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Essays on Financial Institutions and Advisors

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ESSAYS ON FINANCIAL INSTITUTIONS AND ADVISORS

DISSERTATION

A dissertation submitted in partial
fulfillment of the requirements for
the degree of Doctor of Philosophy
in the Gatton College of Business
and Economics at the
University of Kentucky

By
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ABSTRACT OF DISSERTATION

ESSAYS ON FINANCIAL INSTITUTIONS AND ADVISORS

In my first chapter, I examine how index funds vote their proxies on firms in its index that their family does not hold in its actively managed funds. For a given proxy proposal at a given point in time, I find that an index fund is more likely to oppose management on shares its family does not hold in its active funds than on shares its family does hold in its active funds. I further demonstrate that index fund governance has positive effects on the probability a proposal passes and on shareholder value. In my second chapter coauthored with Will Gerken and Steve Dimmock, we document the prevalence and variety of frauds committed by investment managers. We show that prior legal and regulatory violations, conflicts-of-interest, and monitoring disclosures available via the Security and Exchange Commission's Form ADV are useful for predicting fraud. Additional tests show that fraud by rogue employees is more predictable than firm-wide fraud, but both types of fraud are significantly predictable. We revisit the fraud prediction model of Dimmock and Gerken (2012) and test its performance out-of-sample (using fraud cases discovered since that article's publication). We find the model has significant predictive power for the out-of-sample cases. To encourage additional research in this area, we have made the data used in this chapter publicly available at https://doi.org/10.13023/nsjd-rk62. In my third chapter, I find the divergence ratio, the percentage of time funds within a family vote differently from one another on the same proposal at a shareholder meeting, varies significantly across fund families. Funds of families in the highest divergence quintile realize alphas up to 104 basis points higher than funds of families in the lowest quintile. These findings are consistent with the separating equilibrium theory of Evans, Prado, and Zambrana (2017) who find that some families encourage coordination among their funds while others encourage competition.

KEYWORDS: Mutual funds, governance, indexing, advisors, fraud, misconduct

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ESSAYS ON FINANCIAL INSTITUTIONS AND ADVISORS

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1.1 Introduction

Do index funds engage in governance? The recent rise of index investing and contemporaneous fall in active fund ownership underscores the increasing relevance of this question. By the end of 2018, index funds held approximately 18% of the market value of domestic equities, up from 3% in 2000. Over the same time period, active funds' ownership of the U.S. stock market nearly halved to 11% (see Figure 1.1). An op-ed in The Wall Street Journal warns against this growth of indexing, arguing that "passive" index funds adopt a hands-off approach to governance and allow firm management to become progressively unchecked:

> "American investors are increasingly acting on the realization that a broad-based indexing strategy is superior to investing in individual stocks or actively managed funds. That's great news for investors, who will pay less and get better returns. But it has troubling implications for corporate governance. No passive investor cares much about governance of a particular company."[1]

A perceived lack of incentives for index funds to engage in governance fuels these concerns regarding the growth of indexing. Index fund management fees as a percentage of total net assets are low relative to actively managed funds, perhaps curtailing their involvement in costly monitoring activities (Black, 1998; Iliev and Lowry, 2015). Additionally, an index fund ultimately yields the return of its underlying benchmark regardless of its level of participation in governance activities. This could dissuade monitoring involvement because the fund individually bears the costs of governance but shares the benefits of governance with competing funds that have identical investment objectives (Grossman and Hart, 1980; McCahery, Sautner, and Starks, 2016; Shleifer and Vishny, 1986).

There are, however, a number of reasons why an index fund might be incentivized to participate in active governance of its portfolio firms.[2] First, monitoring activities are linked to an increase in firm value (Brav, Jiang, Partnoy, and Thomas, 2008; Cuñat, Gine, and Guadalupe, 2012), and firm value enhancements are linked to higher cash flows to institutional investors through management fees (Lewellen and Lewellen, 2018). Additionally, several studies show that investors value governance and sustainability (Dimmock, Gerken, Ivković, and Weisbenner, 2018b; Hartzmark and Sussman, 2019; Riedl and Smeets, 2017), implying that institutional investors

[1] "Index Funds are Great for Investors, Risky for Corporate Governance." M. Todd Henderson and Dorothy Shapiro Lund. The Wall Street Journal. June 22, 2017

[2] In this paper, active governance refers to participation in governance by either actively managed funds or index funds. I use the terms active funds and actively managed funds interchangeably to describe any fund that has discretion over buying and selling decisions of its portfolio assets.

may be able to use monitoring activity to attract investors when competing for flows (Fisch, Hamdani, and Davidoff Solomon, 2019). Finally, index funds may have a strong incentive to monitor the firms in their portfolio because they are not always able to sell out of positions when they disagree with management. Index funds may be more inclined to exercise their "voice" by voting, since "voting with their feet" through divesting shares is not always possible if those shares represent ownership in a company that is a member of the fund's underlying index. The head of Investment Stewardship and a principal at Vanguard, Glenn Booraem, commented on this relationship between index investors and firm management, stating "we're riding in a car we can't get out of. Governance is the seat belt and air bag."[3]

In this paper, I find evidence that index funds on average *do* participate in active governance by voting their proxy shares. Specifically, I find index funds are more likely to vote proxy proposals against firm management on shares their family does not hold in active funds than on shares its family does hold in active funds. Thus, despite concerns that index funds do not care about the performance of their holdings, I uncover an even higher level of engagement in proxy governance on shares a family only holds its index funds than on shares their family has an active position in.

Figure 1.2 illustrates my identification strategy. The hypothetical fund family depicted in the figure consists of five funds: two index funds A and B, and three active funds X, Y, and Z. The unshaded circles represent shares that are held only by the family's actively managed funds, or *Family Holds Only in Active Funds* shares. The hash-marked circles are *Family Holds in Index & Active* shares, because these firms are held both by the family's active funds and the family's index funds. Finally, the dark circles represent *Family Does Not Hold Actively* shares, or those shares that this family holds only in its index funds. In this paper, I compare how index funds vote their proxies on *Family Does Not Hold Actively* shares such as BAC, XOM, and JPM in this example to governance on *Family Holds in Index & Active* shares such as FB, V, and GOOG.

In Table 1.1, I present the average quarterly rates at which the 25 largest S&P 500 funds in my sample vote against management of their portfolio firms. Overall, these funds oppose management 5.9% of the time (Column 1). However, they appear friendlier to management on Family Holds in Index & Active shares, opposing 5.5% of the time, than on Family Does Not Hold Actively shares, where they submit dissenting votes 9.0% of the time (Columns 2 and 3). Only Columbia and Federated's S&P 500 index funds are friendlier to management on Family Does Not Hold Actively shares than Family Holds in Index & Active shares, as indicated by the negative difference between these average rates of opposition presented in Column 4. Thus, at least in this modest sample of popular S&P 500 funds, I uncover evidence of engaged monitoring by index funds on those shares these institutional families hold exclusively in their index funds.

My identification strategy overcomes many of the empirical challenges of identifying governance by index funds. Extant studies frequently use the Russell 1000/2000

[3] "Meet the New Corporate Governance Power Brokers: Passive Investors." Sarah Krouse, David Benoit, and Tom McGinty. The Wall Street Journal. October 24, 2016.

reconstruction methodology to link index and institutional ownership to corporate governance.[4] Yet, there is considerable debate regarding the application, reliability, and biases of this Russell 1000/2000 strategy. Wei and Young (2017) find pre-existing discontinuities in market capitalization prior to index reconstruction and argue that the results of papers using the reconstruction methodology are attributable to bias rather than a treatment effect. Further, Wei and Young (2017) emphasize that some papers employ a regression discontinuity approach (Chang, Hong, and Liskovich, 2015; Crane, Michenaud, and Weston, 2016) while others use an instrumental variable design (Appel, Gormley, and Keim, 2016, 2019). Boone and White (2015) also document an increase in actively managed fund ownership around this Russell 1000/2000 cutoff, particularly among "quasi-indexers" or active funds that closely mimic an index (Cremers and Petajisto, 2009). This may obscure the effects of index fund ownership on monitoring choices and may instead capture the rise of overall institutional ownership, both by active funds and index funds.

