other	14.79%	7.89%
Undefined	16.70%	7.95%
Panel B: Dynamic ADV-based *Ω*-Score by Year		
Year	Mean	Median
2012	6.93%	2.45%
2013	18.01%	17.70%
2014	14.36%	7.18%
2015	22.04%	16.43%
2016	10.74%	6.68%
2017	5.20%	2.35%
2018	10.92%	10.12%
2019	-7.71%	2.22%
2020	7.43%	6.93%
2021	5.90%	3.25%
2022	-0.53%	0.21%

Table IA. 2 Operational Risk Score Predicting Performance, Leverage, Adverse Liquidation, and Fund Flows (OOS)

This table presents the adverse outcomes out-of-sample (OOS) prediction by using the Canonical Correlation Analysis (CCA; pre-Dodd variables [BGLS, 2008]) and LASSO-constructed Ω-scores (pre-Dodd variables only and pre- and post-Dodd variables) for RIA funds. Panel A presents the fund flows and leverage predictions according to the equations:

$$Flow_{i,t} = \alpha_{i,t} + \beta_1\ Operational\ risk\ score_{i,t-1} + \delta_1\ High\ trank_{i,t-1} + \delta_2 Mid\ trank_{i,t-1} + \delta_3 Low\ trank_{i,t-1} + \delta_4 Log\ assets_{i,t-1} + \delta_5 Stdev_{i,t-1} + \delta_6 Management\ fee_{i,t-1} + \delta_U Umbrella_{i,t-1} + \sum_{j=1}^{13} \gamma_j StyleDummies_{ji} + \sum_{q=1}^{9} \eta_q YearDummies_{qi} + \varepsilon_{i,t}$$

$$Leverage_{i,t}\ or\ Appraisal\ ratio_{i,t}\ or\ Alpha_{i,t} = \alpha_{i,t} + \beta_1 Operational\ risk\ score_{i,t-1} + C_{t-1}^{'}\delta_C + \delta_U Umbrella_{i,t-1} + \sum_{j=1}^{13} \gamma_j StyleDummies_{ji} + \sum_{q=1}^{9} \eta_q YearDummies_{qi} + \varepsilon_{i,t}$$

Panel B presents the appraisal ratio and style-adjusted Return cross-sectional predictions according to the second equation above. Panel C presents the adverse liquidation cross-sectional predictions[53] according to the equations:

$$h_{i,t}(T) = h_{0i,t}(T) \times \exp\left(\beta_1 Operational\ risk\ score_{i,t-1} + C_{t-1}^{'}\delta_C + \delta_U Umbrella_{i,t-1} + \sum_{j=1}^{13} \gamma_j StyleDummies_{ji} + \sum_{q=1}^{9} \eta_q YearDummies_{qi}\right)$$

Coef. columns report year-by-year LASSO- and CCA-based ADV Ω-score coefficients for cross-sectional predictions, with *t*/*z*-statistics and goodness-of-fit. Observations before/after the slash indicate CCA/LASSO samples. Left, center, and right columns show fit for CCA, LASSO pre-Dodd, and LASSO post-Dodd scores. Bottom panels include interactions with post-2016 indicators. ***, **, * indicate the statistically significant at the 1%, 5%, and 10% levels, respectively.

Panel A: Fund Flow Cross-sectional Predictions

	CCA-constructed Score (Pre-Dodd)			LASSO-constructed Score (Pre-Dodd)			LASSO-constructed Score (Pre- and Post-Dodd)				
Year	Coef.	*t*-value		Coef.	*t*-value		Coef.	*t*-value		Adj. R^2	Num. of Obs.
2013	-0.07	-1.09		-0.14	-4.76	***	-0.05	-0.65		96.02%/96.53%/74.54%	1,097/1,429
2014	-0.07	-1.02		-0.63	-6.30	***	-0.60	-1.16		89.91%/89.02%/88.98%	1,032/1,221
2015	-0.46	-4.40	***	-0.27	-2.42	**	-0.09	-1.05		90.66%/91.91%/88.85%	836/957
2016	-0.30	-2.25	**	-0.05	-2.49	**	-0.78	-1.93	*	92.00%/92.75%/88.75%	705/867
2017	-0.03	-0.22		-0.09	-1.66	*	-0.60	-5.64	***	85.00%/85.05%/85.20%	523/675
2018	-0.05	-0.34		-0.03	-1.75	*	-0.66	-5.02	***	74.74%/75.88%/85.88%	481/555
2019	-0.06	-0.44		-0.02	-1.82	*	-0.71	-2.74	***	80.65%/82.70%/82.79%	345/507
2020	-0.27	-0.28		-0.31	-1.64	*	-1.45	-2.83	***	82.72%/90.24%/92.23%	334/404
2021	-0.18	-0.60		-0.18	-1.74	*	-1.53	-3.04	***	82.74%/90.11%/92.13%	274/335
2022	-0.11	-0.18		-0.21	-1.89	*	-1.34	-2.81	***	82.40%/90.41%/90.53%	239/317
2013-17	-0.02	1.67	*	-0.06	-3.03	***	-0.01	-1.75	*	70.93%/71.00%/71.18%	5,866/7,267
2018-22	-0.07	-0.21		-0.03	-1.88	*	-0.22	-2.86	***		
Full	-0.02	-1.67	*	-0.03	-1.65	*	-0.21	-2.71	***	69.30%/70.12%/71.17%	5,866/7,267
Style	Y			Y			Y				
Firm	Y			Y			Y				
Controls	Y			Y			Y				

