The Dodd-Frank Act and Hedge Fund Operational Risk

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Abstract

We examine the impact of the post-Dodd-Frank change in 2011 on hedge fund disclosure. We find that new questions added to the SEC's Form ADV, post-Dodd-Frank, enhance forecasting of adverse operational events compared to pre-Dodd-Frank disclosures. Using machine learning, our analysis yields a unidimensional operational risk score from the public SEC data, effective in predicting liquidation events, leverage changes, and performance metrics. The score also predicts net fund flows, indicating the relevance of disclosed operational risk information to investor decisions. Over the five years of the post-Dodd-Frank Act, fund flow response significantly increased following the amended Form ADV implementation.

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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.**"*[1]

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 institutional and individual investors. According to an authoritative industry source, total hedge fund assets crossed the $4 trillion milestone at the beginning of 2022.[2] Hedge funds seek to generate risk-adjusted returns for their investors through active trading in securities markets.[3] However, due to the competitive nature of the active management industry, they typically maintain informational boundaries concerning their security positions and proprietary strategies. This informational opacity can make it difficult for regulators and investors to independently assess and manage portfolio risk. Occasional large-scale fund failures such as the collapse of Bernard Madoff's fund in 2008 have alerted regulators and investors to the importance of operational risk, i.e., "the risk of loss resulting from inadequate

[1] https://www.sec.gov/news/speech/2014-spch121114mjw

[2] Hedge Fund Research Inc., https://www.hfr.com/news/global-hedge-fund-capital-surpasses-historic-milestone-to-begin-2022.

[3] Cf. Cao, Liang, Lo, and Petrasek (2018), Cao, Chen, Goetzmann, and Liang (2018).

or failed internal processes, people, and systems" in the hedge fund industry.[4]

The Dodd-Frank Wall Street Reform and Consumer Protection Act was passed in 2010 in the wake of the global financial crisis. Its primary goal was the reduction of risk in the financial system. Among other changes, it introduced additional regulatory requirements for hedge funds, including the mandatory filing of Form ADV by all qualifying funds. Consequently, in July 2011, the SEC significantly expanded and enhanced both the scope and the content of this critical disclosure filing. According to 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.*[5]

The hedge fund industry has operated under the new regulatory regime since 2011. The ensuing 11 years provide an opportunity to assess the effects of the Dodd-Frank mandated changes to hedge fund disclosure and explore the materiality of disclosure about conflicts of interest more generally.

In this paper, we examine several questions of interest to regulators 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

[4] 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.

[5] https://www.sec.gov/news/speech/2011/spch062211mls-items-1-2.htm

(LASSO) to identify the most salient predictor variables.[6] Most of the important variables in the estimation were not included in the pre-Dodd Form ADV.[7] 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.

Next, we use the model estimation results to develop a concise set of operational risk predictors, highlighting the types of disclosures linked to increased operational risk. Additionally, newly mandated variables related to potential conflicts of interest from external affiliations are found to be associated with reduced future creditor confidence, as evidenced by diminished access to leverage. Furthermore, enhanced internal controls are correlated with a decreased likelihood of future fund liquidation.[8]

We next 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 termed the ω-score using the short-lived 2006 mandatory disclosure data, which significantly predicted adverse fund events such as liquidation. Our new ADV-based Ω-score uses a more advanced method and updates it with more timely and precise disciplinary history data, covering an 11-year panel following the 2011 SEC expansion of Form ADV under the Dodd-Frank Act, with broader mandatory participation and richer,

[6] 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.

[7] Our selected 42 indicators include 16 external relationship variables that describe the affiliation and 26 internal variables that cover the participation or interest in client transactions, custody, and control person information for hedge funds-related advisory companies.

[8] Cassar and Gerakos (2010) show that internal controls decrease the likelihood of future fraud and financial misstatement related investigations.

standardized disclosures. It employs LASSO regression for weight assignment.[9] We find that the post-ADV Ω-score, utilizing only publicly available information from the SEC, is significantly better at forecasting adverse operational events like liquidation. This method provides a more transparent, replicable, and high-dimensional risk metric that outperforms earlier approaches in predicting adverse outcomes. 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 studied in the 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.

[9] The pre-Dodd benchmark is particularly useful as it relied on ADV variables available before Form ADV was expanded and utilized data from private vendors of hedge fund data. However, the legacy model primarily depends on firms' past 10-year disciplinary history, which raises concerns about potential "staleness" in the data, indicating a need for improvement.

[10] Cf. Brown et al. (2009) for a TASS-based operational risk score, and Brown et al. (2012) for a due diligence (DD) operational risk score.

Especially, 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 for public sentiment. This result is consistent with access to or attention to the disclosed information improving investor decision-making.

We next use an out-of-sample cross-validation process 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 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%.[13]

[Insert Figure 1]

Interestingly, a firm (we referred to it as 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.[14] In 2024, the FBI investigated it as a suspected Ponzi scheme.

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

[11] The two figures are based on the 2-lag model from Table 3 in Section 5 for increased litigation probability and Appendix A Table A.3 (p.83) for adverse liquidation probability.
[12] Specifically, 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.
[13] 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 in the TASS database in 2023.
[14] Specifically, this firm's 2021 ADV filing revealed over 37% of internal relationships linked to custody issues, with almost no existence of good internal and external relationships, and later civil charges in May 2023 for mismanagement and fraud.

stronger evidence of market reactions; and connecting regulatory disclosure improvements with broader systemic implications for financial institutions and regulatory design.

Beyond hedge funds, our findings have implications for banks, insurers, and other financial institutions that rely on due diligence and risk modeling. The evolving value of Form ADV highlights how structured public disclosures can enhance credit decisions, counterparty assessments, and governance. This aligns with the Basel Accord's emphasis on operational risk management and transparency as key pillars of financial stability. As operational risk grows in importance, our results suggest that standardized disclosures can improve risk monitoring and support regulatory objectives across the financial system.

The remainder of the paper is organized as follows. Section 2 presents our research questions and hypotheses. Section 3 summarizes previous literature. Section 4 describes the data. Sections 5 and 6 describe the methodology and display the results. Section 7 reports further robustness tests. Section 8 concludes.

2. Background

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.[15]

In May 2003 motivated in part by "…a growing number of enforcement cases in which hedge 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.[16] 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.[17] 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*.[18] 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

[15, 16] *Registration Under the Advisers Act of Certain Hedge Fund Advisers* https://www.sec.gov/rules/final/ia-2333.htm#I

[17] *Registration Under the Advisers Act of Certain Hedge Fund Advisers* (sec.gov/rules/final/ia-2333.htm)

[18] Rule 206(4)-2 under the Investment Advisers Act of 1940.

(ERAs) need only file an abbreviated version of the new Form ADV with state authorities.[19] 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.[20] The new form also expanded disclosure of internal conflicts of interest, increasing 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 A (p.78). Also, the definition of categorizing the ERA and RIA can be found in Figure A.2 of Appendix A (p.79)).

The amended Form ADV thus provides market participants and regulators with more information potentially material for the assessment of operational risk.[21] 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? Secondly, is there any indication that market participants based their investment decisions on the augmented information set, and is there

[19] A detailed ERA and RIA classification can be found in Figure A.2 Appendix A (p.79).
[20] The structure of the amended Form ADV can be found in Figure A.3 of Appendix A (p.80).
[21] According to the Basel II Committee, operational risk is defined as "the risk of loss resulting from inadequate or failed internal processes, people, and systems or external events."

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. Literature Review

3.1 Hedge Funds and Operational Risk Research

Operational risk has long been an important issue for assessing risk for financial institutions – particularly banks (De Fontnouvelle et al., 2007; Chernobai et al., 2011). Zitzewitz (2012) provides a useful overview of forensic economics that includes a discussion of the importance of operational risk controls. As pointed out above, regulatory attention to hedge fund operational risk and academic research on hedge fund operational risk has evolved over the past two decades.

Broadly speaking, academic research on hedge fund operational risk has taken two approaches – a qualitative top-down approach that focuses on such variables as ownership, governance, procedures, and personnel, and a quantitative bottom-up approach that applies statistical analysis to fund returns to identify suspicious or incongruous patterns in self-reported performance data and due diligence reports (cf. Brown 2012). Examples of the top-down approach include BGLS (2008) which uses Form ADV filing data to study hedge fund operational risk, and Brown et al. (2009) who use TASS data (a vendor of hedge fund information) to construct an Ω-score – a metric for operational risk.

Examples of the bottom-up approach include Liang (2003) who finds inconsistencies in hedge fund reported data, and Bollen and Pool (2009), who show that funds with a discontinuous return distribution at zero likely misrepresent performance. Getmansky et al. (2004) find that hedge fund performance metrics are artificially enhanced by return smoothing, and Getmansky et al. (2005) use style, performance, volatility, and illiquidity to assess the risk of hedge fund failure. Other notable contributions to this research have identified different performance flags indicative of potential misrepresentation.[22] In particular, Dimmock et al. (2018) show that even a parsimonious set of data from Form ADV helps detect misconduct and fraud. They argue for improved data accessibility for investors. Some papers have explicitly considered the effect of Dodd-Frank regulatory changes on hedge funds. For example, Charoenwong, Kwan, and Umar (2019) find that reduced regulator resources due to a shift in jurisdiction over midsized investment advisors increased client complaints. Restrepo (2024) addresses the cost-benefit tradeoff of Dodd-Frank hedge fund regulation, attributing erosion in post-Dodd performance in part to compliance costs and constraints.

Additional research has addressed the relevance of specific sub-sets of variables in ADV filings, particularly those reporting affiliations and conflicts. Some affiliations can be positive. Franzoni and Gianneti (2016) show that hedge funds affiliated with financial conglomerates have more stable capital. Mullally (2022) finds that outside ownership of a fund company has positive effects on fund flows. Conversely, Zheng and Yan (2021) report result consistent with

[22] cf. Bollen and Pool, 2008 and 2012; Straumann, 2008; Bollen and Whaley, 2009; Sun et al., 2012 among others.

pre-Dodd evidence in Brown et al. (2008) that funds with external relationships perform worse and have a higher probability of failure – likely due to agency costs and incentive misalignment. In related results, Sun and Teo (2019) find evidence that agency costs may cause funds managed by listed firms to perform worse.

3.2 Hedge Fund Regulation and Disclosure

Several studies argue that mandated disclosure can enhance information efficiency (cf. Mahoney, 1995; Pinto, 2023) and improve market liquidity (Leuz and Wysock, 2016). In the context of the hedge fund industry, some scholars remain skeptical of increased hedge fund monitoring. Atkins (2006), for instance, contends that wealthy investors are generally capable of effectively assessing and managing operational risk, and that Form ADV might inadvertently replace thorough due diligence. Other research regards disclosure as potentially valuable for investors and regulators. Provided with suitable information, monitoring can take the form of capital requirements and restrictions (Cumming and Dai, 2010) or disclosure requirements to enhance fraud detection by managers (Dimmock and Gerken, 2012) and to reduce misreporting (Honigsberg, 2019). To document this, Dimmock and Gerkin (2016) using a DiD approach, show that improved SEC hedge fund oversight in 2004 decreased misreporting cases, but the rule revocation in 2006 reversed that trend due to exits from the regulatory framework. Furthermore, Dimmock et al. (2020) show that a parsimonious set of operational risk-related disclosures in the post-Dodd-Frank period and previous fraud and

litigation cases can predict future fraud events.[23]

Regarding the impact of the Dodd-Frank Act, Cumming et al. (2020) find that U.S. hedge funds subject to Dodd-Frank regulation experience lower alpha but a reduction in total and idiosyncratic risk. Barth et al. (2021) show that funds reporting to data vendors earn significantly lower performance than those reporting only through Form PF yet receive considerably higher net investor flows.

Our contribution to this literature is to provide empirical evidence that the post-Dodd-Frank disclosure requirements significantly enhanced the potential ability of investors and regulators to predict adverse operational risk-related outcomes. Our findings suggest that the 2011 regulatory change reduced information asymmetry related to operational risk, both by requiring all qualified funds to report and by increasing the amount of information they are required to report. Based on these findings we develop an extension of the BGLS operational risk metric that only relies on publicly disclosed information in Form ADV and demonstrates the potential of machine-learning methods to improve operational risk assessment.

[23] Our study complements Dimmock et al. (2020) in two ways. First, while they focus on fraud predictions, we examine operational risk that may lead to broader litigation cases, including fraud outcomes (which primarily result in criminal cases, as shown in Figure 2B's word cloud of criminal charge descriptions). By assessing operational risk ex ante, investors may potentially avoid losses from litigation outcomes affecting funds' related companies. Second, building on Dimmock et al. (2020)'s approach using Items 8 and 9 (conflict of interest disclosures) and one broker affiliation indicator (five collective dummies from the conflict-of-interest disclosures), we expand the analysis to include all 44 variable indicators from Items 7-10 as our operational risk selection pool. We identify 35 useful variables for constructing a unidimensional operational risk metric, where over 65% of amended Form ADV variables and approximately 46% relate to conflicts of interest from external affiliations with financial, legal, and accounting intermediaries.

4. Data

4.1 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.[24] 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 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.[25] 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.[26] Part 1A data has 12 Items and 3 Schedules.[27] Items 7 to 10 provide self-reported conflicts of interest. Item 7 documents advisory firms' external conflict of interest, and Items 8 to 10 document internal conflicts of

[24] 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.

[25] https://www.sec.gov/help/foiadocsinvafoiahtm.html. BGLS set the SEC investment adviser website (IAPD) as their Form ADV data source. Notice that the information provided by the SEC FOIA service website used in our study contains almost the same information on the IAPD website. The reason for 'switching' to the FOIA service website is that it offers a more accessible format for Form ADV data and provides the complete archive, whereas the IAPD website only offers the most recent years' filing records.

[26] The ADV filing on the FOIA website is updated monthly, and records are aggregated annually. For consistency with the TASS sample period, we use the December filing. The SEC requires the annual Form ADV to be submitted by the end of April.

[27] A detailed explanation of the structure of Form ADV can be found in Figure A.3 of Appendix A (p.80).

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 persons. 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. [28] Figure 2 presents Word Clouds depicting the sanction details for these three types of disciplinary histories.[29]

[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

[28] We include only unique cases based on textual sanction details (e.g., if firm A 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 (e.g., unauthorized trading by both the SEC and CFTC), 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.

[29] Figure 2 includes all cases documented in the 2012-2022 DRP filings. 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%.

issues, with a notable number involving Libor[30] 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.[31]

4.2 Descriptive Statistics

We identify 1,386 management companies in the SEC database out of 2,772 listed in TASS - 50% of the TASS database.[32] 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.[33] We identify 1,717 defunct funds liquidated or unable to be contacted within the

[30] This pertains to the Libor scandals exposed in 2012, which led to additional charges against related firms in the subsequent years.

[31] Some required filings we use are available at a monthly frequency.

[32] We use a two-step procedure to match funds across the two databases. We first identify exact matches in the TASS 'Company Name' and the 'Legal Name' field for From ADV 1A. For the remainder, we use unique keywords in the TASS fund name or parent company name fields to search. firms in Form ADV. We then use additional information such as the domicile country, location address, and website address to confirm matches. We use the same matching process for defunct funds as described above for live funds on TASS.

[33] We remove the TASS funds that report quarterly (instead of monthly returns), or gross-of-fee returns, and funds with less than $10 million assets under management. For each fund, we calculate the annual return as the

prior 10-year period, representing 27.62% of the matched TASS-ADV dataset.[34]

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. In Table B1 of Internet Appendix IA. B (p.92), we compare ERA funds with all TASS live and dead funds. 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.[35] Specifically, UR funds have a higher average return, Sharpe

average of the monthly returns for the related year and then winsorize the top and bottom 1% of these annual returns. Note that the number of observations for both matched funds and TASS is from the winsorized samples. Furthermore, all the foreign-domiciled fund assets under management and returns are converted to USD according to the annual exchange rate provided by OECD data (https://data.oecd.org/conversion/exchange-rates.htm).

[34] Among the 6,216 RIA and ERA funds, 4,819 retained RIA status, 1,124 retained ERA status, and 273 experienced changes between RIA and ERA statuses during our sample period. Of the 1,717 funds with defunct records, 1,186 retained RIA status, 258 retained ERA status, and 273 experienced status switches between RIA and ERA during the sample period.

[35] 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).

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 live longer. [36] These differences caution against pooling UR funds with non-UR funds. Among all fund classes, RIA funds with the UR registration display the highest risk-adjusted performance and higher quality.

4.3 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. [37] 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" [38] – 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 28 for details on how we identify non-duplicated events and

[36] 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.

[37] BGLS define problem funds as if a fund's related company has answered any 'yes' to any query in Item 11, and they found that a set of Form ADV variables significantly predicted this problem measure. However, since Item 11 require firms to report disciplinary histories for the past 10 years, using legacy method may yield staleness concern.

[38] 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/

determine resolution dates).

[Insert Table 2]

Table 2 separates the entire RIA sample (live and defunct funds) into Problem Funds and Non-Problem Funds.[39] 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 frequencies, as well as shorter history.[40]

5. 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).[41] 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

[39] Problem funds for this table are classified based on whether a fund's related company experienced any litigation events during the 2012–2022 sample period, indicating the firm was problematic within this timeframe.
[40] In addition, in untabulated results, we find that both external and internal conflicts of interest were significant predictors of the Problem fund status.
[41] We perform firm-level analysis and estimation for the results in Sections 5, 6.1, and 6.6 to address duplicate records in the Form ADV data, as each advisory firm files Form ADV annually.

investigations typically span two to four years. [42] 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:

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

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

$Pos\Delta ProblemNum_{i,t}$ 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. [43] $\Delta ProblemNum_{i,t}$ 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

[42] https://secwhistlebloweradvocate.com/sec-whistleblower-frequently-asked-questions/

[43] The $Pos\Delta ProblemNum_{i,t}$ is defined by $\mathbf{1}(ProblemNum_{i,t} - ProblemNum_{i,t-1} > 0)$, 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. For instance, if firm i has regulatory or criminal charges, but no civil judicial charges in year t, its $ProblemNum$ will be 2.

in year t.[44] $\boldsymbol{X_{ORV\ i,t-l}}$ 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. Panel A1 and B1 analyze the probability of litigation increases, Panels A2 and B2 predict the magnitude of changes, and Panels A3 and B3 apply a CLMM to account for both the categorical nature and severity of litigation changes. According to the three sub-panels in Panel A, 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. Panels B1, B2, and B3 further confirm that the two-year lag yields the best goodness-of-fit results, with the highest adjusted R^2 and lowest AIC and BIC. 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.[45]

[44] $\Delta ProblemNum_{i,t}$ is calculated by $ProblemNum_{i,t}$- $ProblemNum_{i,t-1}$. The definition of $ProblemNum$ can be found in Footnote 41.