Focusing on *Family Does Not Hold Actively* shares in an index fund is useful for three additional reasons. First, voting behavior by index funds on these shares is more likely to be free of active fund influence. An index fund voting in opposition to management on *Family Holds in Index & Active* shares may not represent true monitoring by the index fund if the fund family's active funds dictate how the family's index funds are to vote at company meetings.[5] When a firm is added to an index, any observed change in governance structure at that firm might not be due to monitoring by index funds but rather by active funds that already held those shares who now leverage the increased size of their fund family's voting bloc. Second, my analysis does not focus on only those firms near the index cutoff or firms that switch from one index to another. In particular, the firms in my sample need not have a market capitalization that places them near the Russell 1000/2000 breakpoint. My results therefore uncover governance by index funds at firms that may not have been in previous analyses.

Third, my research design allows me to incorporate a rich set of fixed effects in multivariate tests that control for firm and proposal characteristics. A firm that

[4]Each year, Russell Investments ranks the largest 3,000 firms to construct its Russell 1000 (R1K) and Russell 2000 (R2K) indexes. The R1K consists of the largest 1,000 firms by market capitalization while the R2K includes the next 2,000 largest firms. Because these indexes are value-weighted, firms at the bottom of R1K comprise a very small portion R1K index whereas firms at the top of the R2K make up a substantial portion of the R2K index. A researcher could therefore compare firms at the bottom of the R1K to the firms at the top of the R2K under the assumption that these firms are similar apart from their index inclusion. Alternatively, a firm's movement from the bottom of the R1K to the top of the R2K can instrument for index ownership.

[5]The merger of Towers Watson & Co. and Willis Group Holdings PLC provides an illustrative example. As a large shareholder of Towers Watson, BlackRock possessed a pivotal vote in this merger. BlackRock's index funds reportedly wished to vote against the merger plan, but managers of BlackRock's active funds persuaded the index funds within their family to vote in favor of the deal ("Meet the New Corporate Governance Power Brokers: Passive Investors." Sarah Krouse, David Benoit, and Tom McGinty. The Wall Street Journal. October 24, 2016). In this instance, votes by index funds did not necessarily represent true governance by index funds. Rather, it indicates influence by active funds within the index fund's family that had an interest in the outcome of the vote.

in one family is classified as *Family Does Not Hold Actively* may simultaneously be classified as either *Family Holds Only in Active Funds* or *Family Holds in Index & Active* shares by other institutions at the same point in time. Revisiting Figure 1.2, the stock BAC is classified as *Family Does Not Hold Actively* for this hypothetical family. However, at the same point in time, it may be held by an active fund by another family. This variation allows me to include firm and firm-year fixed effects in a regression framework. I can therefore observe how variation of the *Family Does Not Hold Actively* measure for many institutions holding the same stock at the same point in time influences the voting choice by institutional investors. The incorporation of these fixed effects absorbs other sources of variation that might have an effect on whether a fund votes against a firm, such as the company's past performance, board structure, governance provisions, or other time-invariant firm characteristics that could explain a fund's decision to vote in opposition to management.

Similarly, *Family Does Not Hold Actively* varies within the proxy proposal itself. As an example, consider the 2016 proposal to elect Matthew Levatich to the board of directors at Harley-Davidson in 2016. Nearly one-fifth of the index funds that voted on this proposal were members of families that did not hold Harley-Davidson in its active funds, and their votes are coded as *Family Does Not Hold Actively* = 1. Approximately 80% of the index funds voting on this proposal held Harley-Davidson in their actively managed funds, coded as *Family Does Not Hold Actively* = 0. This variation of *Family Does Not Hold Actively* at the proposal level allows me to incorporate proposal fixed effects. Such fixed effects look within the proposal, controlling for the effects that proposal quality, proxy advisor recommendations, and other unobservable proposal characteristics might have on the fund's decision to oppose management. All these features of the proposal are the same for every investor voting on that proposal and are absorbed by this fixed effect.

In addition to showing that index funds engage in governance through proxy voting, I consider whether their monitoring activities have consequences. I begin by showing that index fund opposition to a proposal has an incremental effect on whether that proposal passes: a lack of index fund support increases the likelihood a company proposal fails. To control for the mechanical relationship between the probability of failure and lack of direct support by index fund voters, I use the difference in index fund and active fund opposition on a proposal in my regression specifications. As the difference between index fund and active fund opposition widens, the proposal becomes more likely to fail. Additionally, I document positive risk-adjusted returns at firms when proposals supported by index funds pass. These results together provide evidence that investors value the monitoring behaviors of these funds and find their decisions to be informative regarding the prospects of the firm.

To the best of my knowledge, I am the first to identify and isolate the monitoring behavior of index funds, net of influence of active funds, by focusing on *Family Does Not Hold Actively* shares. Appel et al. (2016, 2019) and Heath, Macciocchi, Michaely, and Ringgenberg (2018) have exploited the variation in institutional ownership following the Russell 1000/2000 reconstruction to draw conflicting conclusions regarding the effects of indexed ownership on governance.[6] My results are consistent with Appel et al. (2016), who find that index ownership at a firm is associated with more independent directors, removal of takeover defenses, and more equal voting rights. Additionally, in Appel et al. (2019) the authors identify that an increase in index ownership is associated with an increased use of proxy fights by activists and a higher likelihood that an activist obtains representation on the board of their target firm. Yet, Heath et al. (2018) argue that the rise of index investing shifts power from investors to firm managers as index funds do not engage in voting governance as much as actively managed funds do. In my paper, I cleanly and directly identify that index funds on average do vote their shares against management and are more likely to do so on *Family Does Not Hold Actively* shares than *Family Holds in Index & Active* shares.

This paper also contributes to a literature examining the determinants of proxy voting decisions by institutions. Firm characteristics (Cai, Garner, and Walkling, 2009), fund characteristics (Dimmock et al., 2018b; Iliev and Lowry, 2015) and the relationship between the institution and firm (Cvijanović, Dasgupta, and Zachariadis, 2016; Davis and Kim, 2007) have all been tied to how an institutional investor votes on an issue, with positive past performance, higher net benefits of voting, and business ties between the institution and firm increasing the level of support among institutional shareholders. In this study, I show that an additional institution-firm characteristic, whether a share is held only by index funds within a family, is an additional determinant of the voting decision.

Finally, this paper contributes to the literature on the effects of institutional governance. Gillan and Starks (2000) show that shareholder proposals sponsored by institutions are significantly more likely to pass, while Morgan, Poulsen, Wolf, and Yang (2011) find that high mutual fund approval rates substantially increase the probability that a proposal passes. Other papers explore the effects of governance on shareholder value. Cuñat et al. (2012) uncover positive risk-adjusted returns when shareholder proposals pass by a small margin at firms with concentrated ownership and high preexisting antitakeover provisions. Similarly, Iliev and Lowry (2015) show that the market positively reacts following the passage of a proposal supported by funds that actively engage in monitoring. In this paper, I additionally show that index fund support has an incremental effect on whether a proposal at a company shareholder meeting passes, and that investors respond positively to the passage of proposals that index funds support.

The remainder of this paper proceeds as follows. In Section 2, I discuss the research setting, explain why shareholder voting is a particularly useful area for examining governance activities, and provide an overview of the sample. Section 3 presents the main univariate and multivariate results, demonstrating that index funds are more likely to oppose management on *Family Does Not Hold Actively* shares than *Family Holds in Index & Active* shares. I demonstrate the effects of index fund governance on failure rates of proposals and firm value in Section 4. Section 5 concludes.

[6] Heath, Heath et al. (2018) use a modified approach of the Russell reconstruction, exploiting two new discontinuities around the Russell index cutoff that is described in full detail in their paper.