[53] Since there are no adverse liquidation funds within our sample in 2022, our period ends in 2021 for Panel C.

Panel B: Adverse Liquidation and Leveraged Cross-sectional Predictions																					
	Adverse Liquidation										Leverage										
	CCA-constructed Score (Pre-Dodd)			LASSO-constructed Score (Pre-Dodd)			LASSO-constructed Score (Pre- and Post-Dodd)				CCA-constructed Score (Pre-Dodd)			LASSO-constructed Score (Pre-Dodd)			LASSO-constructed Score (Pre- and Post-Dodd)				
Year	Coef.	*z*-value		Coef.	*z*-value		Coef.	*z*-value		Concordance (%)	Coef.	*z*-value		Coef.	*z*-value		Coef.	*z*-value		Pseudo R^2 (%)	Num. of Obs.
2013	1.08	3.85	***	2.17	4.04	***	0.16	0.73		98.20/98.60/86.80	-0.65	-6.66	***	-1.65	-3.28	***	-0.15	-1.92	*	70.72/19.93/9.88	1,097/1,429
2014	0.49	9.04	***	1.07	2.81	***	0.08	0.06		98.10/98.30/86.40	-1.23	-7.77	***	-1.42	-1.98	**	-0.11	-1.81	*	74.34/26.06/13.26	1,032/1,221
2015	0.13	0.69		0.24	1.77	*	0.36	2.86	***	77.40/78.80/79.50	-1.71	-8.34	***	-0.13	-2.92	***	-0.02	-0.26		78.30/28.84/8.85	836/957
2016	0.61	0.86		0.76	1.80	*	0.22	1.96	*	79.10/79.20/80.60	-0.60	-4.56	***	-1.03	-1.65	*	-1.03	-1.65	*	91.57/19.47/18.52	705/867
2017	1.72	1.01		1.04	2.18	**	1.69	2.57	**	64.60/86.60/85.00	-0.10	-3.22	***	-0.13	-1.65	*	-0.26	-2.05	**	89.14/19.39/19.86	523/675
2018	0.58	0.72		1.57	1.90	*	2.40	3.78	***	94.00/94.20/94.60	-2.12	-0.02		-2.75	-0.27		-2.42	-2.02	**	19.88/20.06/20.37	481/555
2019	1.26	1.80	*	1.24	0.66		1.12	3.18	***	90.80/91.00/91.40	-0.64	-1.82	*	-0.83	-1.75	*	-1.09	-2.25	**	21.68/32.91/33.01	345/507
2020	0.43	0.81		1.13	0.06		1.33	4.67	***	98.00/98.83/98.99	-0.03	-0.23		-0.49	-0.02		-1.51	-3.99	***	35.91/36.03/36.20	334/404
2021	0.19	0.00		1.03	1.65	*	1.23	2.77	***	95.60/96.00/96.10	-0.75	-1.58		-0.82	-1.83	*	-1.65	-4.36	***	35.68/40.12/41.90	274/335
2022											-1.07	1.95	*	-1.73	-1.85	*	-1.54	-3.55	***	37.94/43.50/43.74	239/317
2013-17	0.55	2.63	***	1.36	2.65	**	0.58	1.92	*	77.50/77.86/78.00	-0.28	-2.05	**	-1.13	-1.90	*	-0.53	-1.61		16.22/16.91/16.94	5,866/7,267
2018-22	0.54	1.56		1.86	1.73	*	1.60	3.90	***		-0.14	-1.57		-0.80	-1.40		-1.34	-3.44	***		
Full	0.33	1.69	*	1.05	1.74	*	1.33	3.46	***	76.05/76.50/77.00	-0.18	-0.28		-0.89	-1.77	*	-1.34	-2.89	***	16.16/16.90/16.92	5,866/7,267
Style	Y						Y				Y			Y			Y				
Firm	Y						Y				Y			Y			Y				
Controls	Y						Y				Y			Y			Y				