[45] Our untabulated results further show the results of using lagged operational risk variables to forecast the number of litigation events (level prediction;$ProblemNum_{i,t}$ see Footnote 41 for the definition) 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.

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]

6. Reduced Form Operational Risk Assessment and Estimation

6.1 Operational Risk Indicators Selection

The variables in Items 7, 8, 9, and 10 comprise 44 potential operational risk-related variables. As described above, we group those variables into external and internal relationship categories: variables in Item 7 are considered external relationship-related, while variables in Items 8, 9, and 10 are classified as internal relationship-related variables (the structure and number of the variables in related Items for our variable selection pool can be found in Figure A1 of Internet Appendix IA. A (p.89)).[46]

Given the large number of variables (44) in the amended Form ADV, we use LASSO

[46] 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.

regression (Tibshirani, 1996) to select a parsimonious set of operational risk indicators. [47] We calculate the dependent variable as the sum of the dummy variables for regulatory, criminal, and civil judicial violations for each firm in each year, as outlined in Section 5. We then estimate a linear regression with L1 (LASSO) regularization applied to the set of 44 variables. Those with significant non-zero coefficients are taken as salient explanatory variables. The coefficients allow us to define a unidimensional ADV-based operational risk score called *Ω*-score 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. Among the top 10 variables, seven are newly added. All external variables in Panel A show a positive relationship with increased violation types. Specifically, the presence of a Future Commission Merchant (FCM; *FuturesCommission*) and Swap Dealer (*SwapDealer*) elevates operational risk due to the non-transparent pricing they introduce. Other external variables, such as

[47] In this, we follow the current literature (Chen and Tindall, 2013 and 2014; Wu et al., 2021).

Insurance, *Trust*, and *Banking/Thrifting* also significantly impact the likelihood of problems, as they add complexity to financial transactions through their intricate relationships with hedge funds.

Half of the top 10 variables relate to internal relationships. Many of these variables positively correlate with the summed litigation dummies for the three types of violations. For example, custody processes, conflicts of interest, and ownership play crucial roles in operational risk. Variables like *RelatedQualifiedCustodian* and *AdvisorQualifiedCustodian* highlight custody risks, while *AgencyCrossTransaction* increases operational risk due to conflicts of interest. For instance, if a fund's related broker-dealer executes trades involving client securities, this can lead to front-running or preferential treatment, exacerbating conflicts of interest.

Ownership variables, such as *OtherControlCompany* and *OtherControlPerson*, show opposing effects on operational risk due to the SEC's ADV glossary[48] and our sample examination.[49] *OtherControlCompany*, which involves firms owning or controlling the fund, often results in more structured management oversight and reduced operational risk.[50] Conversely, *OtherControlPerson*, which involves individuals without significant shareholding or voting power (lower than 35% for both powers), can lead to agency problems and increased risk.[51]

[48] https://iard.com/sites/iard/files/glossary.pdf.
[49] Figure A2 (p.90) of Internet Appendix IA. A illustrates these relationships through Word Clouds based on textual descriptions.
[50] They are described by words such as 'stock', 'common', 'subsidiary', etc.
[51] They are described by words such as 'president', 'director', 'chief', etc.

Panel B of Table 4 presents the number, importance rank, and percentage of the selected variables within different groups. Firstly, according to the comparison between Pre-Dodd and Post-Dodd variables, among all the 35 selected variables, 65.71% of the post-Dodd variables are selected, and they have a higher median rank than the pre-Dodd ones. This aligns with the results in Table 3 that the added variables in the amended Form ADV improve Problem Firm identification. Furthermore, the third and fourth rows display the percentages for external and internal relationship groups. External variables have a higher median rank (13.50) compared to internal ones (21.00), despite more internal variables being chosen. This underscores the greater impact of external affiliations on operational risk. 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.[52]

Panel B of Table 4 also shows the summary statistics for the internal and external variables. A negative sign in Panel A indicates a lower likelihood of being a Problem Firm. Out of the 35 selected variables, there are 3 good internal (GI), 16 bad internal (BI), 1 good external (GE), and 15 bad external (BE) variables. BE relationships have a higher median rank than GE (13 versus 14), indicating a greater likelihood of being a Problem Firm.[53] GI relationships have a much higher median rank than the BI variables (16.00 versus 21.50), supporting the hypothesis that GI variables signify better risk management. For instance, the chosen GI variables *ReceiveAuditReport*, *ReceiveAnnualSurpriseExamination*, and

[52] For instance, Bernie Madoff orchestrated his Ponzi scheme through affiliations with a broker-dealer, which was also involved in executing and clearing trades.
[53] Although the median ranks for GE and BE appear similar, it is important to note that there is only one GE.

OtherControlCompany represent the monitoring of financial risk and having extra governance oversight. *ReceiveAuditReport* and *ReceiveAnnualSurpriseExamination* imply firms receiving an audit report and undergoing external examination by an independent public accountant. Panel C reports the result of a Kruskal-Wallis Test of the differences in medians. Consistent with previous results in Panel B, in the Post-Dodd period, external BE, and internal GI have significantly higher median ranks in determining the Problem Firms, suggesting that internal relationships negatively associated with the Problem cases are higher in importance post-Dodd, and conversely external relationships that are positively associated with the Problem Firm events have greater importance post-Dodd.

6.2 Reduced Form Operational Risk Estimation

6.2.1 Operational Risk Indicators Predicting Future Adverse Events and Performance

In this section, we first test whether the selected operational risk indicators have the power to forecast future adverse events and predict future performance. In addition to utilizing individual-level variables for predictive purposes, we also estimate a reduced form using operational risk indicators derived from the results in Table 4, i.e., GE, BE, GI, and BI.[54]

In equation (3) below, $P_t^{ExtGood}$, P_t^{ExtBad}, $P_t^{IntGood}$, P_t^{IntBad} are calculated as the number at time *t* of Good/Bad External/Internal reported fund relationships divided by the

[54] Previous literature mainly predicts hedge funds' performance by either using macro-based (systematic risk-based) factors (Amenc et al., 2003; Bali et al., 2007; Avramov et al., 2013; Bali et al., 2014; Ardia et al., 2022) or using the idiosyncratic risk-based variables (Liang, 1999; BGLS; Brown et al., 2008a, 2009, 2012). In this paper, we adopt BGLS's method to use fund-level performance and characteristic variables as control variables for the empirical prediction process.

total number of the relationships in the relative groups.[55] Equation (3) is a linear prediction model for three other outcomes of interest: the risk-adjusted return measured by the fund appraisal ratio, a style-adjusted return, and an indicator for whether the fund uses leverage.

$$Appraisal\ ratio_{i,t}\ or\ Alpha_{i,t}\ or\ Leveraged_{i,t} = \alpha_{i,t} + \beta_{ExtGood}\, P_{t-1}^{ExtGood} + \beta_{ExtBad} P_{t-1}^{ExtBad} + \beta_{IntGood} P_{t-1}^{IntGood}, + \beta_{IntBad} P_{t-1}^{IntBad} + C_{t-1}^{\prime \delta_C} + \delta_U Umbrella_{i,t-1} + \sum_{j=1}^{13} \gamma_j StyleDummies_{ji} \sum_{q=1}^{9} \eta_q YearDummies_{qi} + \varepsilon_{i,t} \quad (3)$$

Equation (4) estimates a Cox-Proportional Hazard panel model for adverse effects at time t $h_{i,t}(T)$ using variables available at time t-1.

$$h_{i,t}(T) = h_{0i,t}(T) \times \exp\left(\beta_{ExtGood}\, P_{t-1}^{ExtGood} + \beta_{ExtBad} P_{t-1}^{ExtBad} + \beta_{IntGood} P_{t-1}^{IntGood} + \beta_{IntBad} P_{t-1}^{IntBad} + C_{t-1}^{\prime \delta_C} + \delta_U Umbrella_{i,t-1} + \sum_{j=1}^{13} \gamma_j StyleDummies_{ji} + \sum_{q=1}^{9} \eta_q YearDummies_{qi}\right) \quad (4)$$

For performance outcomes in equation (3), $Appraisal\ ratio_{i,t}$ and $Alpha_{i,t}$ are the appraisal ratio and alpha of fund i in year t.[56] $Leveraged_{i,t}$ is one if fund i uses leverage in year t. For adverse events in Equation (4), we adopt the definition proposed by Liang and Park (2010). Fund i is considered adversely impacted in year t with age T if it is liquidated or

[55] Again, good/bad relationships are classified by whether the related variables have negative/positive coefficients according to the LASSO results in Table 4.

[56] We calculate the annual appraisal ratio by regressing the 12-month excess return of fund i on the excess return of the fund's TASS-style index I within the same year (BGLS, 2008). Specifically, $r_{it} - R_{ft} = \alpha_i + \beta_i(r_{it} - R_{ft}) + \varepsilon_{it}$, and $i \in I$. Where R_{ft} is the 3-month US Treasury Bill return.

unable to be contacted according to the TASS data. Plus, it should have a negative average return in the previous 6 months, as well as decreased AUM in the previous 12 months. $Umbrella_{i,t-1}$ equals one if the fund's related firms were under Umbrella Registration in the previous year. We control for various fund performance and characteristic variables.[57] Year and style dummies are also included.[58]

Table 5 presents the results for both individual-level and aggregate-level operational risk indicators for adverse outcome predictions.[59]

Panel A presents the adverse liquidation results. Models 1, 2, and 3 in Panel A show that BE and GI exposure have significant prediction power in the following year. The signs and significance of the coefficients in Panel A are consistent with results in Table 4, suggesting that positive internal and bad external relationship variables play significant roles in predicting adverse outcomes compared to other variables.

[Insert Table 5]

Panel B presents the results for predicting next-period performance and leverage. In

[57] Specifically, C_{t-1} represents a vector of variables, including average and standard deviation of monthly returns, leveraged or not indicator, onshore and high-water mark indicators, logarithm of assets, and fund management fee in year $t-1$. Furthermore, for performance prediction in Equation (2) the 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.

[58] Moreover, all the prediction analysis tables starting from this section report the regression results with clustered standard errors for TASS-style, year, and funds' advisory companies (fund flow analysis) besides the controlled dummies (the clustered errors are only for the OLS models, for rest of the models, we only control the relative dummies). This method is aligned with the clustered error consideration used in the previous literature for hedge fund performance analysis (Brown, Gregoriou, and Pascalau, 2011; Bali, Brown, and Caglayan, 2014).

[59] In untabulated results, we have a full version of regression results with detailed variable-level and aggregate-level percentage variables for adverse liquidation, performance, and leverage.

this panel, Models 1–4 indicate that reduced-form variables are generally predictive of the appraisal ratio and alpha, with coefficient signs aligning with expectations: external variables (both good and bad) and good internal variables exhibit stronger predictive power for performance, particularly for alpha predictions in the case of negative BE and positive GI variables (Model 4). Models 5-7 predict access to leverage, a possible sign of willing lenders. External relationships prove to be more predictive than internal ones, as shown by the coefficients on $\beta_{ExtGood}$ and β_{ExtBad} (Model 7). Notably, external variables, especially negative ones, demonstrate significant predictive power.

6.2.2 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) evaluating 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.

In this section, we use a further reduced form 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 (5) and (6) present those testing strategies with similar settings in the previous two equations.

$$h_{i,t}(T) = h_{0i,t}(T) \times \exp\Big(\beta_1 ADV - Based\ \Omega\ score_{i,t-1} + C_{t-1}^{\prime\delta_C} + \delta_U Umbrella_{i,t-1} + \sum_{j=1}^{13} \gamma_j StyleDummies_{ji} + \sum_{q=1}^{9} \eta_q YearDummies_{qi}\Big) \quad (5)$$

$$Appraisal\ ratio_{i,t}\ or\ Alpha_{i,t}\ or\ Leverage_{i,t} = \alpha_{i,t} + \beta_1 ADV - Based\ \Omega\ score_{i,t-1} + C_{t-1}^{\prime\delta_C} + \delta_U Umbrella_{i,t-1} + \sum_{j=1}^{13} \gamma_j StyleDummies_{ji} + \sum_{q=1}^{9} \eta_q YearDummies_{qi} + \varepsilon_{i,t} \quad (6)$$

Table 6 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 6]

Panel B presents the results of predicting future litigations—regulatory, criminal, and civil judicial charges—using our constructed ADV-based *Ω*-score, according to the logit regression(s) specified in equation (7). 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.

$$Regulatory_{i,t} \text{ or } Criminal_{i,t} \text{ or } Civil\ Judicial_{i,t} = \alpha_{i,t} + \beta_1 ADV - Based\ \Omega\ score_{i,t-1} + C_{t-1}^{\prime\delta_C} + \delta_U Umbrella_{i,t-1} + \sum_{j=1}^{13} \gamma_j StyleDummies_{ji} + \sum_{q=1}^{9} \eta_q YearDummies_{qi} + \varepsilon_{i,t} \quad (7)$$

In addition, Appendix B reports results for the ADV-based Ω-score through canonical correlation analysis (CCA) used by BGLS. Tables B.1 (p.86), B.2 (p.86), and B.3 (p.88) of Appendix B suggest that the LASSO-constructed ADV-based Ω-score provides better prediction power than the CCA-constructed ADV-based Ω-score.[60] This can be partially attributed to the direct utilization of the ADV data in the former, as opposed to the indirect use of private data such as TASS in the latter. Moreover, it demonstrates that public information like the SEC ADV data is effective in constructing meaningful operational risk measures.

[60] This may because of the larger amount of the variables included in the LASSO method. Since for the CCA-constructed ADV-based Ω Score, we find the weights for the variables according to the linear combination of the performance and characteristics information provided by TASS. However, the size for the TASS variables is limited (12 variables according to BGLS), so that to avoid the imbalance issue in the CCA process, we should select a parsimonious set of the operational risk variables instead of using all the key indicators. This may drive the outperformance of the LASSO-constructed ADV-based Ω Score.

6.3 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 (8) specifies a predictive panel model of net fund flows, controlling for past performance, volatility, size, fees, style umbrella status, and year.[61]

$$Flow_{i,t} = \alpha_{i,t} + \beta_1\, ADV - Based\ \Omega\ score_{i,t-1} + \delta_1\, High\ rank_{i,t-1} +$$
$$\delta_2 Mid\ rank_{i,t-1} + \delta_3 Low\ rank_{i,t-1} + \delta_4 Log\ assets_{i,t-1} + \delta_5 Stdev_{i,t-1} +$$
$$\delta_6 Management\ fee_{i,t-1} + \delta_U Umbrella_{i,t-1} + \sum_{j=1}^{13} \gamma_j StyleDummies_{ji} +$$
$$\sum_{q=1}^{9} \eta_q YearDummies_{qi} + \varepsilon_{i,t} \qquad (8)$$

Table 7 presents the results. Model 1 and Model 2 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. 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 25% decrease in future fund flows. Interaction terms in Model 2

[61] $High\ rank$, $Mid\ rank$, and $Low\ rank$ are the fractional ranks for the previous year's return (adjusted by exchange rate) introduced by Liang et al. (2019).

suggest investors in funds in the mid-and low-performance ranks are more responsive to the operational risk metric.

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 be attributable to the more comprehensive post-Dodd Form ADV format and the learning behavior of investors.

[Insert Table 7]

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. Models 3 and 4 present similar predictions to the first two models but control for 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.[62] Results show that the *Ω*-score remains a significant fund flow predictor even with this control. Model 5 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

[62] 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.

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.

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

The ADV-based Ω-score used in the previous results in Tables 5 and 6 is based on the weights from an in-sample LASSO regression. To cross-validate the effectiveness of the LASSO-constructed ADV-based Ω-score in predicting adverse outcomes, Figure 4 presents the out-of-sample (OOS) cross-sectional results for predicting performance, leverage, adverse liquidation, and fund flows from 2013-2022 using 'dynamic' weights. We estimate the LASSO model as described in Section 6.1 using backward-looking data every year for the post-Dodd variables.[63] For comparison, we also report results using the Canonical Correlation Analysis (CCA) estimation of BGLS.[64] There are three differences between the CCA and LASSO-constructed scores (Ω-score).

First, for the CCA method, we use only the 15 variables available before the implementation of the Dodd-Frank Act, effectively retaining the reduced Form ADV inputs for

[63] To construct the dynamic score, we first apply the LASSO regression process (Section 6.1) 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.

[64] 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.

BGLS. The LASSO method includes both pre-Dodd and post-Dodd variables (44). This not only helps compare the operational risk assessment power between the two methods but also tests whether the additional variables help enhance the adverse outcome predictions.

Second, because the CCA method relied on the intersection of the TASS universe and the Form ADV universe, the sample sizes for the CCA measure are mostly in the range of 80% of the number of funds for which the LASSO measure can be calculated, except for 2019.

Third, and more importantly, the indirect CCA-constructed score is based on a linear combination derived from a rotation between (presumably) more informative TASS variables and Form ADV variables, while the LASSO-constructed score is based on the sum of the three types of litigation indicators directly from Form ADV. TASS was (and is) one of the leading vendors of hedge fund information, and major institutional investors are likely to have been subscribers in the pre-Dodd era, although smaller and non-institutional investors may not. Thus, these differences have the potential to test for a shift in the relevance of government-mandated disclosure vs. private-sector research.

Additionally, we provide results using the LASSO-constructed score based solely on pre-Dodd-Frank variables for the previously mentioned OOS predictions.[65] This provides a potential 'middle ground' comparison between methodology (CCA vs. LASSO) and information disclosure enhancement levels in Form ADV before and after the amendments.

Figures 4A, 4B, 4C, 4D, and 4E report results for fund flows, adverse liquidation,

[65] This dynamic score uses a similar method to the LASSO-constructed score based on post-Dodd-Frank variables mentioned previously. The main difference is that this score uses only pre-Dodd-Frank variables for operational risk evaluations.

leveraged, appraisal ratio, and alpha OOS predictions.[66] Note that higher *Ω*-scores generally predict fund outflows (yellow solid line with triangle markers). The elasticity patterns suggest a clear trend. Flows in Figure 4A appear more responsive to *Ω*-scores—particularly LASSO-based *Ω*-scores constructed using amended Form ADV—in later years, especially after 2017. The bottom panels in Internet Appendix Table IA. B4 (p.95) report results with interaction terms between scores and post-2016 indicators (indicating whether dependent variable values occur before or after the end of 2016). The coefficients are higher in the second half for LASSO-constructed Ω-scores.