1.2 Research Setting and Data

1.2.1 Proxy voting as a research setting

Proxy voting records are a useful setting for examining monitoring activities of institutional investors for several reasons, in part due to the legal framework governing fund voting. The SEC adopted Rules 206(4)-6 and 30b1-4 to regulate proxy voting in part because "voting power gives advisers significant ability collectively, and in many cases individually, to affect the outcome of shareholder votes and influence the governance of corporations. Advisers are thus in a position to significantly affect the future of corporations and, as a result, the future value of corporate securities held by their clients."[7] By SEC Rule 206(4)-6, investment advisers and funds owe a "duty of care" that "requires an adviser with proxy voting authority to monitor corporate events and to vote the proxies."[8] This rule implies that institutional investors must vote their proxies, and any fund abstaining or withholding support on a proposal effectively votes against that proposal by submitting a "abstain" or "withhold" vote. In addition, SEC Rule 30b1-4 requires that institutional investors and fund advisors make public their complete proxy voting record each year on an SEC filing, the Form N-PX, that reveals their actual governance behavior and preferences.[9] Crucially, these rules regarding fiduciary duty, voting requirements, and disclosure apply to all registered funds under the Investment Advisers Act of 1940, whether index funds or active funds.

Further, there is substantial evidence in the literature that funds consider proxy voting an important tool when monitoring their portfolio firms. In a survey of institutional investors, McCahery et al. (2016) reveal that funds frequently rely on voice as a disciplinary mechanism, particularly among long-term institutional investors. Aggarwal, Erel, and Starks (2014) present evidence that funds appear to largely adhere to Rule 206(4)-6 by uncovering a strong relationship between institutional voting and shareholder preferences. Dimmock et al. (2018b) show that funds with a tax-sensitive clientele frequently rely on "voice" through voting rather than "exit" because selling out of a position would yield a tax liability if there were an accrued capital gain.

Finally, proxy voting decisions by institutional investors yield changes at portfolio firms and in financial markets. Matvos and Ostrovsky (2010) find that systematic voting differences among institutional investors and peer effects in fund voting behavior are as important as firm and director characteristics in shaping vote outcomes. Iliev and Lowry (2015) show that the market positively reacts following the passage of a proposal supported by funds that actively engage in monitoring, while Morgan et al. (2011) indicate that higher levels of mutual fund support increases the likelihood that a proposal passes.

[7]SEC Release No. IA-2106; File No. S7-38-02. See https://www.sec.gov/rules/final/ia-2106.htm.

[8]Final Rule: Proxy Voting by Investment Advisers. See https://www.sec.gov/rules/final/ia-2106.htm.

[9]Final Rule: Disclosure of Proxy Voting Policies and Proxy Voting Records by Registered Management Investment Companies. See https://www.sec.gov/rules/final/33-8188.htm.

1.2.2 ISS Voting Analytics Database

I use the Institutional Shareholder Services (ISS) Voting Analytics database to obtain fund proxy voting records. This database includes the information that funds furnish to the SEC on the required Form N-PX: the name and issuer of a portfolio security, the shareholder meeting date, a brief description of the matter voted on, whether the matter was proposed by either firm management or a shareholder, and how the registrant cast their vote. Institutions must file this form by the end of each August, covering all the votes they have submitted in the previous N-PX reporting year, from July 1st through June 30th.

In addition to the data included in the N-PX filings, ISS's Voting Analytics database includes ISS's vote recommendation for all proposals at Russell 3000 firms and the outcome of the proposal (i.e., whether it passed or failed). These recommendations are provided to each of ISS's institutional clients prior to an election and are used to inform the fund's voting decision. Following a voluminous literature that documents the importance of ISS recommendations to institutional investors, shareholders, and proposal outcomes, I use ISS's recommendation to identify proposals with value implications.[10] Proposals where ISS disagrees with management and recommends a vote against management's recommendation are referred to as contentious proposals in this study.

An observation in the ISS Voting Analytics database therefore consists of the name of the fund family or institution, the name of the fund, a unique proposal identifier, a description of the proposal up for a vote, the firm management's recommendation, the proposal sponsor, how the fund voted, ISS's recommendation, and the outcome of the vote. Each observation consists of the fund's voting "opinion" for that proposal, not the number of votes the fund submits on a proposal based on the number of shares it holds of the company. For example, one observation in my data shows that Vanguard's 500 Index Fund (VFINX) voted its shares in favor of Robert A. Iger of the Walt Disney Company to retain his position as a member of the Board of Directors on March 3, 2016. Further, this proposal was sponsored by the issuer (The Walt Disney Company), Disney management recommended a vote in favor of this proposal, and this proposal passed. This was not a contentious proposal, as ISS recommended that investors vote in favor of management's candidate. Additional observations show that the Vanguard U.S. Growth Fund and the Fidelity Contrafund also voted their shares of Disney in favor of this proposal.

[10] ISS is the largest of only five proxy advisory firms in the United States, with an estimated 61% market share (Copland, Larcker, and Tayan, 2018; Glassman and Peirce, 2014). Numerous studies document that ISS recommendations are economically meaningful, that ISS support increases the probability a proposal passes, and that the passage of a proposal with ISS support is associated with positive risk-adjusted returns (Bethel and Gillan, 2002; Morgan, Poulsen, and Wolf, 2006; Cai et al., 2009; Alexander, Chen, Seppi, and Spatt, 2010; Cotter, Palmiter, and Thomas, 2010; Morgan et al., 2011; Iliev and Lowry, 2015; Malenko and Shen, 2016; Dimmock et al., 2018b).

1.2.3 Sample and Descriptive Statistics

The ISS Voting Analytics database does not identify index funds. Following Appel et al. (2016), I identify index funds based on fund names, using a similar set of keywords and strings and manually checking for false positives.[11] Additionally, I keep only binding management sponsored proposals and exclude all advisory shareholder sponsored proposals. As in Del Guercio, Seery, and Woidtke (2008), Dimmock et al. (2018b), and Fischer, Gramlich, Miller, and White (2009), I consider all votes where a fund votes "against", "withhold", or "abstain" as a vote against management. I obtain fund and institution characteristics from the CRSP Survivor-Bias Free US Mutual Fund Database and firm characteristics from Compustat.[12]

I manually sort proposals into broad categories to use in conjunction with ISS's recommendation to control for proposal quality. All management sponsored proposals to elect executives to the corporate board make up the *Director Elections* category (72.8% of the proposals). *Compensation* proposals include items where shareholders vote to approve executive pay, such as incentive bonus plans and stock option plans. *Accounting* proposals consist of items regarding financial statements, including ratifying the external auditor and approving financial statements. *Board* proposals consist of all proposal relating to the board, but exclude the recurring annual director elections (i.e., approve change in the size of the board, fix the number of directors, and elect supervisory board members.) *Payout* proposals include items pertaining to the allocation of dividends and authorization of share repurchase programs. Finally, *General* proposals are all other general business items, such as approving reverse stock splits and calling for the adjournment of the annual meeting.

Summary statistics for the final matched sample are presented in Table 1.2. The sample consists of 654 index funds voting on 267,847 management-sponsored proposals at 5,155 firms for a total of 8.8 million fund-proposal observations. The data covers N-PX reporting years 2006-2016.[13] All variables are described in Appendix A. The main variable of interest, *Family Does Not Hold Actively*, has an average of 0.27. That is, index funds in the sample are submitting votes on proposals at companies their family does not hold in its active funds 27% of the time.

[11] The set of strings used are INDEX, IDX, INDX, ␣IND␣, RUSSELL, S & P, S&P, S AND P, ␣SP␣, DOW␣, MSCI, BLOOMBERG, KBW, NASDAQ, NYSE, FTSE, WILSHIRE, MORNINGSTAR, STOXX, 100, 400, 500, 600, 900, 1000, 1500, 2000, 3000, 5000, where "␣" indicates a space.

[12] In univariate tests, I consider the full record of index fund votes in the ISS Voting Analytics database. Multivariate regressions use only the matched sample ISS-CRSP sample. Because there is no unique identifier that maps from the CRSP to ISS databases, I first match manually on institutional family name then programmatically on fund name. The matched sample's index TNA was $2.18 trillion for the N-PX year ending in 2016. The ICI Investment Company Factbook reported 2016 year-end index fund TNA of $2.62 trillion. My matched sample therefore covers an estimated 2.18 / 2.62 = 83% of the market.