Panel C: Performance Cross-sectional Prediction																						
	Alpha											Appraisal Ratio										
	CCA-constructed Score (Pre-Dodd)			LASSO-constructed Score (Pre-Dodd)			LASSO-constructed Score (Pre- and Post-Dodd)					CCA-constructed Score (Pre-Dodd)			LASSO-constructed Score (Pre-Dodd)			LASSO-constructed Score (Pre- and Post-Dodd)				
Year	Coef.	*t*-value		Coef.	*t*-value		Coef.	*t*-value		Num. of Obs.	Adj. R^2 (%)	Coef.	*t*-value		Coef.	*t*-value		Coef.	*t*-value		Num. of Obs.	Adj. R^2 (%)
2013	-0.27	-1.74	*	-2.13	-5.82	***	-3.27	-6.92	***	1,097/ 1,429	76.70/72.11/ 71.11	-0.04	-0.10		-0.60	-1.23		-0.56	-1.23		734/ 970	19.87/25.73/ 25.71
2014	-0.18	-1.35		-2.80	-7.81	***	-2.57	-1.18		1,032/ 1,221	73.98/74.51/ 74.38	-0.52	-0.84		-1.41	-2.20	**	-0.27	-0.44		637/ 773	25.90/18.91/ 18.86
2015	-0.46	-2.21	**	-1.21	-1.93	*	-0.16	-0.63		836/ 957	82.90/78.13/ 79.13	-0.31	-2.03	**	-0.69	-3.22	***	-0.61	-0.35		484/ 534	23.77/47.50/ 46.21
2016	-0.83	-2.27	**	-0.86	1.90	*	-1.64	-2.97	***	672/ 824	78.27/75.20/ 76.21	-1.56	-0.52		-2.11	-3.24	***	-1.57	-2.02	**	366/ 438	22.05/15.00/ 14.91
2017	-0.09	0.15		-0.10	-0.13		-0.90	-5.39	***	333/ 412	70.11/70.00/ 71.70	-0.12	-0.29		-0.38	-1.91	*	-0.84	-2.64	***	239/ 294	60.34/60.38/ 61.67
2018	-0.05	-0.15		-0.20	-1.87	*	-0.81	-5.16	***	295/ 345	85.82/88.70/ 89.71	-0.36	-1.18		-0.36	-1.73	*	-0.44	-2.95	***	131/ 156	80.25/90.25/ 91.34
2019	-0.13	-0.36		-0.54	-1.87	*	-0.72	-3.76	***	231/ 349	90.65/90.76/ 91.31	-0.85	-1.13		-0.90	-0.21		-1.23	-3.52	***	129/ 200	50.72/56.43/ 58.72
2020	-1.56	-0.78		-1.99	-0.64		-2.71	-4.65	***	226/ 265	91.52/91.40/ 91.60	-0.94	-1.63		-1.03	-1.89	*	-1.10	-2.54	**	126/ 157	30.72/40.01/ 40.47
2021	-0.13	-0.28		-0.16	-2.50	**	-1.48	-6.08	***	195/ 230	79.34/81.88/ 82.79	-0.11	-0.19		-0.47	-1.83	*	-1.38	-3.42	***	132/ 145	30.43/30.63/ 31.14
2022	-0.07	-0.13		-0.09	-1.48		-1.81	-4.52	***	165/ 229	90.02/90.86/ 93.64	-0.34	-1.48		-0.17	-1.99	*	-1.02	-4.93	***	88/ 119	90.49/94.86/ 96.26
2013-17	-0.18	-3.31	***	-0.09	-3.19	***	-1.04	-2.70	***	5,082/ 6,261	19.44/20.00/ 20.13	-0.26	-2.33	**	-0.96	-1.86	*	-0.44	-0.65		3,066/ 3,786	25.21/27.90/ 28.02
2018-22	-0.02	-0.30		-0.60	-2.95	***	-1.26	-3.08	***			-0.14	-1.04		-0.48	-1.69	*	-1.22	-2.74	***		
Full	-0.12	-1.92	*	-0.16	-3.55	***	-1.23	-3.84	***	5,082/ 6,261	19.29/19.88/ 20.11	-0.21	-1.73	*	-0.50	-1.80	*	-0.71	-2.63	***	3,066/ 3,786	20.21/27.88/ 27.91
Style	Y			Y			Y					Y			Y			Y				
Firm	Y			Y			Y					Y			Y			Y				
Controls	Y			Y			Y					Y			Y			Y				