[Insert Figure 4]

The blue dashed lines with diamond markers in Figure 4 present OOS prediction elasticities using the LASSO method with only pre-Dodd-Frank variables. Comparing forecasting results across *Ω*-scores (pre- and post-Dodd-Frank variables), LASSO-constructed pre-Dodd-Frank scores, and CCA-constructed scores (legacy model), we find that LASSO-constructed pre-Dodd-Frank scores show stronger prediction power than the legacy model before 2017. *Ω*-scores outperform the legacy model in the post-2017 period. Methodologically, both LASSO-based scores present higher goodness-of-fit and larger elasticity magnitudes than the legacy CCA method, supporting the effectiveness of our LASSO approach. Moreover, the two LASSO-based scores show opposite strengths across the two five-year periods, particularly in flow and adverse liquidation forecasting. This suggests that

[66] Detailed coefficients, *t*/*z* statistics, goodness-of-fit measures, and sample sizes can be found in Internet Appendix IA. B Table B4 (p.95).

investors may increasingly utilize additional information provided by amended Form ADV disclosures in the latter half of the sample.

Furthermore, a closer examination of the LASSO-ADV-based Ω-score coefficients for fund flow reveals two significant increases in magnitude (Panel A of Table B4 in IA. B4 (p.95)): in 2016 (coefficient of -0.78 compared to -0.09 in 2015) and in 2020 (coefficient of -1.45 compared to -0.71 in 2019). This raises the question of what may drive these sharp increases in fund flow elasticity. Figure 5 shows the number of litigation violations by advisory firms and their affiliates from 2012 to 2022. Notably, spikes in advisory firm violations appear to coincide with a one-year lagged response in fund flow predictions, as suggested by the LASSO-constructed Ω-score in Figure 4A. This observation suggests that the heightened sensitivity of fund flows to operational risk may be influenced by elevated litigation activity in the prior year. Such litigation spikes could heighten investor awareness of operational risk, prompting closer scrutiny and adjustments in investment behavior.

[Insert Figure 5]

The contrast between the CCA and LASSO metrics (pre- and post-Dodd) for predicting adverse liquidation events, according to Figure 4B and Panel B of IA. B Table B4 (p.97), is striking. The sample ends in 2021 due to the absence of adverse liquidation events in 2022. While the CCA metric is significant only in the first two years, it becomes insignificant for the remainder of the sample. Conversely, the LASSO metric is consistently significant in the second half of the sample, both individually and in aggregate. This is noteworthy, especially

considering BGLS's evidence that a CCA-based ω-score significantly predicted adverse events in their sample period.

The results for leverage in Figure 4C and the rest of Panel B of Table B4 in IA. B (p.97) suggest a similar 'transition' trend, with creditors possibly incorporating post-Dodd Form ADV variables into their operational risk assessments. The CCA metric outperforms in the first half of the sample, while the LASSO metric shows significant outperformance in the second half. This may reflect a shift in credit suppliers' preference or awareness, particularly as prime brokers might have had privileged access to operational risk and creditworthiness information, leading them to adopt the additional post-Dodd variables in their models. The pattern of higher coefficients for the LASSO metric in the latter half of the sample reinforces this transition.

Figures 4D and 4E, along with Panel C of Table IA. B4 (p.98), present annual cross-sectional results for the appraisal ratio and alpha. The coefficients are predominantly negative for both metrics. Most notably, the LASSO measure shows consistently significant and higher coefficients from 2016 through 2022. The Ω-score, utilizing the full set of Form ADV variables identified by LASSO, significantly explains the cross-sectional differences in future returns, surpassing style and firm characteristics.

Moreover, Table A1 of Internet Appendix IA. A (p.91) provides the median and mean values for the out-of-sample (OOS) ADV-based Ω Score across various TASS investment styles and years. According to Panel A, on average, dedicated short bias funds exhibit the lowest operational risk exposures, perhaps due to their relatively simpler operations and higher

liquidity, which primarily focus on short-selling strategies, thereby reducing fund management complexity. Conversely, Undefined, Fixed Income Arbitrage (FIA), and Other emerge as the top three fund types with the highest operational risk scores. The elevated risk associated with FIA stems from its typical reliance on a high leverage ratio, potentially necessitating managers to seek additional leverage through margin or derivative-based methods. In the case of Undefined, Other, Managed futures, FoFs, and Multi-strategy funds, their heightened operational risk is more straightforward, given that the opacity and complexity inherent in these funds may increase the likelihood of both internal and external conflicts of interest.[67]

Panel B presents the mean and median OOS ADV-based Ω Scores across our 11-year sample. The average operational risk for the funds in our sample shows a general decline in the latter years, particularly after 2019. This trend potentially aligns with our fund flow and leverage prediction results in Panels A and B of Table B4 (p.95) of Internet Appendix IA. B, suggesting that market participants are becoming increasingly aware of the importance of operational risk management.

[67] Cumming et al. (2020) show that fund flows in the post-Dodd-Frank period vary by hedge fund style (e.g., long-short equity and event-driven funds exhibit decreased flows, while macro-oriented, market-neutral, managed futures, and fixed-income funds present positive flow relationships). We acknowledge these important style-based differences in our analysis. First, all our panel predictions include style dummies with clustered standard errors by different styles. Second, while we recognize the cross-style heterogeneity documented by Cumming et al. (2020), our paper focuses on the industry-wide effects of enhanced materiality in operational risk disclosures due to the Dodd-Frank Act.
We emphasize that our fund flow predictions use direct operational risk measures based on post-Dodd-Frank disclosures rather than a generic Dodd-Frank dummy. Our findings suggest that the amended Form ADV provides enhanced materiality for operational risk measurement, which may be increasingly adopted by investors and creditors over time.

6.5 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 8 presents in-sample predictions for adverse outcomes and fund flows using a similar regression setup as in Sections 6.2.2 and 6.3, 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 8]

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 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 6 and 7, 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.

7. Robustness

In this section, we provide further analysis by using a broader sample that includes both RIA and ERA, to determine whether the results hold for a sample including smaller and different types of funds. [68]

In Table B2 (p.93) of Internet Appendix IA. B, we also provide the predictions of the adverse outcome by using the ADV-based Ω-score. Consistent with Table 6, funds with higher operational risk predict lower alpha, appraisal ratios, lender confidence, and increased liquidation risk. It is notable that both the magnitude and significance levels of the ADV-based Ω-score are generally slightly smaller compared to the RIA sample. This may be due to differences in filing requirements between companies associated with ERA and RIA funds. RIA

[68] In untabulated results, we present detailed coefficients for percentage-level External/Internal Good/Bad variables predicting adverse outcomes in the RIA and ERA samples. For variable selection and weights in the ADV-based Ω Score construction, we re-run the LASSO problem fund identification process for both RIA and ERA funds within the 11-year panel sample.

Similar to Tables 4 and 5, firms with BE relationships face higher liquidation risk, lower alpha/appraisal ratios, and reduced leverage access. In contrast, funds with more GI relationships enjoy better performance, lower liquidation risk, and greater leverage availability. Comparing reduced-form results, BE variables show stronger statistical significance than GI metrics. Overall, external relationships (BE, GE) matter more than internal ones (GI, BI).

companies need to file the full amended Form ADV while ERA funds do not need to answer the questions in Items 8 and 9. Those two items include most of the internal variables. As stated in Table 4, good internal variables are relatively important in assessing the operational risk for the funds. Consequently, when combining ERA and RIA funds for score construction, missing values may be present in the ERA samples and may 'decrease' the power of the ADV-based *Ω*-score.

In other results, in Model 3, fund-related companies belonging to UR is positively related to lender trust. However, ERA funds have lower future alpha, appraisal ratio, and leverage opportunity (*Exempt* in Models 1, 2, and 3). This may be due to the SEC's definition of RIA and ERA. Figure A.2 (p.79) in Appendix A shows that the variation between those two categories mainly depends on the AUM for their related companies. There may be performance differences related to fund size.

Table B3 (p.94) in Internet Appendix IA. B presents the results about whether ERA investors are also responsive to operational risk as measured by the ADV-based *Ω*-score. The results are consistent with those in Table 7. The ADV-based *Ω*-score negatively forecasts future fund flows, and investors in funds in the *Low trank* and *Mid trank* categories experience more outflows when the operational risk metric is higher.

8. Discussion

The post-Dodd Form ADV is particularly valuable due to its expanded scope of disclosures, especially regarding operational risk, and its wealth of detailed information, such

as exact litigation dates and textual descriptions of sanctions imposed on both advisors and related persons/parties.

A simple interpretation of our results is that it is (still) possible to build a useful model to predict fund failure and other variables of interest using the SEC-mandated disclosers. More notably, our findings reveal a dynamic interaction among funds, regulators, lenders, and investors. The Dodd-Frank ACT allowed fund regulators to improve Form ADV to address issues they must have learned about during the pre-Dodd regime. Our results suggest that these enhancements provided material information for assessing both risk and return.

A particularly striking result in our analysis is that, at least for some important outcomes such as adverse liquidations, the value of variables in the pre-Dodd Form ADV waned in importance, while the value of an augmented set of variables grew. Perhaps this was due to a strategic response by funds facing what had been until the 2008 financial crisis, a relatively stationary disclosure regime. It suggests the necessity for a dynamic regulatory strategy, despite the obvious value of predictable rules.

Lenders are another category of strategic players in the hedge fund market who have a strong interest in avoiding risky funds. Credit access is vital to most hedge fund operations, and their lenders are relatively sophisticated. Lenders typically have access to fund collateral and information that is not disclosed to regulators or the public. It is not surprising to find that access to leverage is negatively correlated to operational risk metrics. By the same token, we find that the disclosed willingness of firms to extend fund credit is a positive sign to other investors.

Another group of strategic clientele in the hedge fund marketplace is hedge fund investors. We find strong evidence that investors apparently find SEC-mandated filings filled with non-investment information, such as complex conflicts of interest and governance variables, to be material to investment choice. While we cannot be sure that investors themselves are digesting the disclosed data, the information in Form ADV appears to filter to the ultimate decision-makers.

Perhaps the Madoff scandal of 2008 had a permanent effect on investor due diligence. If this were the case, however, we would have expected a more immediate change in investor awareness of operational risk. It is noteworthy that the fund flow response to both omega-score measures was statistically significant only during one of the initial five years in our sample. One possible explanation is that investors learned over time the value of the new variables in the post-Dodd Form ADV. Of course, a lot has changed in the US capital markets as a result of the Dodd-Frank Act. The augmentation of Form ADV was only a small part of the response to the 2008 financial crisis and what Madoff revealed about operational risk in the fund industry.

In sum, the post-Dodd enhancements to Form ADV look like a win for the SEC. More broadly, they give researchers a chance to understand whether and how the new, publicly available information is used in the marketplace. While they do not supplant the need for private information provision, our analysis demonstrates their efficacy. Overall, compared with the previous literature, the present paper's contribution lies in a broader data scope, methodological innovation, richer regulatory context, stronger market reaction, and

enhanced predictive power of the operational risk score.

Beyond the hedge fund industry, our findings have broader implications for banking institutions, insurers, and other financial intermediaries that rely on due diligence, risk modeling, and regulatory disclosures. The evolving informational value of Form ADV offers a blueprint for how structured public disclosures can complement proprietary risk assessments in credit allocation, counterparty evaluations, and client onboarding. In particular, the observed shifts in predictive power over time highlight the importance of regulatory adaptability and the potential gains from harmonizing disclosures across financial sectors. As operational risk becomes an increasingly salient concern for banks and other financial institutions—especially in the context of reputational damage, compliance failures, and interconnected exposures—our study suggests that leveraging detailed, standardized public disclosures can significantly improve institutional risk monitoring and governance practices 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.[72] 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:

$$\hat{h}_{i,2023}(T) = \hat{h}_{0i}(T) \times \exp\left(\widehat{\boldsymbol{\beta}}_{\boldsymbol{ORV}}\boldsymbol{X}_{\boldsymbol{ORV\ i,2021}} + C_{2021}^{\prime\hat{\delta}_C} + \hat{\delta}_U Umbrella_{i,2021} + \sum_{f=1}^{353}\hat{\theta}_f FirmDummies_{fi}\right)$$

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. C_{2021} 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 2021. $Umbrella_{i,2021}$ indicates whether the firm is under the Umbrella Registration in the 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 A Table A.3 (p.83). The chart includes a yellow dashed line representing the total accumulative AUM in the sample ($188.86 billion).[73] Labeled points indicate unaffected asset values (total AUM minus accumulative AUM at each point) 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:

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

Where $Pos\Delta\widehat{ProblemNum}_{i,t}$ is the predicted positive litigation change probability, representing if there will be 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 2023. $\hat{\alpha}_i$, $\widehat{\boldsymbol{\beta}}_{\boldsymbol{ORV}}$ and $\widehat{\theta}_f$ are estimated from the two-lag model presented in Table 3. 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%.

[72] 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.

[73] 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

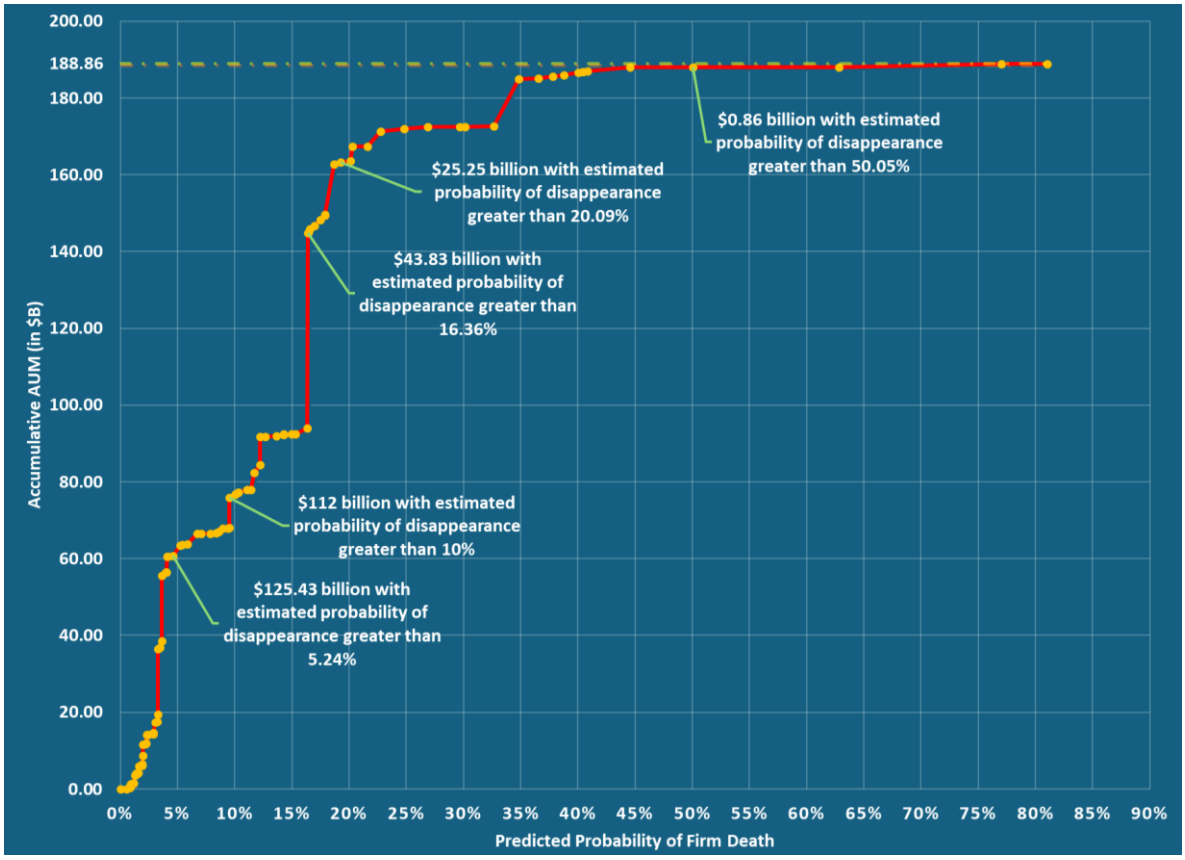

Figure 1B Predicted Increased Litigation Changes and Accumulative AUM in 2023

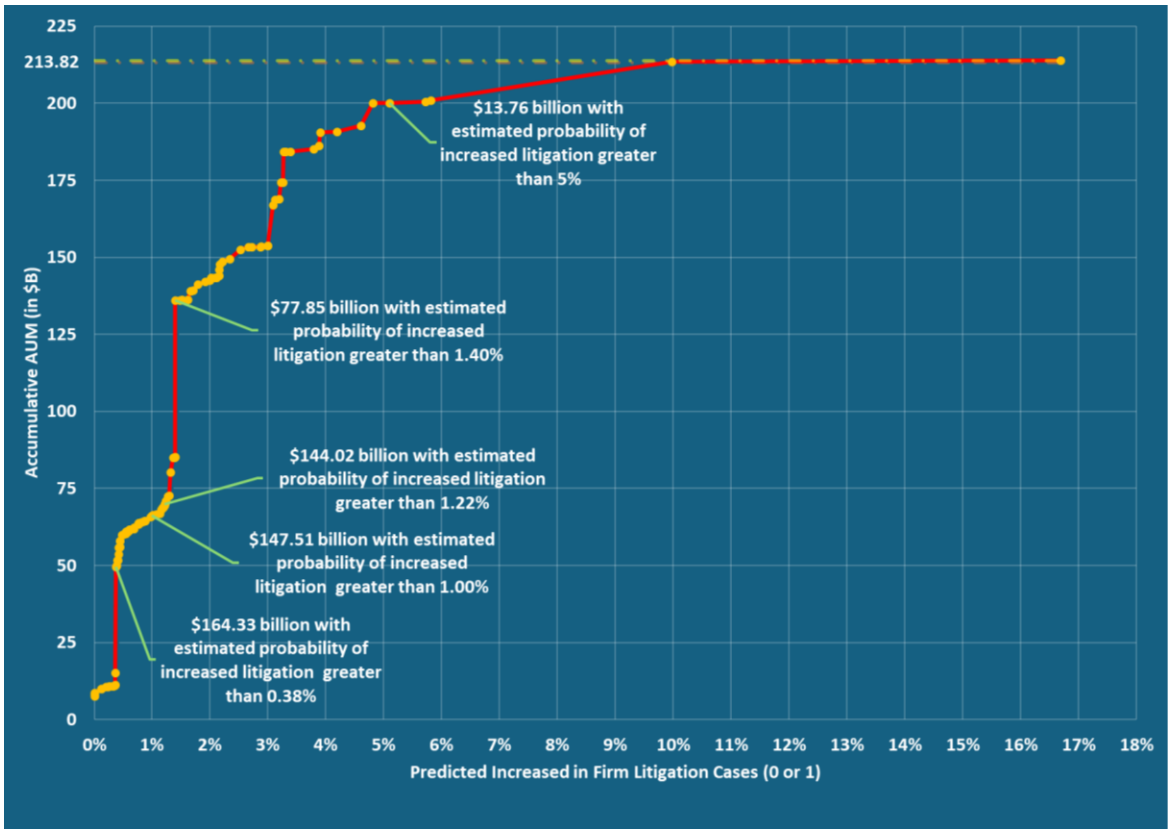

Figure 2 Word Clouds for Sanction Descriptions

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.