[13] Although the ISS Voting Analytics data begins in 2003, years prior to 2006 have limited coverage and are not included in this study.

1.3 Index Funds and Engagement in Governance

1.3.1 Univariate Tests

To provide context on the levels at which index funds engage in governance of their portfolio firms, I compare their proxy voting behaviors to that of actively managed funds. There is ample evidence that institutional investors, in particular active funds, influence management and monitor their portfolio firms through voting and voice (Aghion, Van Reenen, and Zingales, 2013; Del Guercio and Hawkins, 1999; Gillan and Starks, 2003; Iliev and Lowry, 2015; Matvos and Ostrovsky, 2010; McCahery et al., 2016). I present the average rates of opposition for actively managed funds and index funds on management sponsored proposals in Panel A of Table 1.3. Overall, funds submit a vote against management 7.1% of the time (Column 1). Index funds and active funds do not differ greatly in their average rates of opposition to management, as the difference in their average rates of opposition is 0.3% (t-stat = 0.89). On contentious proposals where ISS recommends a vote against management, the rate of opposition is much higher: funds submit votes against management's recommendation 54.5% on the time. Noticeably, index funds do not appear to strictly rely on the advice of ISS as their votes align with this proxy advisor's recommendation only half of the time (Column 2). Active funds, on the other hand, appear more likely to align with ISS as they vote against management 58.1% of the time when ISS recommends a vote against management (Column 3). Index funds also are slightly more likely to vote against management when ISS recommends a vote in favor of management's proposal. On non-contentious proposals, index funds vote against management 3.5% of the time (Column 2), 0.5% more than actively managed funds, though this difference is not statistically significant (t-stat = 1.41).

The average rate of opposition by index funds on contentious proposals (Table 1.2, Panel A, Column 2) could imply that half of index fund votes follow management's recommendation, and that half of index fund votes follow ISS's recommendation. A fund, however, that always follows management's recommendation or a fund that always follows ISS's recommendation should not be considered an engaged monitor. Therefore, the 50.0% average rate of opposition by index funds on contentious proposals cannot necessarily be interpreted as evidence of governance by index funds. To address the possibility that index funds either always follow management or always follow ISS, I compute each fund's average rate of opposition on contentious proposals during that fund's life in the sample. Then, I sort the funds into 12 bins (10 deciles and 2 overflow bins) based on how frequently that fund voted against management. A graph of this distribution is presented in Figure 1.3. The two left-most vertical bars indicate that approximately 4.8% of active funds and 5.0% of index funds in the sample always vote with management on contentious proposals. These funds have an average rate of opposition of 0% on the horizontal axis. The two right-most vertical bars show that approximately 13.3% of active funds and 8.9% of index funds always vote with ISS on contentious proposals, as these funds have an average rate of opposition of 100% on the horizontal axis. Thus, a vast majority of index funds fall somewhere between these opposite extremes: 16% of index funds in the sample oppose management between 30 and 40% of the time on contentious proposals (the highest dark vertical bar), and a majority (nearly 54% of index funds in the sample) oppose management between 20 and 60% of the time. Thus, index funds do not always align with management or always align with ISS.

The results presented in Panel A of Table 1.3 and Figure 1.3 show that index funds and active funds in general do not meaningfully differ in their average rates of voting opposition to management overall, and index funds are slightly less likely to submit a vote that agrees with ISS's recommendation than active funds. Noticeably, active funds are substantially more likely than index funds to vote in the same way as ISS recommends on contentious proposals, though I make no claim that this relationship is causal. This preliminary evidence, however, dispels the concern that index funds, at least in the aggregate, completely disregard voting responsibilities by either always siding with management or always siding with ISS.

There remains the possibility that index funds vote largely the same as active funds due to overlapping holdings. For example, a number of S&P 500 member firms are present both in the Vanguard 500 Index Fund (VFIAX) and Vanguard's actively managed Capital Value Fund (VCVLX). When the VFIAX index fund manager submits a vote against management, it could be doing so at the behest of the active fund VCVLX whose managers seek to take advantage of the index fund's large voting power at a firm. I address this possibility by comparing the two types of shares held within an index fund: *Family Holds in Active & Index* shares and *Family Does Not Hold Actively* shares. Panel B of Table 1.3 presents these results. Here, the sample consists of index funds alone. The average rates of opposition presented in Column 1 of Panel B repeat the summary statistics from Column 3 of Panel A. Index funds on average oppose management 7.3% of the time overall and 50.0% of the time on contentious proposals. Columns 2 and 3 separately show the average rates of opposition by index funds on shares that only they, and not actively managed funds within their family, hold as well as the average rates of opposition by index funds on shares that both they and active funds within their family concurrently hold. Index funds oppose management more frequently on *Family Does Not Hold Actively* shares (10.0%) than they do on *Family Holds in Active & Index* shares (6.0%), and this difference is statistically significant (t-stat = 4.82, Column 4). Thus, index funds appear to be more aggressive when voting on shares that are only held in index funds by their families than on shares that are held in active funds by their family. Of note, the average rate of opposition by index funds is higher for *Family Does Not Hold Actively* shares than *Family Holds in Active & Index* shares on non-contentious proposals (t-stat of difference = 2.52, Column 4); therefore, index funds do not appear to blindly follow ISS's recommendation when voting on shares their families do not hold in their active funds. Panel C of Table 3 shows this positive and significant difference between average rates of opposition on *Family Does Not Hold Actively* shares and *Family Holds in Active & Index* shares generally holds across a broad range of proposal categories. Therefore, index funds do not appear to concentrate all their governance efforts on one type of proposal category.

For a given proposal, the measure *Family Does Not Hold Actively* can vary. Recalling the hypothetical institutional fund family in Figure 1.2, stock BAC is classified as a *Family Does Not Hold Actively* share, or *Family Does Not Hold Actively* $= 1$ for this stock in this institutional family. This same stock at the same point in time may also be classified as *Family Does Not Hold Actively* $= 0$ for another institutional fund family if the share is held by both active and index funds or only by active funds within that family. Therefore, for a given proposal, I compute the average *Family Does Not Hold Actively* value, which ranges from 0 and 1. I then sort proposals into quintiles based on their average value of *Family Does Not Hold Actively*. Proposals with the highest average value of *Family Does Not Hold Actively* are in the fifth quintile and are mostly held by index funds alone within families. Proposals with the lowest average value of *Family Does Not Hold Actively* are in the first quintile and are most held by both active and index funds by institutions. Within each of these quintiles, I then compute the average rate of opposition by index funds.

These results are presented in Table 1.4. From the full sample results in Panel A, the average difference in the average rate of opposition by index funds on proposals in the fifth and first quintile of the *Family Does Not Hold Actively* distribution is a statistically significant 8.34%. That is, the average rate of opposition by index funds on shares that are largely held only by index funds is significantly higher than on shares that are largely held both by active and index funds. Further, the average rate of opposition monotonically increases from the first to the fifth quintile. The positive and significant difference between the average rate of opposition on proposals in the fifth and first quintiles is statistically significant for all proposals categories except accounting proposals. In Panels B and C of Table 1.4, I split the sample to show this relationship for both contentious and non-contentious proposals. The positive and significant difference between the highest and lowest quintile generally holds: regardless of the recommendation of ISS, index funds have substantially higher rates of opposition on shares that are largely held only by index funds across institutional fund families than on shares that are frequently held by both active and index funds.

The summary statistics discussed in this subsection indicate that index funds, on average, monitor by voting proxy shares at least as much as active funds. Further, index funds appear to exert even greater effort on monitoring portfolio firms that their institutional family does not hold in its active funds. However, these averages do not control for the endogenous choice by institutions to select certain firms to hold in their active funds. That is, active funds may choose to avoid holding certain firms that are members of an index because they perform poorly or are not well governed. One might therefore expect greater levels of monitoring, and therefore higher rates of opposition to management, by index funds that are required to hold these shares that active funds within their family can choose to avoid. In the next subsection, I address this possibility by including a number of firm, fund, family, and proposal controls as well as various fixed effects.