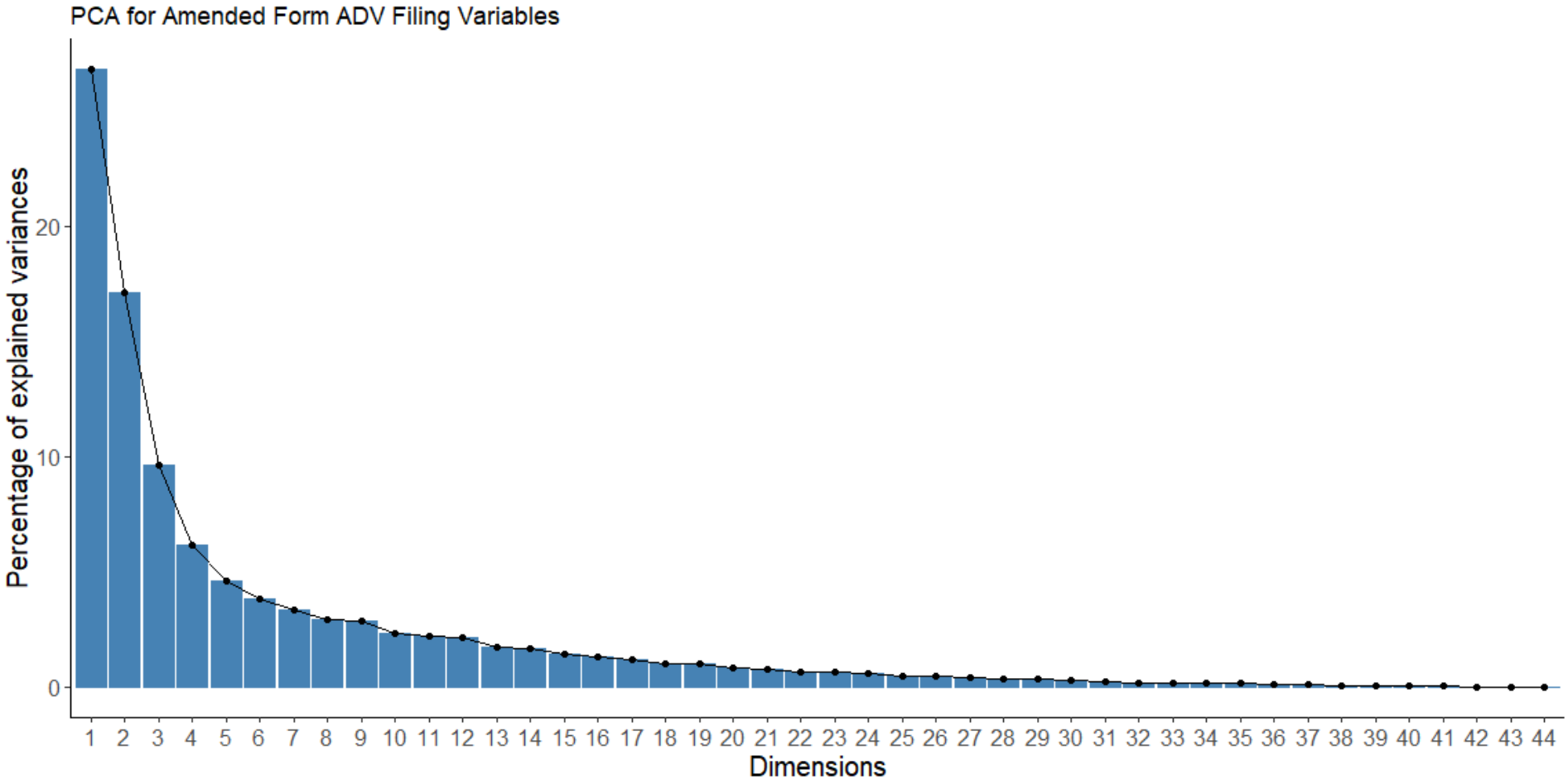

Figure 4 Operational Risk Scores Predicting Flows, Adverse Liquidation, Leverage, and Performance (OOS)

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).[74] 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:[75]

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

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

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

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).[76] 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 B4 (p.95) in Internet Appendix IA. B presents detailed coefficients, *t*/*z* statistics, goodness-of-fit measures, and sample sizes.

[74] The CCA-constructed and LASSO-constructed *Ω*-scores in this table are calculated by year. For CCA-constructed score, we follow the method conducted by BGLS (2008). We implement CCA on the 15 pre-Dodd ADV variables (*BrokerDealer*, *InvestmentAdvisor*, *CommodBroker*, *Banking*, *Insurance*, *LimitedPartnership*, *ManagingMember*, *BuySellYourOwnSecurity*, *BuySellYourselfClientSecurity*, *RecommendSecurityYourOwn*, *AgencyCrossTransaction*, *RecommendUnderwriter*, *RecommendSalesInterest*, *RecommendBrokers*, and *OtherResearch*) and a set of TASS fund performance and characteristic variables (*Return*, *Stdev.*, *Age*, *High water mark*, *Minimum investment*, *Log assets*, *Personal capital*, *Onshore*, *Open to public*, and *Accepts managed accts.*). Raw coefficients for the pre-Dodd variables each year are used as the weight for constructing the CCA-based *Ω*-score. Similarly, for each year we use LASSO by regressing Problem Fund indicator on 44 Form ADV variables and use the related weights for the LASSO-constructed *Ω*-score.

[75] Fund flow for fund i in year t is calculated by $Flow_{i,t} = Assets_{i,t} - Assets_{i,t-1} * (1 + Return_{i,t})/Assets_{i,t-1}$. $Leveraged_{i,t}$ indicates whether fund i uses leverage for the predicted year t. We calculate the annual appraisal ratio by 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. C_{t-1} 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 $t-1$. 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.

[76] To construct the dynamic score, we first apply the LASSO regression process (Section 6.1) to select pre-Dodd and post-Dodd 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 15 (pre-Dodd) or 44 (post-Dodd) 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 LASSO-constructed scores of the funds under this firm for year t.

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

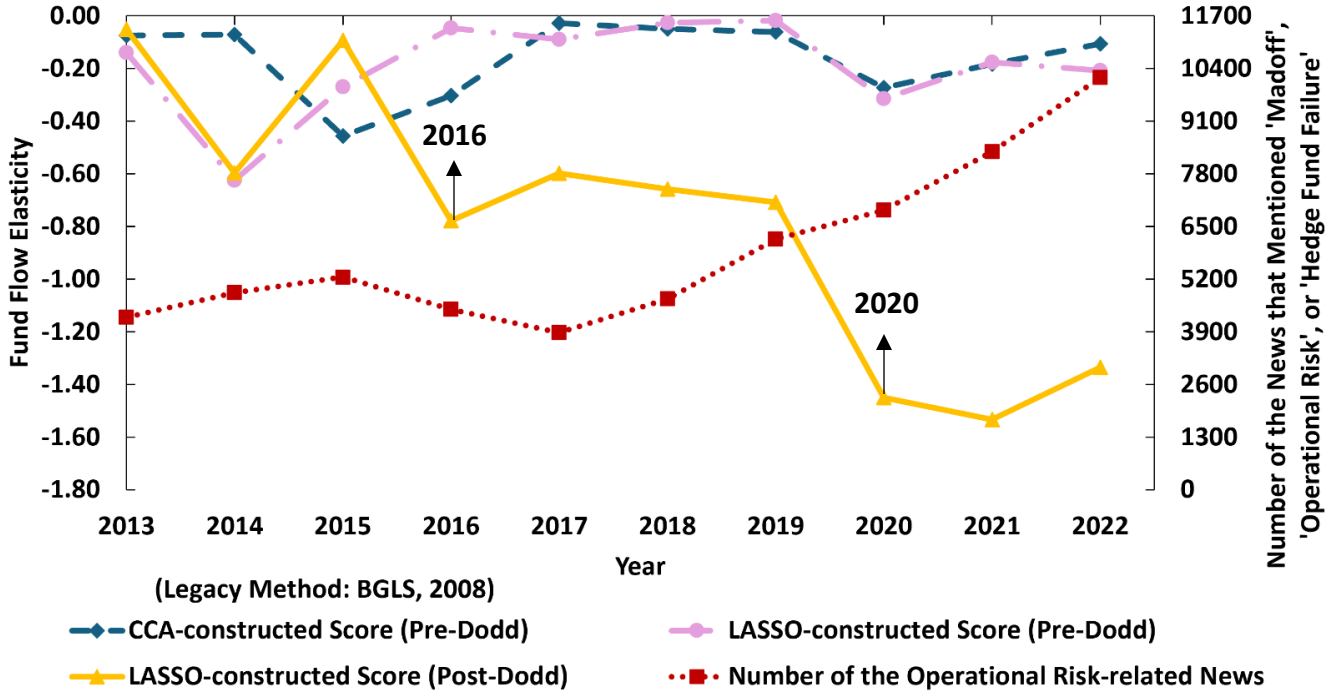

Figure 4B Out-of-Sample Adverse Liquidation Elasticities

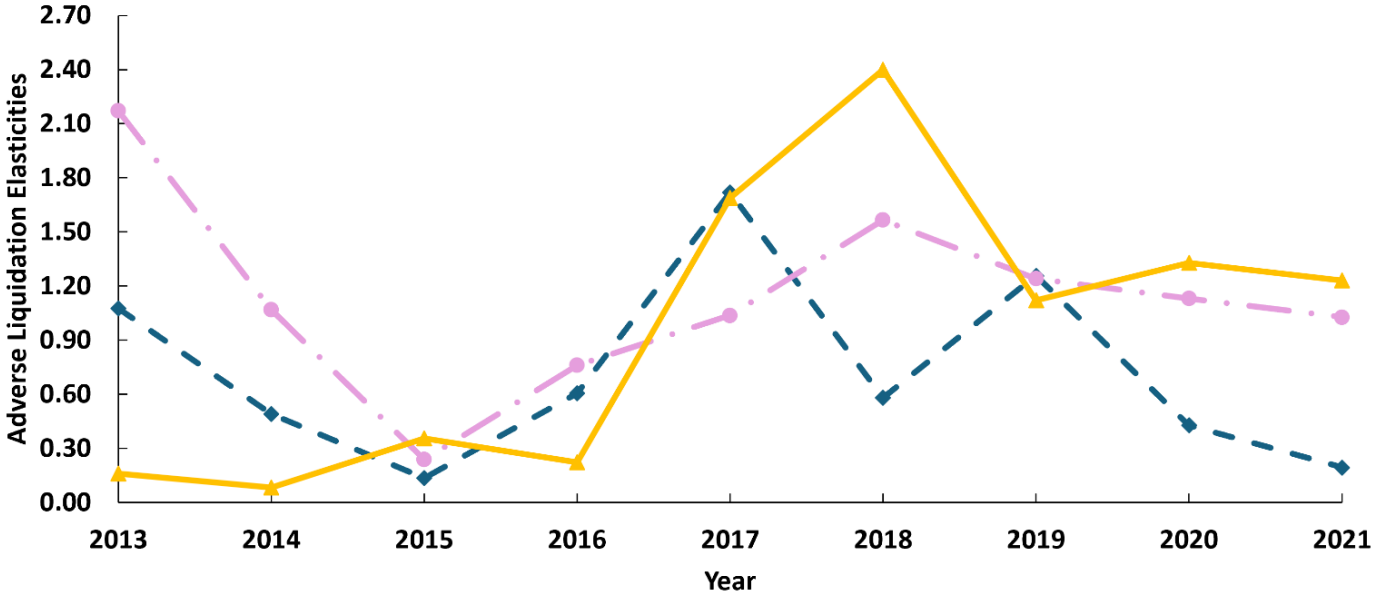

Figure 4C Out-of-Sample Leveraged Elasticities

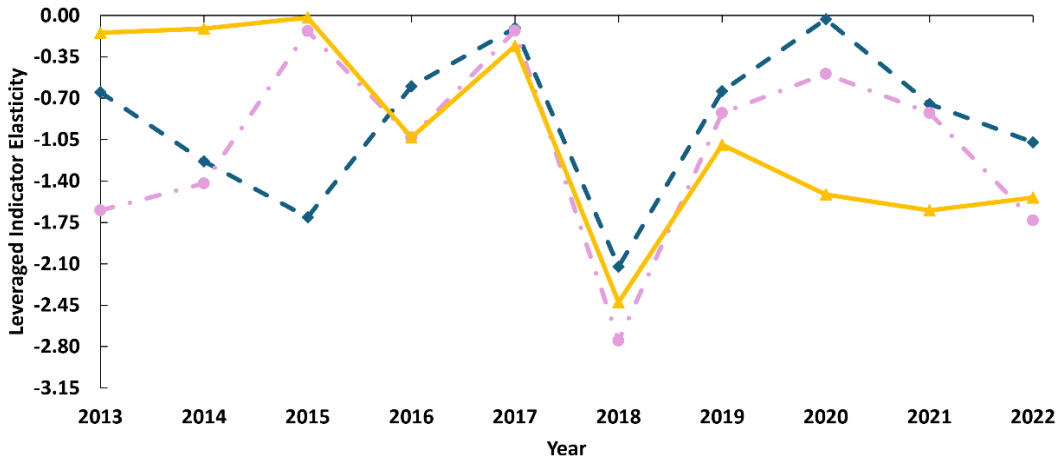

Figure 4D Out-of-Sample Appraisal Ratio Elasticities

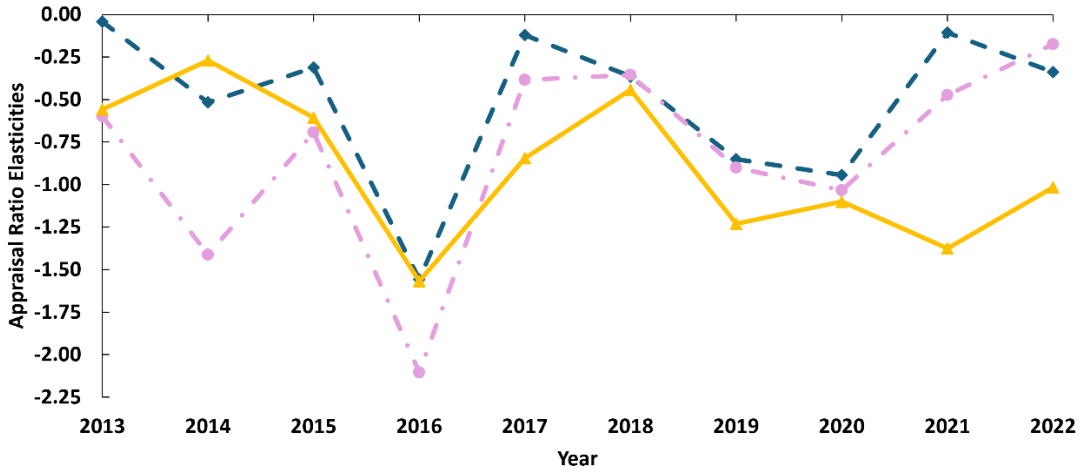

Figure 4E Out-of-Sample Alpha Elasticities

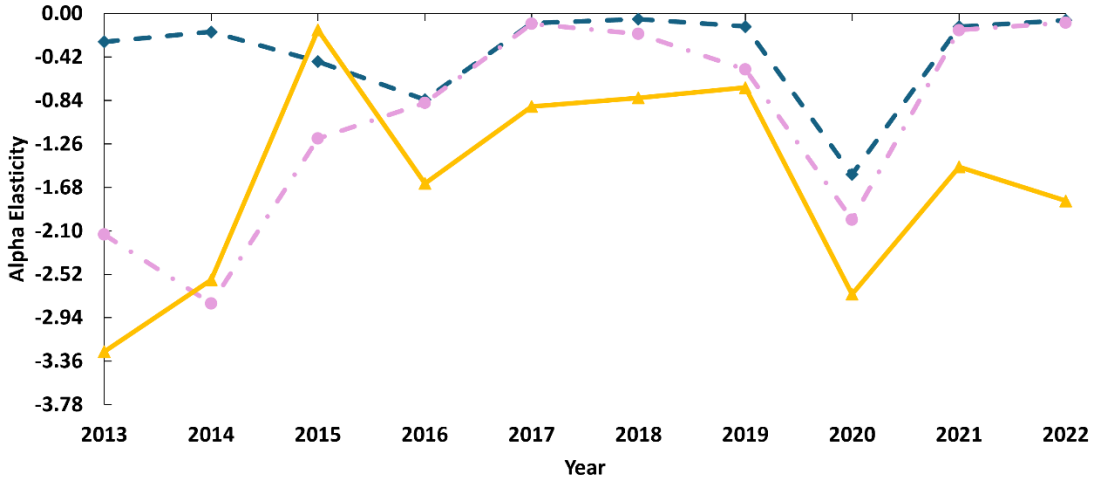

Figure 4 Number of the Charges Violated by Advisory Firms and Affiliates

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.