1.3.2 Multivariate Results

1.3.2.1 Index Fund Ownership and Opposition to Management

To better identify whether index funds are active monitors, I examine the relationship between an index fund's choice to vote against management and a portfolio firm's characteristics in a multivariate setting. Specifically, I estimate the following linear probability model:

$$Pr(Oppose\ Management_{f,c,p,t}) = \beta(Family\ Does\ Not\ Hold\ Actively)_{f,c,t} + \gamma X + \tau_t + \epsilon_{f,c,p,t} \quad (1.1)$$

The dependent variable is equal to 1 if index fund f opposes management at company c on proposal p in year N-PX reporting year t. The main independent variable of interest, *Family Does Not Hold Actively*, is equal to 1 if the index fund's family does not hold company c in any of its actively managed funds at time t. *Family Does Not Hold Actively* takes the value of 0 if both index funds and active funds within the family vote on the proposal. X is vector of company, proposal, fund, and family controls, as summarized in Table 1.2 and defined in Appendix A. τ_t represents N-PX reporting year fixed effects.

The results of this regression are presented in Table 1.5. For legibility, the dependent variable has been multiplied by 100. Consistent with the main findings of the univariate results, an index fund is 1.3% more likely to oppose management of a firm if that firm is not held by any of its actively managed funds (the coefficient on *Family Does Not Hold Actively* from Column 1, statistically significant at the 1% level.) This finding is robust to the inclusion of firm characteristics (market value, book assets, return on assets, book to market ratio, leverage, excess return) as well as fund and family characteristics (total net assets, age, number of funds). On contentious proposals, where ISS recommends a vote against management, index funds are 8.4% more likely to vote against management if the family does not hold the firm's shares in active funds (Column 2). This does not necessarily imply that index funds are more likely to passively following ISS's recommendations on these shares: index funds are also 0.69% more likely to oppose management on *Family Does Not Hold Actively* shares on non-contentious proposals (Column 3). Looking to the control variables in the full specification of Column 1, index funds are more likely to oppose management at smaller firms by book assets and firms with lower profitability as measure by ROA. Perhaps surprisingly, index funds are more likely to oppose management with positive past excess return, though this result is consistent with a finding in Morgen, Poulsen, Wolf, and Yang (2011).

1.3.2.2 Controlling for Firm Quality: Firm Fixed Effects

Within a firm, there is variation in the *Family Does Not Hold Actively* measure: some index funds voting at a firm's shareholder meeting belong to families whose active funds simultaneously hold shares of that firm. Other index funds voting on proposals at that same firm belong to families that do not hold shares of that firm in their active funds. This variation allows me to incorporate firm fixed effects in my analysis. The regression specification becomes:

$$Pr(Oppose\ Management_{f,c,p,t}) = \beta(Family\ Does\ Not\ Hold\ Actively)_{f,c,t} + \gamma X + \tau_t + \zeta_c + \epsilon_{f,c,p,t} \quad (1.2)$$

where ζ_c is the firm fixed effect. This fixed effect eliminates the impact that any time-invariant firm-specific characteristics might have in informing a fund's voting decision. I thus identify the effect of *Family Does Not Hold Actively* on a fund's decision to oppose management by exploiting the differences across funds in whether their family holds a firm actively, for the same company at the same point in time. Alternatively, I substitute $\tau_t + \zeta_c$ with $\zeta_{c,t}$ to include a firm-year fixed effect that controls for any time-invariant characteristics of the firm within an N-PX reporting year that might influence a fund's vote.

Table 1.6 presents the results of Equation (1.2). Columns 1 through 3 include the year and firm fixed effects while Columns 4 through 6 substitutes $\tau_t + \zeta_c$ with a firm-year fixed effect $\zeta_{c,t}$. The same set of controls from Table 1.5 are included, but suppressed for brevity.[14] Reaffirming the findings of Table 1.5, Table 1.6 shows that index funds are more likely to oppose management when active funds within their family do not hold shares of the firms they are voting on. This is indicated by the positive and statistically significant coefficient on *Family Does Not Hold Actively* coefficient across all columns. Because index funds are more likely to oppose management on *Family Does Not Hold Actively* shares on non-contentious proposals, it cannot be claimed that index funds blindly follow the recommendations of ISS.

1.3.2.3 Controlling for Proposal Quality: Proposal Fixed Effects

Family Does Not Hold Actively varies also within a proposal. Some index funds voting on a given proposal belong to families whose active funds simultaneously vote on that proposal while other index funds belong to families that only have index funds voting on that proposal. This variation allows me to incorporate proposal fixed effects. The regression specification is:

$$Pr(Oppose\ Management_{f,c,p,t}) = \beta(Family\ Does\ Not\ Hold\ Actively)_{f,c,t} + \gamma X + \delta_p + \epsilon_{f,c,p,t} \quad (1.3)$$

where δ_p represents proposal fixed effects. These fixed effects control for the effect that firm or proposal characteristics, including ISS's recommendation and perceived proposal quality, has on the fund's choice to vote against management. I therefore identify the effect of *Family Does Not Hold Actively* on a fund's decision to oppose

[14] Firm controls are not absorbed in this specification because they vary quarterly within the firm.

management by exploiting the differences across funds in whether their family holds a share in their active funds, for the same share at the same point in time.

Table 1.7 shows the results of Equation (1.3). By incorporating the proposal fixed effects, all proposal and firm controls are absorbed because they do not vary within a proposal. Similarly, ISS's recommendation does not vary within a proposal, so the independent variable *Contentious* is absorbed. An index fund is 1.3% more likely to oppose management overall if the firm it is voting on is not held by active funds within its family (Column 1). Splitting proposals into contentious and non-contentious proposals reveals that the positive and significant relationship holds across both subsamples of proposals (Columns 2 and 3). Therefore, the results are robust to the inclusion of these highly stringent proposal fixed effects, mitigating the concern that some omitted variable pertaining to the quality of firm or quality of proposal drives the main results in Table 5.

The collective results of Tables 1.5, 1.6 and 1.7 in conjunction with the univariate findings in the previous subsection present evidence that index funds do engage in active voting governance. I indicate that index funds are more likely to vote against management on shares their family holds only in index funds relative to shares their families also holds in its active funds. By including year, firm, and proposal fixed effects, as well a host of other controls, I rule out numerous other reasons that might explain the higher propensity by index funds to oppose management on *Family Does Not Hold Actively* shares. These fixed effects allow me to conclude that year trends, firm quality, and proposal quality are not driving the higher level of opposition by index funds.

1.4 The Effects of Index Fund Governance

1.4.1 Election Outcomes

In this section, I explore the effects of index fund opposition on proposal outcomes and firm value. First, I test whether index fund opposition to a proposal increases the likelihood that a proposal fails. To overcome the mechanical relationship between the number of votes submitted against a proposal and the probability that the vote fails, I follow Morgan et al. (2011) and consider the difference between index and active opposition. Specifically, I estimate a linear probability model that relates an indicator variable *Fail* set to 1 if the proposal fails and zero otherwise (multiplied by 100) to the difference of index and active fund opposition:

$$\begin{aligned} Pr(Fail_{p,c,t}) = \beta_1(Index\ Oppose\ \% - Active\ Oppose\%)_{p,c,t} \\ + \beta_2(Active\ Oppose\ \%) + \gamma X + \tau_t + \zeta_c + \epsilon_{p,c,t} \quad (1.4) \end{aligned}$$

The unit of observation is a proposal p at firm c in N-PX reporting year t. *Index Oppose % - Active Oppose %* is the difference in opposition rates of index and active funds voting on proposal p at firm c at time t. The index (active) fund opposition rate is calculated as the number of votes submitted by index (active) funds against management on a company proposal divided by the total number of votes submitted by index (active) funds on that proposal. Following Morgan et al. (2011), I include a vector of the proposal categories, X, as defined in the previous section to control for the quality of the proposal. τ_t and ζ_c are year and firm fixed effects, respectively.