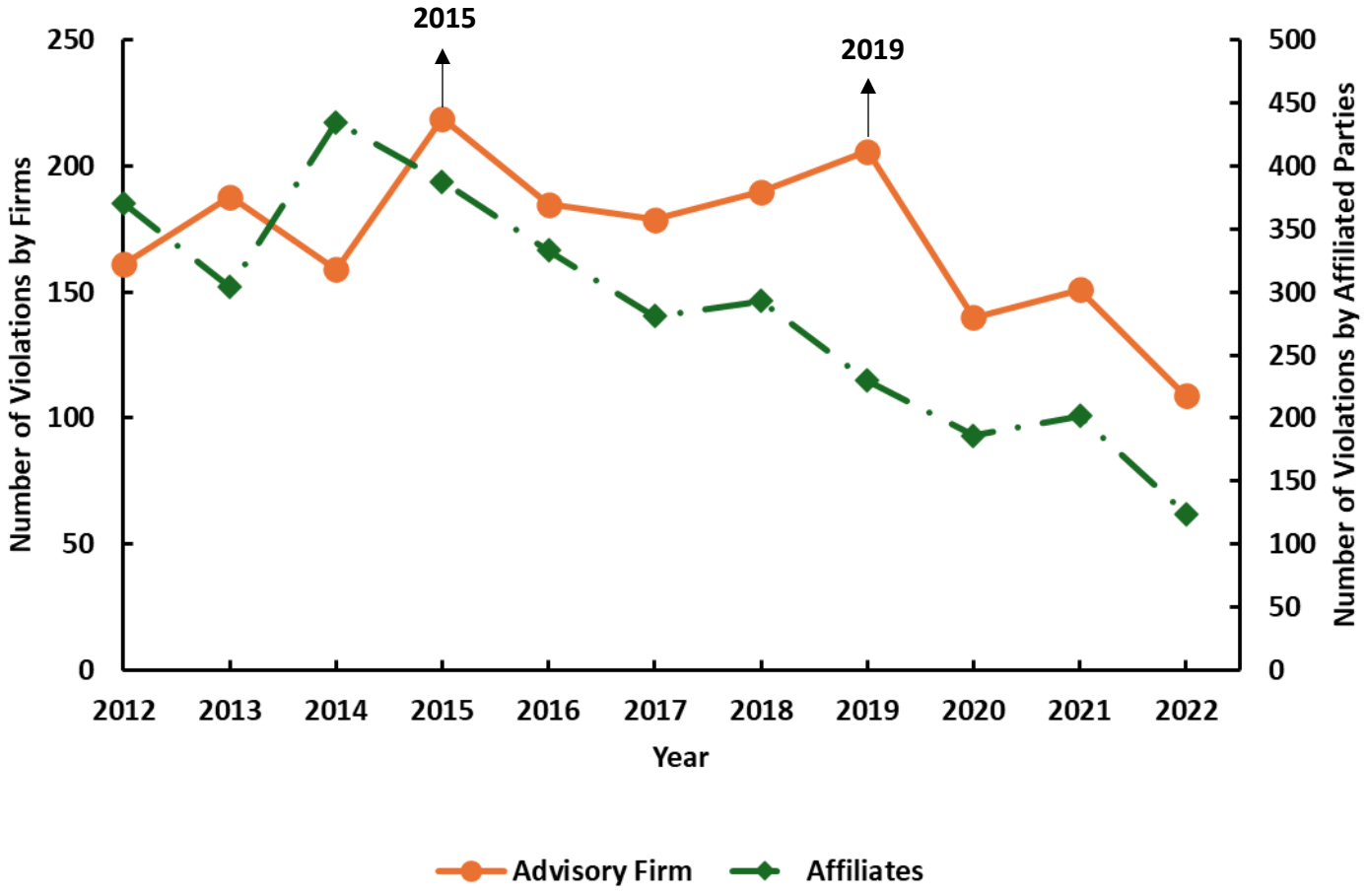

Table 1 Descriptive Statistics of TASS and Matched RIA Funds Panel Sample

This table reports descriptive statistics for RIA funds in the TASS database that have Form ADV filed by their advisory companies.[77] 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. [78] 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	
StdDev	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	***

[77] The sample size varies because TASS includes funds not required to file Form ADV with the SEC. For the TASS database, we remove the funds that report quarterly (instead of monthly return) or gross-of-fee returns, and the funds with less than $10 million assets under management. Moreover, we winsorize the top and bottom 1% for the Return. Furthermore, all the foreign-domiciled funds' assets under management and returns are converted to US dollars according to the annual exchange rate provided by OECD data (https://data.oecd.org/conversion/exchange-rates.htm).

[78] 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.[79] '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	
StdDev	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	***

[79] 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, 8, 9, and 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.[80] Panel A reports the *F*-test[81] and Likelihood Ratio Test (LRT), [82] and Panel B reports the Goodness of Fit for the prediction models.

Panel A1 presents the increased disciplinary history prediction (Logit), comparing models based on LRT, using the following equation:

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

Where $Pos\Delta ProblemNum_{i,t} = \mathbf{1}(ProblemNum_{i,t}\text{-}\ ProblemNum_{i,t-1} > 0)$ 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. $\boldsymbol{X_{ORV\ i,t}}$ 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).[83] Both the pre-Dodd and post-Dodd models include the firm and year dummies. Panel B1 presents the Goodness-of-fit statistics (Pseudo R^2, AIC, and BIC) for litigation events identification and predictions using all post-2011 Form ADV variables (44).

Panel A2 and A3 present the changes in disciplinary history prediction by using the OLS and Cumulative Link Mixed Model (CLMM), comparing models based on *F*-tests and LRT, using the following equation:

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

Where $\Delta ProblemNum_{i,t} = ProblemNum_{i,t}\text{-}\ ProblemNum_{i,t-1}$ 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. Panel B2 and B3 presents the Goodness-of-fit statistics (Adjusted/Pseudo R^2 AIC, and BIC) for liquidation events identification/predictions using all post-2011 Form ADV variables (44). All pre-Dodd and post-Dodd models in the panels include the firm and year dummies. ***, **, * indicate the statistically significant at the 1%, 5%, and 10% levels, respectively.

[80] Since Form ADV is submitted annually by advisory companies, we conduct firm-level tests for the analyses in this table.

[81] 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.

[82] Likelihood-ratio test (LRT): $-2log_e\big(\mathcal{L}_R(\hat{\theta})/\mathcal{L}_F(\hat{\theta})\big) = Deviance_R - Deviance_F$. Where R and F represent reduced (pre-2011) and the full model (post-2011), respectively.

[83] The maximum lag is set to 4 years, based on guidance from SEC Whistleblower Advocates (https://secwhistlebloweradvocate.com/sec-whistleblower-frequently-asked-questions/), which suggests SEC investigations typically take two to four years to complete.

Panel A: *F*-test and LRT										
		Panel A1: LRT (Logit)			Panel A2: *F*-test (OLS)			Panel A3: 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	

Table 3 Continued

Panel B: Goodness of Fit

Panel B1: Increased in Litigation Changes Prediction (Logit)

	Pseudo R^2		Changes (in %)		AIC		Changes (in %)		BIC		Changes (in %)	
Lag(s)	Pre-2011	Post-2011	Pre-2011	Post-2011	Pre-2011	Post-2011	Pre-2011	Post-2011	Pre-2011	Post-2011	Pre-2011	Post-2011
0	52.48%	58.44%			2,268.81	2,255.63			8,092.41	7,920.00		
1	52.58%	59.30%	0.19%	1.47%	1,852.36	1,841.60	-18.36%	-18.36%	6,424.94	6,250.14	-20.61%	-21.08%
2	53.76%	60.31%	2.24%	1.70%	1,505.13	1,485.97	-18.75%	-19.31%	5,160.49	4,962.14	-19.68%	-20.61%
3	52.51%	59.63%	-2.33%	-1.13%	2,269.89	2,266.69	50.81%	52.54%	8,109.87	7,921.08	57.15%	59.63%
4	50.14%	52.70%	-4.51%	-11.62%	3,023.38	3,001.09	33.20%	32.40%	10,718.46	10,497.50	32.17%	32.53%

Panel B2: Litigation Changes Prediction (OLS)

	Adj. R^2		Changes (in %)		AIC		Changes (in %)		BIC		Changes (in %)	
Lag(s)	Pre-2011	Post-2011	Pre-2011	Post-2011	Pre-2011	Post-2011	Pre-2011	Post-2011	Pre-2011	Post-2011	Pre-2011	Post-2011
0	12.69%	14.52%			1,465.89	1,343.67			7,186.85	7,123.47		
1	13.07%	14.66%	2.99%	0.96%	1,403.02	1,255.15	-4.29%	-6.59%	5,844.68	5,806.99	-18.68%	-18.48%
2	15.87%	16.12%	21.42%	9.96%	1,112.16	1,087.40	-20.73%	-13.36%	4,773.50	4,569.55	-18.33%	-21.31%
3	10.87%	14.21%	-31.51%	-11.85%	1,471.22	1,416.55	32.28%	30.27%	7,266.13	7,128.81	52.22%	56.01%
4	8.92%	12.97%	-17.94%	-8.73%	1,840.83	1,875.23	25.12%	32.38%	9,576.94	9,343.87	31.80%	31.07%

Panel B3: Litigation Changes Prediction (CLMM)

	Pseudo R^2		Changes (in %)		AIC		Changes		BIC		Changes	
Lag(s)	Pre-2011	Post-2011	Pre-2011	Post-2011	Pre-2011	Post-2011	Pre-2011	Post-2011	Pre-2011	Post-2011	Pre-2011	Post-2011
0	19.19%	19.87%			2,250.94	2,232.36			2,628.54	2,417.96		
1	20.75%	21.54%	8.13%	8.40%	1,884.49	1,880.84	-16.28%	-15.75%	2,245.78	2,063.87	-14.56%	-14.64%
2	33.92%	35.88%	63.47%	66.57%	1,516.70	1,499.47	-19.52%	-20.28%	1,869.10	1,672.69	-16.77%	-18.95%
3	16.27%	17.72%	-52.03%	-50.61%	2,685.89	2,672.70	77.09%	78.24%	3,076.62	2,864.75	64.60%	71.27%
4	0.32%	2.22%	-98.03%	-87.47%	2,752.02	2,709.28	2.46%	1.37%	3,142.73	2,901.32	2.15%	1.28%

Table 4 LASSO Regression and Relative Importance

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

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

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, categorized into three main groups: regulatory issues, criminal offenses, and civil judicial matters. $\boldsymbol{X_{ORV\ i,t,j}}$ 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 ($p = 44 + 1 = 45$), and λ is the tuning parameter.[84]

Panel A presents the LASSO regression result for the top 10 important variables. Columns report the LASSO coefficients, whether a variable belongs to external or internal (E/I) groups, whether the variable is newly added or originally (N/O) presented in the pre-Dodd Form ADV (BGLS, 2008), and the importance rank of each variable according to the absolute values of coefficients. Panel B presents summary statistics (total number, percentage, median, and sum rank) for the selected Pre- vs. Post-2011 and External vs. Internal operational risk variables. Panel C provides the Kruskal-Wallis Test[85] comparing the relative importance of LASSO-selected relationships.

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

[84] 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.

[85] 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 4 Continued

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

		Num. of the Selected Variables	% of the Selected Variables Among the Total Num. of the 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
External	Good	1.00	6.25%	14.00	14.00
	Bad	15.00	93.75%	13.00	242.00
Internal	Good	3.00	15.79%	16.00	48.00
	Bad	16.00	84.21%	21.50	326.00

Panel C: Relative Importance Comparison--Kruskal-Wallis Test

	Pre-2011 vs. Post-2011	External vs. Internal	External Good vs. External Bad	Internal Good vs. Internal Bad
H	136,347.83	133,567.44	46,257.89	84,416.85
p-value	0.00	0.00	0.00	0.00
Decision	**Post-2011**	**External**	**External Bad**	**Internal Good**

Table 5 Operational Risk External and Internal Good or Bad Percentage Variables Predicting Adverse Outcomes

This table presents the performance, leverage, and adverse liquidation prediction results for RIA funds by using the LASSO-selected external and internal good or bad percentage variables. Models in Panel A use the Cox Proportional-Hazards Model used in this analysis is presented below:[86]

$$h_{i,t}(T) = h_{0i,t}(T) \times \exp\left(\beta_{ExtGood}\, P_{t-1}^{ExtGood} + \beta_{ExtBad} P_{t-1}^{ExtBad} + \beta_{IntGood} P_{t-1}^{IntGood}, + \beta_{IntBad} P_{t-1}^{IntBad} + C_{t-1}^{\prime \delta_C} + \delta_U Umbrella_{i,t-1} + \sum_{j=1}^{13} \gamma_j StyleDummies_{ji} + \sum_{q=1}^{9} \eta_q YearDummies_{qi}\right)$$

Models in Panel B use the equation below for the alpha and appraisal ratio (OLS), as well as leveraged or not (Logit) predictions:[87]

$$Appraisal\ ratio_{i,t}\ or\ Alpha_{i,t}\ or\ Leveraged_{i,t} = \alpha_{i,t} + \beta_{ExtGood}\, P_{t-1}^{ExtGood} + \beta_{ExtBad} P_{t-1}^{ExtBad} + \beta_{IntGood} P_{t-1}^{IntGood}, + \beta_{IntBad} P_{t-1}^{IntBad} + C_{t-1}^{\prime \delta_C} + \delta_U Umbrella_{i,t-1} + \sum_{j=1}^{13} \gamma_j StyleDummies_{ji} \sum_{q=1}^{9} \eta_q YearDummies_{qi} + \varepsilon_{i,t}$$

$P_{t-1}^{ExtGood}$, P_{t-1}^{ExtBad}, $P_{t-1}^{IntGood}$, and P_{t-1}^{IntBad} represent the percentage of the number of Good or Bad[88] All models use TASS style controls and year dummies. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Percentage-level Relationship Variables Predicting Adverse Liquidation									
	Model 1			Model 2			Model 3		
	Coef.	*z*-Value		Coef.	*z*-Value		Coef.	*z*-Value	
ExtGood	-0.60	-1.58					-0.51	-1.36	
ExtBad	1.41	3.98	***				1.75	5.34	***
IntGood				-1.88	-4.19	***	-1.42	-3.27	***
IntBad				0.32	0.93		0.38	1.22	
Return	-0.48	-6.52	***	-0.47	-6.54	***	-0.46	-6.42	***
Stdev.	0.03	0.82		0.03	0.95		0.03	1.02	
Management fee	-0.11	-1.17		-0.07	-0.69		-0.11	-1.15	
Log(Asset)	-0.37	-7.85	***	-0.37	-8.03	***	-0.37	-8.13	***
Leveraged	-0.19	-1.69	*	-0.18	-1.60		-0.17	-1.48	
Onshore	-0.36	-2.46	**	-0.29	-1.98	**	-0.39	-2.76	***
High water mark	-0.11	-0.87		-0.22	-1.67		-0.13	-1.05	
Umbrella	-0.47	-1.12		-0.45	-1.09		-0.45	-1.07	
Num. of Obs.	7,267			7,267			7,267		
Concordance	80.70%			80.80%			79.40%		
External	N			Y			N		
Internal	Y			N			N		
Style	Y			Y			Y		
Year	Y			Y			Y		

[86] A fund i will be considered to be adversely impacted at year t with age T if it is liquidated or unresponsive 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).

[87] We calculate the annual appraisal ratio and alpha by regressing the 12 months excess returns of fund i on the excess return of the fund's TASS-style index j within the same year (BGLS, 2008). $r_{it} - R_{ft} = \alpha_{it} + \beta_i(r_{jt} - R_{ft}) + \varepsilon_{it}$, where R_{ft} is the 3-month US Treasury Bill return. The α_{it} is fund i's alpha in year t and the appraisal ratio is calculated as α_{it} devided by standard deviation of the residuals (ε_{it}). C_{t-1} represents a vector of variables, including average and standard deviation of monthly returns, leveraged or not indicator, onshore and high-water mark indicators, logarithm of assets, and fund management fee in year $t-1$. Furthermore, for performance prediction in the first equation, the 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.

[88] Good/Bad relationships are classified by whether the related variables have negative/positive coefficients according to the previously reported LASSO results. External or Internal relationships the funds are involved in according to the total number of the relationships in the relative groups. 'External' and 'Internal' at the bottom of the table represent whether a model uses the selected variable-level external or internal relationships.

Panel B: Percentage-level Relationship Variables Predicting Performance and Leverage																				
	Model 1			Model 2			Model 3			Model 4			Model 5			Model 6			Model 7		
	Appraisal Ratio									Alpha			Leverage								
	Coef.	*t*-Value		Coef.	*t*-Value		Coef.	*t*-Value		Coef.	*t*-Value		Coef.	*z*-Value		Coef.	*z*-Value		Coef.	*z*-Value	
ExtGood	0.20	2.04	**				0.24	2.64	***	0.16	1.31		0.27	1.44					0.65	3.37	***
ExtBad	-0.96	-6.47	***				-1.51	-7.51	***	-0.23	-3.06	***	-1.38	-5.82	***				-1.03	-7.44	***
IntGood				0.72	3.17	***	1.04	6.21	***	0.17	2.39	**				1.14	-7.21	***	0.29	1.61	
IntBad				-0.04	-0.20		-0.39	-2.32	**	-0.03	-0.54					0.24	1.12		-0.18	-1.08	
Return													0.07	2.26	**	0.06	1.95	*	0.06	2.04	**
Stdev.	-0.21	-9.89	***	-0.19	-9.68	***	-0.22	-9.41	***	-0.07	-5.29	***	-0.03	-1.81	*	-0.02	-1.71	*	-0.02	-1.38	
Management fee	0.34	8.91	***	0.27	7.49	***	0.35	8.99	***	0.03	1.87	*	0.23	5.87	***	0.26	6.48	***	0.22	5.67	***
Log(Asset)	0.01	0.63		0.03	1.50		0.00	0.03		0.02	3.00	***	0.03	1.65	*	0.02	1.32		0.01	0.74	
Leveraged	0.06	1.23		0.09	1.85	*	0.03	0.64		0.02	0.77										
Onshore	0.17	3.46	***	0.10	1.97	**	0.23	4.78	***	0.06	1.97	**	0.43	7.40	***	0.41	4.05	***	0.30	5.57	***
High water mark	0.27	5.28	***	0.17	3.24	***	0.38	7.63	***	0.06	2.17	**	0.22	3.62	***	0.24	7.13	***	0.31	5.43	***
Umbrella	0.39	4.35	***	0.42	4.90	***	0.39	4.30	***	0.16	2.09	**	0.22	1.07		0.56	3.57	***	0.49	3.13	***
Num. of Obs.	3,786			3,786			3,786			6,261			7,267			7,267			7,267		
Adj. R^2	19.40%			22.13%			18.30%			4.96%			17.31%			16.59%			15.53%		
External	N			Y			N			N			N			Y			N		
Internal	Y			N			N			N			Y			N			N		
Style	Y			Y			Y			Y			Y			Y			Y		
Year	Y			Y			Y			Y			Y			Y			Y		

Table 6 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. In Panel A, Models 1 to 3 present results for predicting alpha and appraisal ratio as well as the leveraged indicator (via logistic regression) according to the equation below:[89]

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

Where $ADV - Based\ \Omega\ score_{i,t}$ is the Lasso-based score described in section 6. $Umbrella_{i,t}$ indicates umbrella fund status.

Model 4 presents the liquidation event prediction using the ADV-based *Ω*-score according to the equation below:[90]

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

Models 1-3 in Panel B presents the regulatory, criminal, and civil judicial charges predictions using the ADV-based *Ω*-score according to the equation (via logistic regression) below:[91]

$$Regulatory_{i,t}\ or\ Criminal_{i,t}\ or\ Civil\ Judicial_{i,t} = \alpha_{i,t} + \beta_1 ADV - Based\ \Omega\ score_{i,t-1} + C_{t-1}^{'\delta_C} + \delta_U Umbrella_{i,t-1} + \sum_{j=1}^{12} \gamma_j StyleDummies_{ji} + \sum_{q=1}^{9} \eta_q YearDummies_{qi} + \varepsilon_{i,t}$$

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.

[89] We calculate the annual appraisal ratio and alpha by regressing the 12 months excess returns of fund i on the excess return of the fund's TASS-style index j within the same year (BGLS, 2008). Specifically, $r_{it} - R_{ft} = \alpha_{it} + \beta_i(r_{jt} - R_{ft}) + \varepsilon_{it}$, where R_{ft} is the 3-month US Treasury Bill return. The α_{it} is fund i's alpha in year t and the appraisal ratio is calculated as α_{it} devided by the standard deviation of the residuals (ε_{it}). $Leveraged_{i,t}$ is whether the fund i uses leverage or not for the predicted year t. C_{t-1} represents a vector of variables, including average and standard deviation of monthly returns, leveraged or not indicator, onshore and high-water mark indicators, logarithm of assets, and fund management fee in year $t-1$. Furthermore, for performance prediction in the first equation, the 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.

[90] 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).

[91] $Regulatory_{i,t}$, $Criminal_{i,t}$, 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.

Panel A: ADV-based *Ω* Score predicts 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	
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%		

Table 6 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 7 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:[92]

$$Flow_{i,t} = \alpha_{i,t} + \beta_1\, ADV - Based\ \Omega\ score_{i,t-1} + C_{t-1}^{'\delta_C} + TR_{t-1}^{'\delta_{TR}} + \delta_{ORA} Log(OR\ attention)_{i,t-1} + \delta_U Umbrella_{i,t-1} + \sum_{j=1}^{13} \gamma_j StyleDummies_{ji} + \sum_{q=1}^{9} \eta_q YearDummies_{qi} + \varepsilon_{i,t}$$

$Flow_{i,t}$ is the annual net fund flow in year *t* for fund *i*. [93]

Model 2 includes interaction terms between the *ADV-based Ω-score* and three average monthly return ranks in the previous year (*High trank*, *Mid trank,* and *Low trank;* TR_{t-1}).[94] *ADV-based Ω-score* represents the fund's previous year's operational risk score, *Stdev.*, *Log(Asset),* and *Umbrella* are the standard deviation for monthly return, log of the average monthly assets, and Umbrella Registration indicator of the funds in the previous year. *Management fee* is the management fee for funds. All flows for offshore funds are currency-adjusted where appropriate. 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.

[92] C_{t-1} 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 $t-1$.

[93] Fund flow for fund i in year t is calculated by $Flow_{i,t} = [Assets_{i,t} - Assets_{i,t-1} * (1 + Return_{i,t})]/Assets_{i,t-1}$.

[94] Specifically, *High rank*, *Mid rank,* and *Low rank* are computed as $Min(\frac{1}{3}, Frank_{i,t-1})$, $Min(\frac{1}{3}, Frank_{i,t-1} - High\ trank_{i,t-1})$ and $Min(\frac{1}{3}, Frank_{i,t-1} - High\ trank_{i,t-1} - Mid\ trank_{i,t-1})$ respectively (Franzoni and Giannetti, 2017; Liang et al., 2019). Where $Frank_{i,t-1}$ is the fractional rank for RIA funds from 0 to 1, according to their average monthly return in the previous year.

	Model 1			Model 2			Model 3			Model 4			Model 5		
	Coef.	*t*-Value		Coef.	*t*-Value		Coef.	*t*-Value		Coef.	*t*-Value		Coef.	*t*-Value	
ADV-based *Ω* Score	-0.25	-2.98	***	-2.28	-9.73	***	-0.27	-3.13	***	-2.30	-9.67	***	-2.73	-3.83	***
ADV-based *Ω* Score*High trank				0.53	0.54					0.38	0.68		0.67	0.79	
ADV-based *Ω* Score*Mid trank				-0.91	-3.49	***				-0.97	-3.52	***	-0.71	-1.86	*
ADV-based *Ω* Score*Low trank				-5.56	-9.99	***				-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(OOR attention)													-2.24	-4.07	***
High trank	3.41	9.53	***	3.77	9.32	***	3.44	9.98	***	3.79	9.06	***	3.80	2.49	**
Mid trank	-0.72	-7.20	***	-0.93	-7.40	***	-0.70	-7.91	***	-0.92	-7.29	***	-5.21	-1.67	*
Low trank	-3.31	-9.03	***	-3.98	-9.75	***	-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	-1.97	**	-0.01	-2.00	**	-0.01	-2.08	**	-0.01	-2.09	**	-0.01	-1.70	*
Management fee	0.00	0.50		0.00	-0.51		0.00	0.55		0.00	0.57		0.00	-0.41	
Log(Asset)	0.02	4.42	***	0.02	4.14	***	0.02	4.41	***	0.02	4.10	***	0.02	4.13	***
High water mark	0.02	0.96		-0.02	-1.27		0.02	0.82		0.02	1.12		0.02	1.00	
Onshore	0.01	0.40		0.01	0.55		0.01	0.41		0.01	0.55		0.01	0.41	
Umbrella	0.01	0.35		0.00	0.05		0.01	0.24		0.00	0.02		0.01	0.35	
Style	Y			Y			Y			Y			Y		
Firm	Y			Y			Y			Y			Y		
Year	Y			Y			Y			Y			Y		
Num. of Obs.	7,267			7,267			7,267			7,267			7,267		
Adj. R^2	71.16%			72.81%			71.18%			72.83%			73.12%		

Table 8 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 (via logistic regression) according to the equation below:[95]

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

Where $Regulatory$, $Criminal$, and $Civil\ Judicial$ indicate if a fund i has any regulatory charges, civil judicial matters, or criminal offenses in the previous year. $Umbrella_{i,t}$ indicates umbrella fund status.

Model 4 presents the liquidation event prediction according to the equation below:[96]

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

Panel B reports fund flow predictions by using previous problem charges indicators according to the equation below:[97]

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

$Flow_{i,t}$ is the annual net fund flow in year t for fund i.[98] 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 column labeled 'VIF' represents the Variance Inflation Factor.[99] 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.

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[95] We calculate the annual appraisal ratio and alpha by regressing the 12 months excess returns of fund i on the excess return of the fund's TASS-style index j within the same year (BGLS, 2008). Specifically, $r_{it} - R_{ft} = \alpha_{it} + \beta_i(r_{jt} - R_{ft}) + \varepsilon_{it}$, where R_{ft} is the 3-month US Treasury Bill return. The α_{it} is fund i's alpha in year t and the appraisal ratio is calculated as α_{it} devided by standard deviation of the residuals (ε_{it}). $Leveraged_{i,t}$ is whether the fund i uses leverage or not for the predicted year t.
C_{t-1} represents a vector of variables, including average and standard deviation of monthly returns, leveraged or not indicator, onshore and high-water mark indicators, logarithm of assets, and fund management fee in year $t-1$. Furthermore, for performance prediction in the first equation, the 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.

[96] 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).

[97] TR_{t-1} are three average monthly return ranks in the previous year (*High trank*, *Mid trank,* and *Low trank*). Specifically, *High rank*, *Mid rank,* and *Low rank* are computed as $Min(\frac{1}{3}, Frank_{i,t-1})$, $Min(\frac{1}{3}, Frank_{i,t-1} - High\ trank_{i,t-1})$ and $Min(\frac{1}{3}, Frank_{i,t-1} - High\ trank_{i,t-1} - Mid\ trank_{i,t-1})$ respectively (Franzoni and Giannetti, 2017; Getmansky et al., 2019). Where $Frank_{i,t-1}$ is the fractional rank for RIA funds from 0 to 1, according to their average monthly return in the previous year.

[98] Fund flow for fund i in year t is calculated by $Flow_{i,t} = [Assets_{i,t} - Assets_{i,t-1} * (1 + Return_{i,t})]/Assets_{i,t-1}$.

[99] $VIF_i = 1/1 - R_i^2$. Where R_i^2 is the unadjusted coefficient of determination for regressing the i th independent variable on the remaining ones. A variable with a VIF score greater than 5 is considered to have a higher potential for multicollinearity.

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		VIF	Coef.	*t*-Value		VIF	Coef.	*z*-Value		VIF	Coef.	*z*-Value		VIF
Regulatory	-0.05	-2.22	**	1.08	-0.04	-0.49		1.09	-0.06	-0.65		1.08	0.39	1.86	*	1.12
Criminal	-0.26	-1.19		1.01	-0.68	-3.01	***	1.09	-1.11	-1.87	*	1.01	0.31	0.31		1.02
Cvil Judicial	-0.01	-0.08		1.01	-0.26	-2.72	***	1.02	-0.48	-1.17		1.02	7.10	0.00		1.00
Return									0.04	1.26		1.13	-0.46	-5.34	***	1.16
Stdev.	-0.07	-5.29	***	1.40	-0.22	-9.68	***	1.47	-0.02	-1.44		1.44	0.05	1.24		1.38
Management fee	0.03	1.88	*	1.12	0.37	9.17	***	1.11	0.17	3.96	***	1.11	-0.11	-0.95		1.18
Log(Asset)	0.02	2.90	***	1.20	0.01	0.78		1.20	0.01	0.57		1.17	-0.31	-5.99	***	1.20
Leveraged	0.02	0.75		1.22	0.01	0.25		1.23					-0.09	-0.66		1.16
Onshore	0.08	2.78	***	1.18	0.19	4.77	***	1.22	0.46	7.66	***	1.17	-0.55	-3.50	***	1.19
High water mark	0.07	2.40	**	1.46	0.39	7.83	***	1.51	0.36	5.86	***	1.35	-0.28	-1.86		1.48
Umbrella	0.17	2.19	**	2.64	0.35	3.95	***	2.77	0.44	2.81	***	3.38	-0.44	-1.08		3.17
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		VIF	Coef.	*t*-Value		VIF	Coef.	*t*-Value		VIF	Coef.	*t*-Value		VIF
Regulatory	-0.01	-0.59		2.39	-0.01	-0.29		2.32								
Criminal	-0.09	-0.60		1.33					-0.08	-0.54		1.30				
Cvil Judicial	-0.16	-1.89	*	1.30									-0.16	-1.87	*	1.29
High trank	3.44	9.15	***	2.34	3.44	9.10	***	2.34	3.44	9.08	***	2.34	3.44	9.08	***	2.34
Mid trank	-0.70	-7.88	***	3.22	-0.70	-7.87	***	3.22	-0.70	-7.86	***	2.28	-0.70	-7.96	***	3.22
Low trank	-3.26	-9.63	***	2.28	-3.26	-9.60	***	2.28	-3.26	-9.59	***	2.28	-3.27	-9.72	***	2.28
Stdev.	-0.01	-2.03	**	2.76	-0.01	-2.03	**	2.76	-0.01	-2.05	**	2.76	-0.01	-2.02	**	2.75
Management fee	0.00	0.59		1.90	0.00	-0.57		1.90	0.00	0.51		1.90	0.00	0.57		1.90
Log(Asset)	0.02	4.43	***	2.51	0.02	4.40	***	2.51	0.02	4.47	***	2.51	0.02	4.39	***	2.51
High water mark	0.02	0.83		2.72	0.02	0.84		2.72	0.02	0.85		2.71	0.02	0.80		2.71
Onshore	0.01	0.47		3.20	0.01	0.49		3.20	0.01	0.44		2.20	0.01	0.43		2.20
Umbrella	0.01	0.19		3.00	0.01	0.34		2.96	0.01	0.26		2.09	0.01	0.18		2.99
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 Internet Appendix (IA)

Appendix

A Variable Explanation, Regulatory Information, and Sample Construction

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 provides a detailed explanation of the external and internal conflict relationship variables according to Form ADV Part 1A, as well as the variables used in our empirical analysis. Panel A presents the variables and relative explanations that belong to Item 7 (Financial Industry Affiliations and Private Fund Reporting). Panel B presents the variables and relative explanations that belong to Item 8 (Participation or Interest in Client Transactions), 9 (Custody), and 10 (Control Person). Panel C presents the fund performance, characteristics from TASS, and the constructed operational risk-related score according to the Form ADV filing.

Panel A: External Relationships (Item 7)	
Variables	Explanations
BrokerDealer	Whether a fund has a related person that is a broker/dealer, municipal securities dealer, or government securities broker or dealer.
InvestmentAdvisor	Whether a fund has a related person that is another investment adviser.
SwapDealer	Whether a fund has a related person that is a registered security-based swap dealer.
CommodBroker	Whether a fund has a related person that is a commodity pool operator or commodity trading advisor.
FuturesCommission	Whether a fund has a related person that is a futures commission merchant.
Banking	Whether a fund has a related person that is a banking or thrift institution.
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.
ManagingMember	Whether a fund has a related person that is a sponsor, general partner, or managing member (or equivalent) of pooled investment vehicles.

Panel A: External Relationships (Item 7)	
Variables	Explanations
BrokerDealer	Whether a fund has a related person that is a broker/dealer, municipal securities dealer, or government securities broker or dealer.
InvestmentAdvisor	Whether a fund has a related person that is another investment adviser.
SwapDealer	Whether a fund has a related person that is a registered security-based swap dealer.
CommodBroker	Whether a fund has a related person that is a commodity pool operator or commodity trading advisor.
FuturesCommission	Whether a fund has a related person that is a futures commission merchant.
Banking	Whether a fund has a related person that is a banking or thrift institution.
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.

ManagingMember	Whether a fund has a related person that is a sponsor, general partner, or managing member (or equivalent) of pooled investment vehicles.

Panel C: Variables used in the Empirical analysis

Variable	Definition
1st-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	Appraisal ratio of a fund according to the performance for the relative year.
Log (Asset)	Log of the average monthly asset of a fund in the previous year.
Exempt	Whether a fund's related company is an ERA.
ExtBad	Percentage of the external bad variables (with positive LASSO coefficients in Table 4) among all the external relationships.
ExtGood	Percentage of the external good variables (with negative LASSO coefficients in Table 4) among all the external relationships.
Fund age	The age of a fund started from its inception date in the previous year.
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.
IntBad	Percentage of the internal bad variables (with positive LASSO coefficients in Table 4) among all the internal relationships.
IntGood	Percentage of the internal good variables (with negative LASSO coefficients in Table 4) among all the internal relationships.
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 $Min\left(\frac{1}{3}, Frank - High\ trank - Mid\ trank\right)$, where $Frank$ is the fractional rank for funds from 0 to 1, according to their average historical return in the relative year.
Management fee	Management fee of a fund.
Margin	Whether a fund leverage using margin for borrowing.
Mid trank	Calculated by $Min\left(\frac{1}{3}, Frank - High\ trank\right)$, where $Frank$ is the fractional rank for funds from 0 to 1, according to their average historical return in the relative year.
Min. Investment	Minimum investment of a fund.
Onshore	Whether a fund is domiciled in the US in the previous year.
Open to public	Whether a fund is open to public.

Personal capital	Whether the principals of a fund have money invested.
Return	The average monthly return of a fund according to the performance on TASS in the relative year (for Table 1 and Table 2, and Table 10) and the previous year (other tables).
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 (Table 1, Table 2, and Table 10) or previous year (other Tables).
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.

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).