Panel A of Table 1.8 presents the descriptive statistics for the dependent and independent variables of Equation (1.4). The sample includes ten years of voting data, from 2006 to 2016, across 276,979 proposals and 5,326 firms. Only 1% of management sponsored proposals in the sample fail overall, though 6% of contentious management sponsored proposals fail. The median rate of opposition by index (active) funds is approximately 2% (1%), and the average of the difference between the levels of index fund and active fund opposition is approximately -1

Panel B of Table 1.8 presents these results of Equation (1.4). All columns include year fixed effects, while Columns 3 and 4 include company or firm fixed effects. Across all specifications, there is a positive and significant relationship between the probability a proposal fails and the difference between index fund and active fund opposition. As the rate at which index funds oppose a proposal increases relative to the rate at which active funds oppose a proposal, the probability that the proposal fails increases. The results in Columns 3 and 4 control for omitted and time-invariant characteristics associated with the company that the funds are voting on, including the firm's performance or governance qualities. Thus, after controlling for the voting behavior of actively managed funds, proposal quality, and company characteristics, index fund opposition to a proposal has a statistically significant effect on whether a proposal fails. These real effects of governance activism by index funds perhaps incentivize them to devote resources to monitoring in the first place.

1.4.2 Implications for Shareholder Value

In the previous sections, I demonstrated that index funds engage in governance and that their voting behavior has an incremental effect on whether a proposal passes. But do investors value this engagement in monitoring? To test this, I follow the methodology employed in Iliev and Lowry (2015) and regress abnormal returns the day of a company's election on the level of support by index funds. Positive risk-adjusted returns around the passage of a proposal that index funds support would indicate that the market finds value in their voting opinion and governance activities. Alternatively, if index funds support a proposal that ultimately fails, negative abnormal returns would indicate that the market perceives such a proposal passing to be value reducing. Similar to Cuñat et al. (2012) and Iliev and Lowry (2015), I consider only close votes to concentrate the analysis on those proposals where the probability of passing is less likely to be accurately predicted and factored into stock returns. The regression specification is therefore:

$$\begin{aligned}\alpha_{c,t} = \beta_1(Pass \times Index\%For)_p + \beta_2(Index\%For)_p + \beta_3(Pass)_p \\ + \beta_4(Pass \times ISSFor)_p + \beta_5(Overall\%For)_p + \\ \beta_6(Pass \times Overall\%For)_p + \epsilon_{c,t} \quad (1.5)\end{aligned}$$

$\alpha_{c,t}$ is the Fama-French four factor alpha for company c on election day t, estimated using the CRSP value-weighted market index. The alpha estimation period is 255 trading days, ending 46 trading days before the event date. $Pass_p$ is equal to 1 if proposal p passes and 0 otherwise. $Index(Overall)\%For_p$ is the percentage of index funds (all funds) that vote in favor of proposal v. Lastly, ISSForp is equal to 1 if ISS supports proposal v and 0 otherwise. The sample is all proposals that have between either 45 and 55% or 40 and 60% support by funds in the ISS Voting Analytics database.

Panel A of Table 1.9 presents the summary statistics associated with the dependent and independent variables of Equation (1.5). The risk-adjusted returns on the day of a company election are 0.01%, with a minimum of -1.57% and a maximum of 0.96%. The average level of support by index funds (all funds) is 49% (44%). These "close" proposals are far less likely to pass than proposals in the overall sample: 89

The regression results of Equation (1.5) are presented in Panel B of Table 1.9. Columns 1 and 2 show the results for the sample of proposals with between 45 and 55% support by index and active funds, while Columns 3 and 4 include all proposals with between 40 and 60% support by index and active funds. The positive and significant coefficient on $Pass \times Index\%For$ in indicates that of the proposals that passed, those that were favored most by index funds were more likely to be value increasing. The coefficient in Column 1 (0.20) is similar in magnitude to that in the analysis of Iliev and Lowry (2015) who examined the effects that engaged voters among actively managed funds had on abnormal returns. Proposals that index funds supported but failed to pass are associated with negative abnormal returns on the day of the election, as indicated by the negative and statistically significant coefficient on *Index % For*. These results are robust to the inclusion of ISS's recommendation and the overall support by institutional investors in Columns 2 and 4.

1.5 Conclusion

The rapid rise of index investing calls into question whether these funds monitor the firms in their portfolio that they, by construction, are required to hold. To determine if these funds are active monitors, I focus on shares that are only held in index funds at the fund family level. I find that index funds are more aggressive when voting their proxies on these *Family Does Not Hold Actively* shares than when voting on *Family Holds in Active & Index* shares that are held in both the family's active and index funds. This identification strategy rules out the possibility that index funds are primarily voting at the discretion of active fund managers within their family. By considering separately contentious proposals and proposals across different categories, I control for the quality of the item on the ballot as well as the potential for the proposal to affect shareholder value. The incorporation of proposal-level fixed effects rules out the possibility that other firm-specific characteristics, such as the past performance of a given stock, profitability, leverage, or board structure, are driving the results.

In addition to showing that index funds engage in governance through proxy voting, I find that their voting behavior has an effect on the passage of a proposal and the underlying firm's value. A lack of support by index funds significantly reduces the likelihood a proposal passes. Additionally, investors value the governance choices of index funds as a proposal passing with index fund support is associated with positive abnormal returns around the company election.

My results contribute to the growing literature in the area of corporate governance by institutional investors by being the first to identify index fund engagement in governance, net of influence by actively managed funds. These results supplement the Fisch et al. (2019) theory that index funds have an incentive to engage in corporate governance to compete with active funds that have discretion over their holdings. Lewellen and Lewellen (2018) introduce an additional motivation for index funds to engage in governance by demonstrating that institutions increase their cash flow through management fees when, through effective monitoring, they increase the value of their portfolio shares.

Although the evidence presented in this paper indicates that index investors participate in governance, it is important that researchers and regulators monitor the influence of proxy advisors and large institutional investors into the future. Recent actions undertaken by the Securities and Exchange Commission seek to address the rise of institutional investing and its effects on corporate governance. In September of 2018, the SEC rescinded two letters authored by its staff that suggested mutual fund managers could satisfy their fiduciary duty to vote their shares by outsourcing decisions to proxy advisors.[15] This action limits the power that proxy advisory services like ISS, Egan-Jones Rating Company, and Glass, Lewis & Co. exert over the governance process. Additionally, the Chairman and Commissioners of the SEC in November of 2018 hosted a roundtable discussion with academic, government, and industry panelists, with the goal of "review[ing] whether our existing rules are achieving their objectives effectively in light of changes in our marketplace." As index investing continues to grow and the regulatory environment changes, the relative impact of index funds' governance choices will become increasingly important, and the area will remain ripe for research into their motivations for being engaged owners.

[15] The SEC's discussion of these letters and their withdrawal are available at https://www.sec.gov/news/public-statement/statement-regarding-staff-proxy-advisory-letters.

Table 1.1: Rates of Voting Opposition by S&P 500 Index Funds

This table presents average rates of opposition for the largest twenty-five S&P 500 funds in the ISS Voting Analytics database based on their total net assets as reported in the CRSP Mutual Fund database. The funds are ordered based on their family's size. Column 1 presents the fund's average quarterly opposition rate on management-sponsored proposals, calculated as the number of times the fund voted against management divided by the total number of management-sponsored proposals the fund voted on within a quarter. A fund's vote is how the fund voted on a proposal across all its shares of the company. Column 2 presents each fund's average quarterly opposition rate on shares within the S&P 500 index that the fund's family concurrently holds in any of its actively managed funds. Column 3 presents each fund's average quarterly opposition rate on shares within the S&P 500 index that the fund's family does not concurrently hold in its any of its actively managed funds. Column 4 presents the difference between Columns 3 and 2.

	(1)	(2)	(3)	(4)
S&P 500 Index Fund	Overall	*Family Holds in Index & Active*	*Family Does Not Hold Actively*	Difference
Vanguard	3.7%	3.6%	21.8%	18.2%
BlackRock	4.6%	4.5%	5.0%	0.6%
Fidelity	10.7%	10.7%	14.0%	3.3%
State Street	7.1%	4.7%	9.0%	4.3%
T. Rowe Price	5.4%	5.0%	7.0%	2.0%
AIM/Invesco	5.9%	5.4%	6.6%	1.2%
DFA	8.9%	8.3%	23.5%	15.3%
J.P. Morgan	5.4%	5.2%	6.1%	0.8%
Charles Schwab	7.4%	7.2%	22.7%	15.5%
TIAA-CREF	2.9%	2.9%	7.2%	4.3%
Columbia	6.7%	6.7%	5.9%	-0.8%
Principal	4.4%	4.4%	5.7%	1.3%
Legg Mason	5.6%	5.1%	6.3%	1.2%
Prudential	6.0%	5.8%	6.6%	0.7%
American Century	8.4%	7.5%	11.3%	3.8%
SEI Investments	5.3%	5.3%	10.1%	4.8%
Wells Fargo	4.3%	4.3%	5.1%	0.8%
BNY Mellon	6.1%	5.7%	7.2%	1.5%
Northern Trust	2.3%	2.2%	2.7%	0.5%
Federated	7.5%	8.0%	7.0%	-1.0%
NYL MainStay	5.6%	5.6%	6.1%	0.5%
Morgan Stanley	6.7%	6.3%	9.3%	3.0%
Deutsche	5.6%	5.1%	6.8%	1.8%
Victory	4.6%	4.6%	5.3%	0.8%
UBS	5.8%	3.8%	6.6%	2.8%
Average	5.9%	5.5%	9.0%	3.5%

Table 1.2: Summary Statistics

This table presents summary statistics for the proxy proposals, firms, and funds in the merged ISS Voting Analytics and CRSP Survivor-Bias Free Mutual Fund database. Firm characteristics for the portfolio firms come from Compustat. The final matched sample covers 654 index funds voting on 267,847 management-sponsored proposals at 5,155 firms for 11 Form N-PX voting years beginning July 1, 2006 and ending June 30, 2016. All variables are described in Appendix A. The unit of observation is a fund-proposal pair.

	N	Median	Mean	S.D.	P5	P25	P75	P95
Family Does Not Hold Actively	8,797,576	0	0.27	0.44	0	0	1	1
Contentious	8,797,576	0	0.08	0.27	0	0	0	1
Firm Characteristics								
Ln(Market Value)	7,840,136	8.1	8.16	1.8	5.4	6.8	9.4	11.2
Ln(Book Assets)	7,888,231	8.35	8.39	1.9	5.3	7.1	9.7	11.7
ROA	7,880,799	0.01	0.01	0.04	-0.03	0	0.02	0.04
Book to Market	6,828,001	0.47	0.73	28	0.1	0.3	0.8	1.4
Leverage	7,772,509	0.21	0.75	40.5	0	0.1	0.5	1.7
Excess Return	8,266,259	0.01	0.02	0.2	-0.2	-0.1	0.1	0.3
Proposal Categories								
Accounting Proposal	8,566,075	0	0.11	0.31	0	0	0	1
Board Proposal	8,566,075	0	0.02	0.13	0	0	0	0
Compensation Proposal	8,566,075	0	0.12	0.32	0	0	0	1
Director Election Proposal	8,566,075	1	0.73	0.44	0	0	1	1
Payout Proposal	8,566,075	0	0	0.03	0	0	0	0
General Proposal	8,566,075	0	0.03	0.16	0	0	0	0
Fund & Institution Characteristics								
Ln(Family Size)	8,786,836	11.9	11.8	2.4	7.8	10.1	13.9	14.9
Ln(Fund Size)	8,731,348	6.7	6.7	2.5	2.5	5	8.5	10.7
S&P 500 Fund	8,797,576	0	0.1	0.3	0	0	0	1
Fund Age (years)	8,797,576	10	11	8.3	1.2	4.7	14.9	24.4
Family Age (years)	8,797,576	62.5	55.1	31.3	14.2	24	88.1	88.1
Number of Funds	8,797,576	106	117.8	91.8	13	48	132	324

Table 1.3: Differences in Active and Index Fund Opposition to Management

This table presents average rates of opposition to management by index and active funds on proposals in the Institutional Shareholder Services Voting Analytics Database by fund type and proposal type from 2006 to 2016. Panel A presents the overall level of opposition by all funds, then compares the average rates of opposition by index funds to active funds on contentious and non-contentious proposals. Panel B compares average rates of opposition by index funds on Family Does Not Hold Actively shares and Family Holds in Index & Active shares for contentious and non-contentious proposals. Panel C compares average rates of opposition by index funds on Family Does Not Hold Actively shares and Family Holds in Index & Active shares for contentious and non-contentious proposals across proposal categories. Family Does Not Hold Actively shares are shares that the index fund is voting on that no active fund within its fund family concurrently holds. Family Holds in Index & Active shares are shares that the index fund is voting on that active funds within its family concurrently hold. Proposal categories are defined in Appendix A. The opposition rates in columns (1) through (3) are calculated as the number of votes submitted by funds in opposition to management's recommendation divided by the total number of votes submitted by funds. A fund's vote is how the fund voted on a proposal across all its shares of the company. Column (4) presents the difference between columns (2) and (3), as well as the t-statistic and statistical significance of that difference. Standard errors are clustered at the fund level. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels.

Panel A: Active Fund and Index Fund Voting					
	(1)	(2)	(3)	(4)	
	Overall Oppose	Index Fund Oppose	Active Fund Oppose	Difference	t-stat
All Proposals	7.10%	7.30%	6.90%	0.30%	0.89
Contentious	54.50%	50.00%	58.10%	-8.10%	-4.31***
Non-contentious	3.30%	3.50%	3.10%	0.50%	1.41

Panel B: Index Fund Voting by Share Type

	(1)	(2)	(3)	(4)	
	Index Fund Oppose	Family Does Not Hold Actively	Family Holds in Index & Active	Difference	t-stat
All Proposals	7.30%	10.00%	6.00%	3.90%	4.82***
Contentious	50.00%	53.60%	47.50%	6.00%	3.37***
Non-contentious	3.50%	4.90%	2.90%	2.00%	2.52**

Panel C: Index Fund Voting by Type of Share across Proposal Categories

	(1)	(2)	(3)	(4)	
	Index Fund Oppose	Family Does Not Hold Actively	Family Holds in Index & Active	Difference	t-stat
Director Elections	6.40%	9.20%	5.20%	4.00%	4.05***
Contentious	45.50%	47.90%	43.70%	4.30%	2.23**
Non-contentious	3.30%	4.90%	2.60%	2.30%	2.29**
Compensation	14.30%	18.50%	12.40%	6.10%	7.95***
Contentious	55.50%	61.90%	51.70%	10.20%	4.98***
Non-contentious	6.80%	8.60%	6.00%	2.60%	3.81***
Accounting	1.10%	1.30%	0.90%	0.40%	2.86***
Contentious	59.40%	68.30%	55.80%	12.50%	4.05***
Non-contentious	0.70%	0.90%	0.50%	0.40%	3.10***
General	19.90%	24.40%	17.30%	7.10%	14.94***
Contentious	70.10%	77.60%	64.60%	12.90%	7.53***
Non-contentious	7.80%	8.80%	7.30%	1.50%	0.6
Board	9.80%	12.10%	8.90%	3.20%	6.14***
Contentious	56.70%	65.40%	53.10%	12.30%	4.13***
Non-contentious	2.70%	3.50%	2.40%	1.20%	4.12***
Payout	6.60%	9.90%	5.80%	4.10%	4.12***
Contentious	56.10%	66.10%	52.00%	14.00%	3.52***
Non-contentious	2.20%	1.90%	2.20%	-0.30%	-0.55

Table 1.4: Opposition Rates Across the *Family Does Not Hold Actively* Distribution

For each proposal-index fund pair in the full ISS Voting Analytics sample, a value of Family Does Not Hold Actively = 1 is assigned if that index fund's family does not hold that share in any of its active funds (and thus the shares of that company are held by index funds alone within that family). A value of Family Does Not Hold Actively = 0 is assigned if that index fund's family concurrently holds that share in any of its active funds (and thus the shares of that company are thus held by both index funds and active funds within that family). Proposals are sorted into quintiles based on their average value of Family Does Not Hold Actively. Proposals in the 5th quintile have an average Family Does Not Hold Actively value nearer to 1 and are more frequently held only by index funds within a family. Proposals in the 1st quintile have an average Family Does Not Hold Actively value nearer to 0 and are more frequently held both by active funds and index funds within a family. This table presents the average rate at which index funds oppose management for proposals in each of these quintiles. Panel A presents the opposition rates for all management sponsored proposals while Panels B and C present the opposition rates for contentious and non-contentious proposals, respectively. The Difference columns present the difference in opposition rates between the highest (5th) and lowest (1st) quintiles of Family Does Not Hold Actively, as well as the t-statistic and statistical significance of that difference. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels.