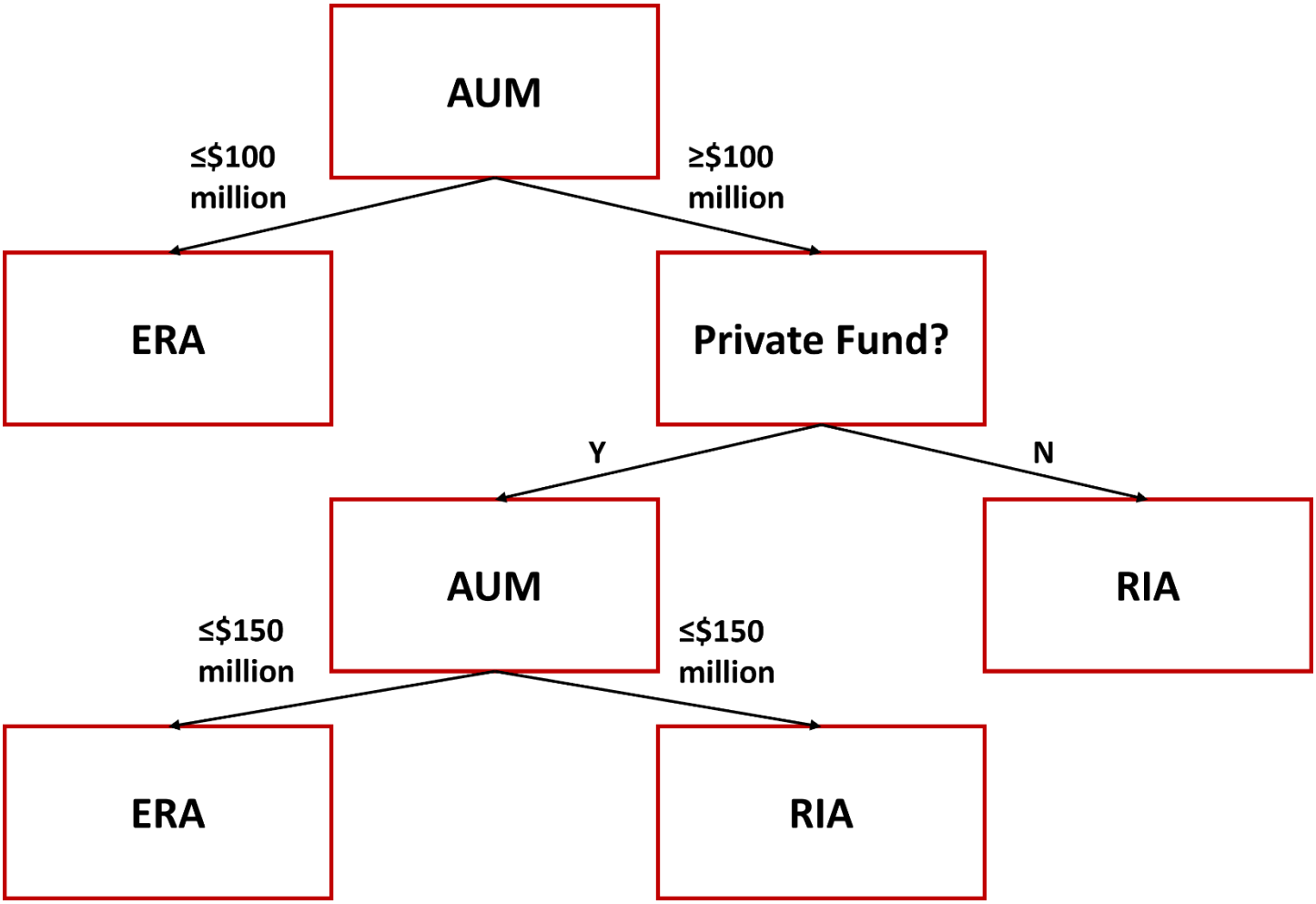


Figure A.3 Form ADV Structure

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

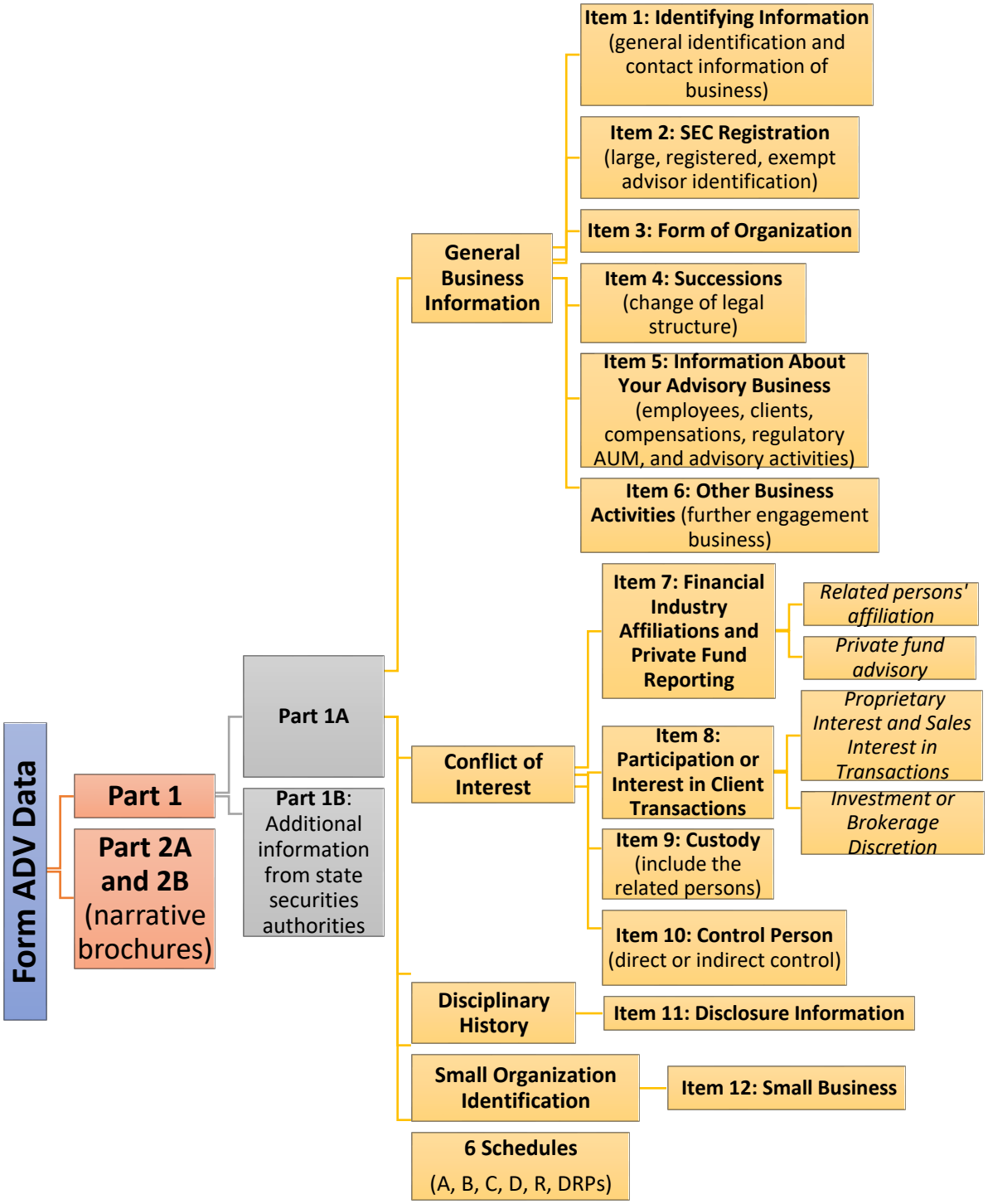


Table A.2 Sample and Subgroups Composition

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. Panel C breaks down the sample by RIA, ERA, and funds whose related firms changed status during the sample period. Panels D and E 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 – RIA vs. ERA and Adverse Liquidation Records				
	RIA vs. ERA		Adverse Liquidation Records	
	Funds	Firms	Funds	Firms
Always RIA	4,819	1,038	1,186	455
Always ERA	1,124	277	258	94
Switching between RIA and ERA	273	71	273	71
Total	6,216	1,386	1,717	620

Table 2 Continued

Panel D: 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 E: 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. Panel A reports the F-test and Likelihood Ratio Test (LRT) and Panel B reports the Goodness of Fit for the prediction models.

Panel A1 presents the identification and prediction of litigation events, comparing models based on *F*-tests, 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 (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).[100] Panel B1 presents the Goodness-of-fit statistics (Adjusted R^2, AIC, and BIC) for litigation events identification and predictions using all post-2011 Form ADV variables (44).

Panel A2 presents a comparison of adverse liquidation identification and predictions using an LRT with the Cox Proportional-Hazard model:

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

Where $h_{i,t}(T)$ is an adverse event as described in the body of the paper for RIA funds. A fund i is considered to be adversely impacted at year t with age T if it is liquidated or unresponsive to contact according to TASS and has a negative average return in the previous 6 months, and a decreased AUM in the previous 12 months (Liang and Park, 2010). 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 $t-2$. Panel B2 presents the Goodness-of-fit statistics (Concordance ratio, AIC, and BIC) for liquidation events identification/predictions using all post-2011 Form ADV variables (44). 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.

[100] The maximum lag is set to 4 years, based on guidance from SEC Whistleblower Advocates (https://secwhistlebloweradvocate.com/sec-whistleblower-frequently-asked-questions/), which suggests SEC investigations typically take two to four years to complete.

Panel A: *F*-test and LRT

		Panel A1: *F*-test			Panel A2: 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	

Panel B: Goodness of Fit

Panel B1: Litigation Cases Prediction

	Adj. R^2		Changes (in %)		AIC		Changes		BIC		Changes	
Lag(s)	Pre-2011	Post-2011	Pre-2011	Post-2011	Pre-2011	Post-2011	Pre-2011	Post-2011	Pre-2011	Post-2011	Pre-2011	Post-2011
0	39.74%	40.29%			-566.15	-594.4			6,943.91	7,114.34		
1	39.93%	41.90%	0.48%	4.00%	-809.95	-858.23	-243.79	-263.82	3,656.85	1,897.86	-3,287.07	-5,216.48
2	46.48%	49.70%	16.40%	18.62%	-1,071.48	-1,293.11	-261.53	-434.88	2,967.94	2,855.37	-688.9	957.5
3	40.64%	43.81%	-12.56%	-11.85%	-616.83	-712.63	454.65	580.48	3,990.07	3,958.99	1,022.13	1,103.63
4	40.22%	41.88%	-1.03%	-4.41%	-322.08	-451.89	294.75	260.74	5,740.41	5,677.51	1,750.34	1,718.52

Panel B2: Adverse Liquidation Prediction

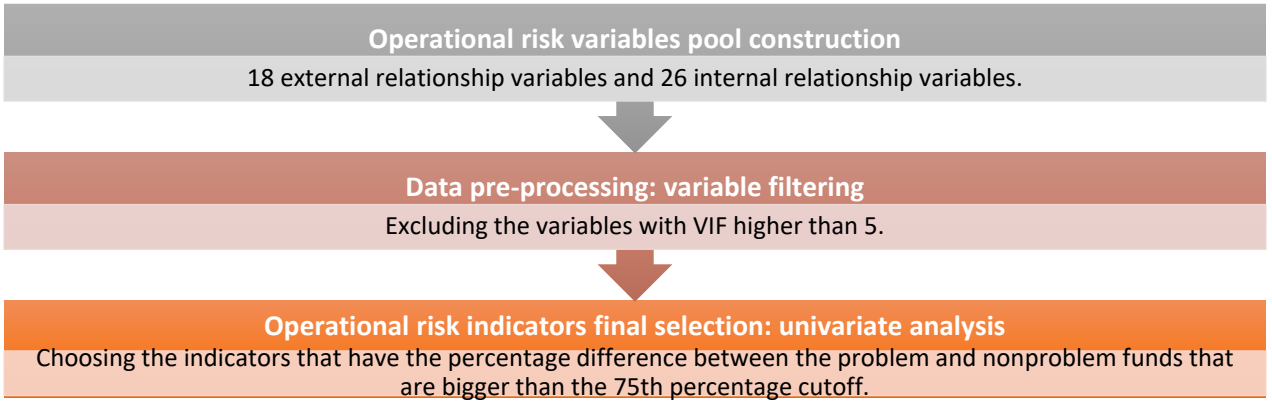
	Concordance		Changes (in %)		AIC		Changes		BIC		Changes	
Lag(s)	Pre-2011	Post-2011	Pre-2011	Post-2011	Pre-2011	Post-2011	Pre-2011	Post-2011	Pre-2011	Post-2011	Pre-2011	Post-2011
0	96.50%	96.60%			11,021.47	11,020.44			15,064.09	15,195.32		
1	96.50%	96.60%	0.00%	0.00%	7,924.52	7,664.20	-3,096.95	-3,356.24	11,803.77	11,667.27	-3,260.32	-3,528.05
2	97.70%	98.70%	1.24%	2.17%	3,284.07	3,243.30	-4,640.45	-4,420.90	5,420.30	5,283.59	-6,383.47	-6,383.68
3	97.20%	97.90%	-0.51%	-0.81%	4,877.86	4,202.86	1,593.79	959.56	7,627.82	6,844.97	2,207.51	1,561.38
4	94.90%	94.60%	-2.37%	-3.37%	5,836.12	5,797.39	958.26	1,594.53	9,123.55	8,968.65	1,495.74	2,123.68

B BGLS (2008) ω (style)-Score Predicting Future Adverse Outcomes and Fund Flows for RIA Funds

In this section, we use the ω (style)-Score constructed by BGLS (2008) to predict the future performance, liquidation, and fund flows for RIA funds, as a comparison with our constructed ADV-based Ω-Score by using the pure LASSO regression described in the main text. The main challenge for the CCA method is that the imbalanced number of the two sets of variables may cause inaccurate results. However, the number of the TASS variables is limited, compared with the 42 selected variables by LASSO regression in our study. Consequently, we use a three-step univariate analysis-combined indicator selection process to find out the key operational risk indicators from the amended Form ADV filing. A potential problem is the multi-collinearity issue within the operational risk variables. Thus, we first filter the variables according to the Variance Inflation Factor (VIF) score. A variable with a VIF that is higher than 5 should be considered a high collinearity variable, which will be dropped from our operational risk variable pool. Secondly, we adopt the univariate analysis conducted by BGLS (2008) to identify the variables that have a stronger relationship with the problem funds. Specifically, we choose the variables that have a percentage difference between the problem and non-problem funds that are bigger than the 75th percent cutoff compared with external and internal relationships respectively. A visualized variable selection process for this method can be illustrated in Figure 4 below.

Figure 4 Operational Risk Indicator Selection Process for BGLS (2008) CCA-based method

This figure illustrates our operational risk indicator selection process for the CCA-based method of operational risk score construction for RIA funds.



According to the selection process, 13 variables (7 external and 6 internal relationships) are selected for the CCA-ADV-based Ω-Score.[101] Table 5 presents the CCA results using the method conducted by BGLS (2008) for the operational risk score metric. The maximum correlation between the TASS variables and ADV operational risk indicators is 70%, which increases by more than 67% to the 42% reported by BGLS (2008). The value for each variable is the correlation between the constructed CCA-ADV-based Ω-Score by using the raw coefficient (unshown) and the related variables for each fund.[102] We then can compare the prediction power for this BGLS (2008)-style score and the ADV-based Ω-Score developed in our paper for future adverse outcomes and fund flows.

[101] The main difference between the score constructed in this section and the CCA-ADV-based Ω-Score constructed in Table 9 of main text is that in the operational risk variables pool construction process, we use the full set of 44 variables that include both pre-Dodd and post-Dodd ADV variables in the amended Form ADV. While the CCA-ADV-based Ω-Score constructed in Table 9 (main text) only includes pre-Dodd variables during the CCA process.

[102] According to BGLS (2008), Form ADV was terminated then so that they use the raw coefficients of TASS variables to construct the ω-Score. Since the amended Form ADV is fully public after 2011, we adopt the same CCA process but use the raw coefficients for selected ADV indicators for the CCA-ADV based Ω-Score construction.

Table B.1 ADV-based *Ω*-Score Construction According to the Canonical Correlation Analysis (CCA)

This table presents the CCA results for the ADV-based *Ω*-Score using the method conducted by BGLS (2008). ***, **, * indicate the statistically significant at the 1%, 5%, and 10% levels, respectively. It presents the performance and liquidation prediction for RIA funds by using the CCA-ADV-based *Ω*-Score prediction for the adverse outcome for RIA funds.

TASS Variables			ADV Indicators		
Return	-0.10	***	BrokerDealer	0.74	***
Stdev	-0.39	***	InvestmentAdvisor	0.44	***
Log(Asset)	-0.43	***	CommodBroker	-0.14	***
Leveraged	-0.73	***	BankingThrifting	0.89	***
Age	-0.23	***	Trust	0.45	***
Margin	-0.40	***	Insurance	0.59	***
Personal capital	-0.43	***	ManagingMember	-0.26	***
Onshore	-0.56	***	BuySellYourselfClientSecurity	0.13	***
Personal capital	-0.31	***	RecommendSecurityYourOwn	0.33	***
Accepts managed accts.	-0.40	***	RecommendUnderwriter	0.10	***
			RecommendSalesInterest	0.37	***
			OtherReserach	-0.14	***
			CompensateNonEmpClientsRef	-0.36	***
Correlation between TASS and ADV panels	0.70	***			

Table B.1 presents the future appraisal ratio, style-adjusted return, leveraged, and liquidation prediction for RIA funds by using the CCA-ADV-based *Ω*-Score constructed in the spirit of BGLS (2008). Panel A presents the performance and leveraged predictions. Compared with our pure LASSO-based regression (in the main text), the operational risk score in the style-adjusted return is insignificant, although the sign of the coefficient is negative. Furthermore, the appraisal ratio prediction finds out that the CCA-based operational risk score can negatively and significantly predict the funds that were not leveraged in the previous year. However, compared with the significant level in our main regression in Table B.2, our ADV-based *Ω*-Score that uses the weights defined by the LASSO process outperforms the CCA-style operational risk score. Similarly, according to Panel B, the coefficient for ADV-based *Ω*-Score (LASSO) presents significance at a 1% level, compared with 5% for the CCA-style score.

Table B.2 CCA-ADV-based *Ω*-Score Predicting Future Adverse Outcomes

Table B.2 presents the future appraisal ratio, alpha, leveraged, and liquidation prediction for RIA funds by using the CCA-ADV-based *Ω*-Score constructed in the spirit of BGLS (2008). Panel A presents alpha, appraisal ratio, and leverage prediction, and all models control for the TASS style and the year (as well as the clustered standard errors) for predictions. Panel B presents the adverse impacted funds' prediction. All models control the TASS style, age, and year (as well as the clustered standard errors) for predictions. Values in parentheses represent the hazard ratio. ***, **, * indicate the statistically significant at the 1%, 5%, and 10% levels, respectively.

Panel A: CCA-ADV-based Ω-score Predicting Style-adjusted Return and Leveraged																					
	Model 1			Model 2			Model 3			Model 4			Model 5								
	Alpha			Appraisal Ratio									Leveraged								
	Full Sample						Previously Leveraged			Previously non-leveraged			Full Sample								
	Coef.	*t*-Value		Coef.	*t*-Value		Coef.	*t*-Value		Coef.	*t*-Value		Coef.	*z*-Value							
ADV-based Ω-score (CCA)	-0.54	-0.98		-0.50	-0.73		-1.47	-1.85	*	0.20	0.12		-27.16	-6.90	***						
Return													0.01	0.27							
Stdev.	0.00	-0.96		-0.04	-7.00	***	-0.04	-5.27	***	-0.04	-4.15	***	-0.03	-0.90							
Management fee	-0.01	-0.74		0.02	1.14		-0.01	-0.42		0.12	2.54	**	0.02	0.18							
Log(Asset)	0.02	2.60	**	0.03	3.73	***	0.05	4.53	***	0.02	1.45		0.02	0.48							
Leveraged	0.00	0.17		0.01	0.47																
Onshore	0.00	-0.14		-0.02	-0.64		-0.04	-0.92		0.00	-0.01		1.55	10.38	***						
High water mark	0.07	2.78	***	0.11	3.81	***	0.12	2.59	***	0.14	3.29	***	-0.03	-0.22							
Umbrella	0.12	3.90	***	0.01	0.36		-0.08	-1.52		0.09	1.64		0.36	1.97	**						
Style	Y			Y			Y			Y			Y								
Year	Y			Y			Y			Y			Y								
Num. of Obs.	5,082			3,066			1,530			1,536			5,866								
Adj. R^2	3.78%			12.26%			17.97%			7.49%											
Pseudo R^2													25.49%								

Panel B: CCA-ADV-based Ω-score Predicting Future Adversely Impacted Events									
	Model 1			Model 2			Model 3		
	Full Sample			Previous Problem Funds			Previous Nonproblem Funds		
	Coef.	*z*-Value		Coef.	*z*-Value		Coef.	*z*-Value	
ADV-based Ω-score (CCA)	-9.10	-0.99		0.35	2.01	**	-17.17	-1.47	
Return	-0.05	-0.33		-0.31	-1.56		-0.89	-1.91	*
Stdev.	-0.22	-2.61	**	0.00	0.04		-0.01	-0.10	
Management fee	-0.14	-0.50		0.00	0.02		-0.21	-2.44	**
Log(Asset)	-0.21	-2.17	**	-0.65	-4.27	***	-0.17	-0.49	
Leveraged	0.12	0.42		-0.01	-0.04		-0.15	-1.48	
Onshore	-0.36	-1.31		-0.18	-0.42		0.24	0.81	
High water mark	-1.50	-3.13	***	0.28	0.75		-0.18	-0.64	
Umbrella	-0.81	-1.85	*	-0.35	-0.40		-1.36	-2.67	***
Style	Y			Y			Y		
Year	Y			Y			Y		
Num. of Obs.	5,866			756			5,110		
Concordance	77.70%			96.70%			78.50%		

Furthermore, consistent with the prediction results, the CCA-based operational risk score can still negatively predict the future fund flow for the full RIA fund sample (although the significant level is lower than that of the LASSO-ADV-based Ω-score), as presented in Table B.3 below. However, when restricting the analysis to a less noisy sample, with winsorized flows and with clustered standard errors for firms, there is no significant relationship between the operational risk (CCA-based) and the investor's future decision. To summarize, the analysis in this section shows that the BGLS-style ADV-based Ω-score still has the power to forecast performance, liquidation, and fund flows, while the ADV-based Ω-score based on the LASSO regression coefficients is better at predicting adverse outcomes and investors' future decisions.

Table B.3 CCA-ADV-based Ω-Score Predicting Future Fund Flows

Table B.3 presents the results for predicting fund flow for RIA funds by using the CCA-ADV-based Ω-Score constructed in the spirit of BGLS (2008). All models control the TASS-style and year-clustered standard errors for predictions. ***, **, * indicate the statistically significant at the 1%, 5%, and 10% levels, respectively.

	Model 1			Model 2		
	Full Sample			Winsorize top and bottom 1% fund flows		
	Coef.	*t*-Value		Coef.	*t*-Value	
ADV-based Ω-score (CCA)	-1.79	-2.14	**	-0.38	-0.62	
High trank	5.02	16.82	***	3.45	16.23	***
Mid trank	-0.37	-2.68	***	-0.98	-9.57	***
Low trank	-4.82	-16.65	***	-3.44	-14.83	***
Stdev.	-0.01	-0.82		0.00	-0.26	
Management fee	-0.01	-0.54		-0.01	-0.68	
Log(Asset)	0.03	2.79	***	0.02	1.80	*
Umbrella	-0.08	-1.46		-0.01	-0.36	
Style	Y			Y		
Firm	Y			Y		
Year	Y			Y		
Num. of Obs.	5,866			5,613		
Adj. R^2	70.50%			69.91%		

Internet Appendix for

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

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July 2025

Abstract

This document provides supplementary materials to the paper "The Dodd-Frank Act and Hedge Fund Operational Risk". Appendix IA. A of the document provides regression tables and a figure with detailed results for the analysis of RIA funds. We also present the tables of robustness analysis for the combined RIA and ERA sample, as well as the detailed Out-of-Sample predictions (discussed in Section 7 of the paper) in Appendix IA. B. The table of contents for the related results in this document is presented below.

IA. A Detailed Results of the Analysis for RIA Funds

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 1). Tables 2-4 provide the full regression results for the percentage-level RIA funds' adverse events (Table 2), performance (Table 3), and leverage (Table 4) predictions displayed in Section 6.2.1. Table 5 presents the summary statistics for ADV-based Ω-Score for different TASS-styles.

Figure IA. A1 Operational Risk Variable Selection Pool

This figure presents the construction of the variables for our operational risk variables 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 filling. 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 variable).

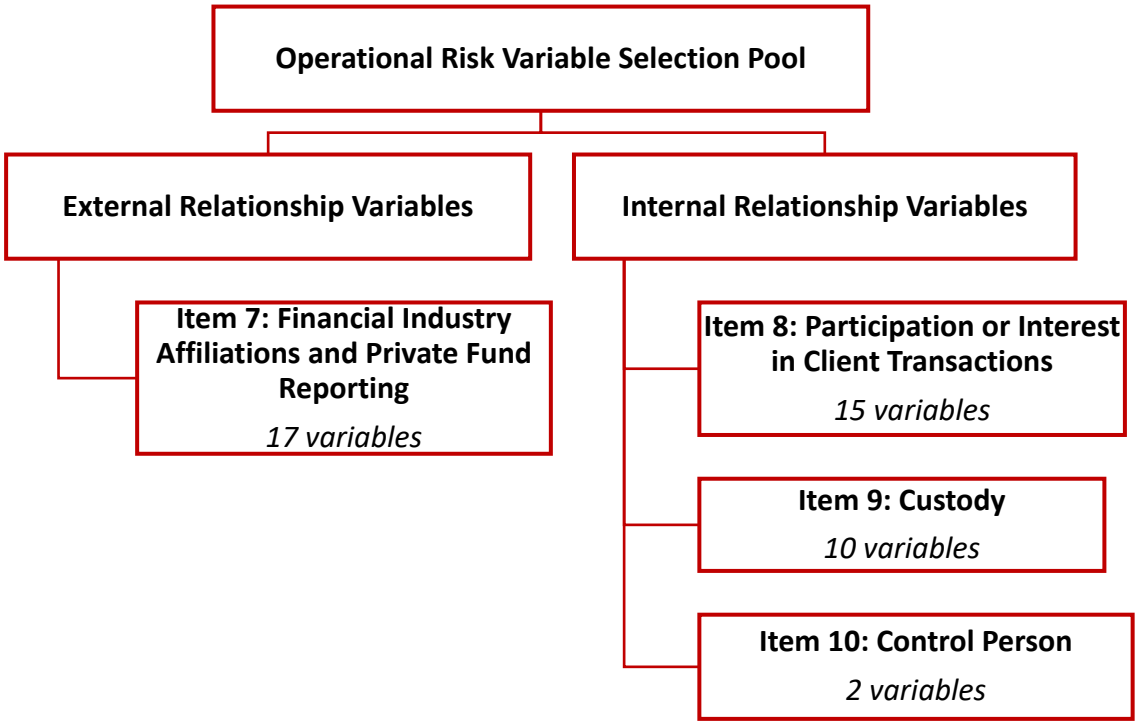

Figure IA. A2 Word Clouds for Other Control Person or Company Description

The two figures below present Word Clouds for the words' frequency according to the description of Item 10, *OtherControlCompany/Person* of RIA funds. For each of the plots, the bigger the word, the higher the frequency of the word. The color scale from blue to orange represents the frequency of the words from bigger to smaller as well. Figure 2A presents Word Cloud for control, interests, and ownership in the Company classification. Figure 2B presents Word Cloud for other controls, ownerships, and monitoring in the Person classification.

Figure 2A Word Cloud Plot for OtherControlCompany

Figure 2B Word Cloud Plot for OtherControlPerson

Table IA. A1 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%

IA. B Robustness Results

This section provides the results (RIA and ERA samples) mentioned in the Robustness section. Table 5 presents the summary statistics for RIA and ERA funds. Table 6 presents the univariate results for the RIA and ERA samples. Tables 7-9 present the percentage-level adverse outcome predictions. Tables 10 and 11 provide the prediction results for the adverse events, performance, leverage, and fund flows by using the ADV-based Ω-score.

Table IA. B1 Performance and Characteristics Comparison Between the ERA and all TASS Live and Dead Funds

This table reports descriptive statistics for ERA and RIA funds in the TASS database that have Form ADV filed by their advisory companies.[103] The final two columns report a *t*-test for sample differences. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively.

	ERA			All TASS Live and Dead Funds				
	N	Mean	Median	N	Mean	Median	Diff	
Return	1,397	0.35	0.34	11,782	0.32	0.29	0.02	
StdDev	1,396	2.24	1.78	11,776	2.62	1.61	-0.38	*
Skewness	1,388	-0.05	-0.09	11,752	-0.11	-0.11	0.06	***
Kurtosis	1,388	-0.68	-0.79	11,752	-0.67	-0.81	-0.01	
1st-order AC	1,388	-0.01	-0.02	11,752	-0.04	-0.04	0.03	***
Sharpe ratio	1,270	0.34	0.23	11,752	0.26	0.20	0.08	***
Appraisal ratio	978	0.64	0.40	11,782	0.21	0.13	0.43	***
Alpha	1,278	0.01	0.12	11,782	0.08	0.13	-0.07	
Management fee	1,346	1.45	1.50	11,430	1.41	1.50	0.04	**
Incentive fee	1,237	14.94	20.00	10,259	12.64	15.00	2.30	***
Min. Invt. ($M)	1,381	4.93	0.10	11,677	2.22	0.10	2.70	
Asset ($M)	685	159.86	51.84	7,293	288.95	45.22	-129.09	
Fund age	1,397	8.99	8.00	11,782	8.32	7.50	0.68	***
Leveraged	1,397	0.47	0.13	11,782	0.45	0.00	0.01	
Margin	801	0.25	0.00	6,135	0.24	0.00	0.02	
High water mark	1,384	0.59	1.00	11,630	0.50	0.33	0.09	***
Lockup period	1,397	1.65	0.00	11,782	1.69	0.00	-0.04	
Sub. Freq.	1,397	17.42	21.00	11,782	15.72	21.00	1.69	***
Red. Freq.	1,397	26.31	21.00	11,782	26.77	21.00	-0.46	

[103] For the TASS database, we remove the funds that reports quarterly (instead of monthly return) or gross-of-fee returns, and the funds with less than $10 million assets under management. Moreover, we winsorize the top and bottom 1% for average monthly return. Furthermore, all the foreign domiciled funds' assets under management and returns are converted to US-dollar according to the annual exchange rate provided by OECD data (https://data.oecd.org/conversion/exchange-rates.htm).

Among the 1,397 ERA funds, 1,124 retained ERA status, while 273 experienced a change in status to or from RIA within our sample period.

Table IA. B2 ADV-based Ω-score and Future Adverse Outcomes for the Combined RIA and ERA Sample

This table presents the result of estimating a prediction model for adverse outcomes. Models 1 to 3 present results for predicting alpha and appraisal ratio as well as the leveraged indicator (via logistic regression) according to the equation below:[104]

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

Where $ADV - Based\ \Omega\ score_{i,t}$ is the Lasso-based score described in section 6. $Umbrella_{i,t}$ indicates umbrella fund status. Model 4 presents the liquidation event prediction using the ADV-based Ω-score according to the equation below:[105]

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

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.

	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	-0.22	-4.41	***	-0.43	-2.88	***	-0.36	-2.59	***	1.03	3.19	***
Return							0.04	1.80	*	-0.42	-6.57	***
Stdev.	-0.08	-6.29	***	-0.23	-9.12	***	0.00	-0.36		0.03	1.01	
Management fee	0.01	1.24		0.34	9.72	***	0.19	6.10	***	-0.06	-0.78	
Log(Asset)	0.02	3.47	***	0.00	0.23		0.02	1.40		-0.37	-8.83	***
Leveraged	0.00	0.18		0.03	0.60					-0.23	-2.24	**
Onshore	0.09	3.66	***	0.24	6.98	***	0.38	8.04	***	-0.53	-4.27	***
High water mark	0.08	3.29	***	0.38	9.00	***	0.30	6.50	***	-0.08	-0.75	
Umbrella	0.08	1.09		0.17	2.49	**	0.41	3.34	***	-0.09	-0.25	
Exempt	-0.06	-2.35	**	-0.09	-1.65	*	-0.56	-9.64	***	0.12	0.83	
Style	Y			Y			Y			Y		
Year	Y			Y			Y			Y		
Num. of Obs.	7,696			3,786			8,986			8,986		
Adj. R^2	5.75%			17.48%								
Pseudo R^2							20.32%					
Concordance										80.30%		

[104] We calculate the annual appraisal ratio and alpha by regressing the 12 months excess returns of fund i on the excess return of the fund's TASS-style index j within the same year (BGLS, 2008). Specifically, $r_{it} - R_{ft} = \alpha_{it} + \beta_i(r_{jt} - R_{ft}) + \varepsilon_{it}$, where R_{ft} is the 3-month US Treasury Bill return. The α_{it} is fund i's alpha in year t and the appraisal ratio is calculated as α_{it} devided by the standard deviation of the residuals (ε_{it}). $Leveraged_{i,t}$ is whether the fund i uses leverage or not for the predicted year t.
C_{t-1} represents a vector of variables, including average and standard deviation of monthly returns, leveraged or not indicator, onshore and high-water mark indicators, logarithm of assets, and fund management fee in year $t-1$. Furthermore, for performance prediction in the first equation, the 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.

[105] 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).

Table IA. B3 ADV-based *Ω*-score and Fund Flows for the Combined RIA and ERA Sample

This table presents the result of estimating the following model of the combined ERA and RIA sample of fund flows predicted by ADV-based *Ω*-score:

$$Flow_{i,t} = \alpha_{i,t} + \beta_1\, ADV - Based\ \Omega\ score_{i,t-1} + C_{t-1}^{'\,\delta_C} + \delta_U Umbrella_{i,t-1} + \sum_{j=1}^{13}\gamma_j StyleDummies_{ji} + \sum_{q=1}^{9}\eta_q YearDummies_{qi} + \varepsilon_{i,t}$$

$Flow_{i,t}$ is the annual net fund flow in year *t* for fund *i*.[106] Model 2 includes interaction terms between the *ADV-based Ω-score* and three average monthly return ranks in the previous year.[107] *ADV-based Ω-score* represents the fund's previous year's operational risk score, *Stdev.*, *Log(Asset),* and *Umbrella* are the standard deviation for monthly return, log of the average monthly assets, and Umbrella Registration indicator of the funds in the previous year. 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		
	Coef.	*t*-Value		Coef.	*t*-Value	
ADV-based *Ω* Score	-0.30	-4.38	***	-2.42	-10.15	***
ADV-based *Ω* Score*High trank				0.12	0.60	
ADV-based *Ω* Score*Mid trank				-4.66	-9.57	***
ADV-based *Ω* Score*Low trank				-6.36	-12.82	***
High trank	3.36	9.02	***	3.84	9.32	***
Mid trank	-0.54	-7.45	***	-0.59	-7.96	***
Low trank	-3.27	-9.57	***	-3.96	-9.89	***
Stdev.	-0.02	-2.46	**	-0.02	-2.37	**
Management fee	0.00	0.41		0.00	0.81	
Log(Asset)	0.02	5.18	***	0.02	5.03	***
High water mark	0.00	0.22		0.01	0.47	
Onshore	0.01	0.72		0.02	0.77	
Umbrella	0.08	2.35	**	0.07	2.32	**
Exempt	-0.02	-0.35		-0.01	-0.21	
Style	Y			Y		
Firm	Y			Y		
Year	Y			Y		
Num. of Obs.	8,986			8,986		
Adj. R^2	72.27%			73.01%		

[106] Fund flow for fund i in year t is calculated by $Flow_{i,t} = [Assets_{i,t} - Assets_{i,t-1} * (1 + Return_{i,t})]/Assets_{i,t-1}$. All flows for offshore funds are currency-adjusted where appropriate

[107] Specifically, *High rank*, *Mid rank,* and *Low rank* are computed as $Min(\frac{1}{3}, Frank_{i,t-1})$, $Min(\frac{1}{3}, Frank_{i,t-1} - High\ trank_{i,t-1})$ and $Min(\frac{1}{3}, Frank_{i,t-1} - High\ trank_{i,t-1} - Mid\ trank_{i,t-1})$ respectively (Franzoni and Giannetti, 2017; Getmansky et al., 2019). Where $Frank_{i,t-1}$ is the fractional rank for RIA funds from 0 to 1, according to their average monthly return in the previous year.

Table IA. B4 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.[108] Panel A presents the fund flows and leveraged or not[109] cross-sectional 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[110] cross-sectional predictions according to the second equation above.[111] Panel C presents the adverse liquidation cross-sectional predictions[112] according to the equations:

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

The Coef. columns present the coefficients for the year-by-year LASSO- and CCA-constructed ADV-based *Ω*-score for the relative years' cross-sectional predictions. The *t*/*z*-statistics, as well as the goodness of fit values are also reported. Among the three panels, the observations on the LHS and RHS of the slash represent the sample used in the CCA and LASSO methods, respectively. The left, center, and right columns show goodness-of-fit values for predictions using CCA-constructed, LASSO-constructed pre-Dodd, and LASSO-constructed post-Dodd scores, respectively. The bottom panels report results with interaction terms between the scores and post-2016 indicators (indicating whether the dependent variable values occur before or after the end of 2016). ***, **, * indicate the statistically significant at the 1%, 5%, and 10% levels, respectively.

[108] The CCA-constructed and LASSO-constructed *Ω*-scores in this table are calculated by year. For CCA-constructed score, we follow the method conducted by BGLS (2008). We implement CCA on the 15 pre-Dodd ADV variables (*BrokerDealer*, *InvestmentAdvisor*, *CommodBroker*, *Banking*, *Insurance*, *LimitedPartnership*, *ManagingMember*, *BuySellYourOwnSecurity*, *BuySellYourselfClientSecurity*, *RecommendSecurityYourOwn*, *AgencyCrossTransaction*, *RecommendUnderwriter*, *RecommendSalesInterest*, *RecommendBrokers*, and *OtherResearch*) and a set of TASS fund performance and characteristic variables (*Return*, *Stdev.*, *Age*, *High water mark*, *Minimum investment*, *Log assets*, *Personal capital*, *Onshore*, *Open to public*, and *Accepts managed accts.*). Raw coefficients for the pre-Dodd variables each year are used as the weight for constructing the CCA-based *Ω*-score. Similarly, for each year we use LASSO by regressing Problem Fund indicator on 44 Form ADV variables and use the related weights for the LASSO-constructed *Ω*-score.

[109] Fund flow for fund i in year t is calculated by $Flow_{i,t} = [Assets_{i,t} - Assets_{i,t-1} * (1 + Return_{i,t})]/Assets_{i,t-1}$. $Leveraged_{i,t}$ indicates whether fund i uses leverage for the predicted year t.

[110] We calculate the annual appraisal ratio by 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. The style-adjusted return is calculated by $Return_{it} - \mu_{jt}$. $Return_{it}$ is the average monthly return for fund i in year t and μ_{jt} is the average monthly return for the fund i's relative TASS-style j in year t. The Style-adjusted returns sample is winsorized by top and bottom 1%. This explains the sample variation between appraisal ratio and style-adjusted return cross-sectional predictions in Panel B.

[111] C_{t-1} 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 $t-1$. 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.

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

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%	1097/1429
2014	-0.07	-1.02		-0.63	-6.30	***	-0.60	-1.16		89.91%/89.02%/88.98%	1032/1221
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
2013-2017	-0.02	1.67	*	-0.06	-3.03	***	-0.01	-1.75	*	70.93%/71.00%/71.18%	5866/7267
2018-2022	-0.07	-0.21		-0.03	-1.88	*	-0.22	-2.86	***		
Full Panel Sample	-0.02	-1.67	*	-0.03	-1.65	*	-0.21	-2.71	***	69.30%/70.12%/71.17%	5866/7267
Style	Y			Y			Y				
Firm	Y			Y			Y				
Controls	Y			Y			Y				

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%	1097/1429
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%	1032/1221
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
2013-2017	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%	5866/7267
2018-2022	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 Panel Sample	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%	5866/7267
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	***	1097/1429	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		1032/1221	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%
2013-2017	-0.18	-3.31	***	-0.09	-3.19	***	-1.04	-2.70	***	5082/6261	19.44%/20.00%/20.13%	-0.26	-2.33	**	-0.96	-1.86	*	-0.44	-0.65		3066/3786	25.21%/27.90%/28.02%
2018-2022	-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 Panel Sample	-0.12	-1.92	*	-0.16	-3.55	***	-1.23	-3.84	***	5082/6261	19.29%/19.88%/20.11%	-0.21	-1.73	*	-0.50	-1.80	*	-0.71	-2.63	***	3066/3786	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				