Panel A: All Management Sponsored Proposals

	Quintiles of Family Does Not Hold Actively					Difference	
	1	2	3	4	5	$5^{th} - 1^{st}$	t-stat
Director Elections	4.50%	6.20%	7.90%	9.40%	12.90%	8.38%***	72.86
Compensation	11.30%	9.80%	13.20%	15.70%	21.20%	9.98%***	22.27
Accounting	1.00%	0.80%	0.90%	1.00%	1.10%	0.03%	0.24
General	14.10%	15.80%	22.20%	23.30%	28.30%	14.19%***	13.72
Board	8.50%	6.30%	8.70%	10.90%	18.60%	10.10%***	7.91
Payout	6.00%	2.80%	11.80%	9.80%	22.70%	16.74%***	3.15
Overall	5.50%	7.10%	8.70%	10.30%	13.90%	8.34%***	75.86

Panel B: Contentious Proposals							
	Quintiles of Family Does Not Hold Actively					Difference	
	1	2	3	4	5	$5^{th} - 1^{st}$	t-stat
Director Elections	41.10%	45.40%	45.60%	47.20%	48.10%	7.03%***	13.79
Compensation	50.90%	51.70%	54.80%	55.70%	62.50%	11.62%***	9.51
Accounting	53.20%	48.00%	57.70%	62.20%	63.30%	10.12%	1.17
General	59.40%	65.10%	71.10%	72.10%	73.50%	14.02%***	6.3
Board	53.80%	63.60%	58.40%	65.50%	66.30%	12.47%***	3.24
Payout	42.80%	62.20%	75.30%	48.10%	52.50%	9.67%	0.41
Overall	46.70%	50.00%	50.60%	51.70%	53.90%	7.22%***	15.63

Panel C: Non-Contentious Proposals							
	Quintiles of Family Does Not Hold Actively					Difference	
	1	2	3	4	5	$5^{th} - 1^{st}$	t-stat
Director Elections	2.80%	3.30%	4.00%	4.70%	5.90%	3.17%***	48.48
Compensation	6.40%	4.90%	5.90%	7.40%	8.80%	2.41%***	8.72
Accounting	0.70%	0.70%	0.70%	0.70%	0.70%	0.00%	-0.19
General	7.20%	7.60%	8.20%	9.50%	9.90%	2.69%***	4.71
Board	1.80%	1.50%	2.80%	2.70%	7.30%	5.42%***	7.46
Payout	4.40%	1.80%	1.90%	1.90%	6.30%	1.87%	0.64
Overall	3.00%	3.60%	4.20%	4.80%	5.90%	2.89%***	48.4

Table 1.5: Index Fund Ownership and Opposition to Management

This table presents regression results relating a fund's vote to proposal, firm, and fund characteristics as defined in Equation (1.1) of the text. The dependent variable is an indicator variable for a fund's vote against management (multiplied by 100). The unit of observation is a fund-proposal pair. A fund's vote is how the fund voted on a proposal across all its shares of the company. All variables are defined in Appendix A. Column (1) presents the results for all proposals, column (2) presents the results for contentious proposals where ISS recommends a vote against management, and column (3) presents the results for non-contentious proposals where ISS agrees with management's recommendation. Standard errors, presented in parentheses under coefficient estimates, are clustered at the fund level. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)
	All Proposals	Contentious	Non-contentious
Family Does Not Hold Actively	1.33***	8.41***	0.69**
	(0.42)	(3.16)	(0.34)
Contentious	47.86***		
	(2.67)		
Ln(Market Value)	0.01	-0.81	0.08
	(0.10)	(0.78)	(0.10)
Ln(Book Assets)	-0.13**	-0.29	-0.13**
	(0.05)	(0.32)	(0.05)
ROA	-4.88***	1.55	-5.39***
	(0.90)	(4.39)	(0.93)
Book to Market	-0.01	-0.09*	0.00
	(0.00)	(0.05)	(0.0)
Leverage	0.00	0.06	-0.00
	(0.00)	(0.04)	(0.00)
Excess Return	0.28**	0.66	0.25***
	(0.11)	(0.63)	(0.08)
Ln(Family TNA)	-0.76***	-5.50**	-0.37**
	(0.22)	(2.26)	(0.18)
Ln(Fund TNA)	-0.10	-2.04*	0.03
	(0.10)	(1.16)	(0.09)
S&P 500 Fund	-0.62	9.81	-1.23**
	(0.63)	(6.02)	(0.59)
Fund Age	0.03	0.30	0.01
	(0.03)	(0.23)	(0.02)
Family Age	0.01	0.06	0.01
	(0.01)	(0.11)	(0.01)
Number of Funds	0.02***	0.15***	0.01***
	(0.0)	(0.03)	(0.0)
Proposal Category Controls	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	6,325,499	452,063	5,873,436
Adj. R-squared	0.291	0.086	0.011

Table 1.6: Index Fund Ownership and Opposition to Management: Firm Fixed Effects

This table presents regression results relating a fund's vote to proposal, firm, and fund characteristics as defined in Equation (1.2) of the text. The dependent variable is an indicator variable for a fund's vote against management (multiplied by 100). The unit of observation is a fund-proposal pair. A fund's vote is how the fund voted on a proposal across all its shares of the company. All variables are defined in Appendix A. Columns 1 and 4 present the results for all proposals, Columns 2 and 5 present the results for contentious proposals where ISS recommends a vote against management, and Columns 3 and 6 present the results for non-contentious proposals where ISS agrees with management's recommendation. Standard errors, presented in parentheses under coefficient estimates, are clustered at the fund level. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)	(5)	(6)
	All Proposals	Contentious	Non-contentious	All Proposals	Contentious	Non-contentious
Family Does Not Hold Actively	1.26***	8.05**	0.68*	1.31**	8.11**	0.72*
	(0.48)	(3.64)	(0.37)	(0.51)	(3.88)	(0.40)
Contentious	46.46***			46.62***		
	(2.72)			(2.68)		
Proposal Category Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fund Controls	Yes	Yes	Yes	Yes	Yes	Yes
Family Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	No	No	No
Firm Fixed Effects	Yes	Yes	Yes	No	No	No
Firm × Year Fixed Effects	No	No	No	Yes	Yes	Yes
Observations	6,325,497	452,040	5,873,430	6,325,499	452,060	5,873,436
Adj. R-squared	0.329	0.202	0.063	0.305	0.158	0.029

Table 1.7: Index Fund Ownership and Opposition to Management: Proposal Fixed Effects

This table presents regression results relating a fund's vote to proposal, firm, and fund characteristics as defined in Equation (1.3) of the text. The dependent variable is an indicator variable for a fund's vote against management (multiplied by 100). The unit of observation is a fund-proposal pair. A fund's vote is how the fund voted on a proposal across all its shares of the company. All variables are defined in Appendix A. Column 1 presents the results for all proposals, Column 2 presents the results for contentious proposals where ISS recommends a vote against management, and Column 3presents the results for non-contentious proposals where ISS agrees with management's recommendation. Standard errors, presented in parentheses under coefficient estimates, are clustered at the fund level. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)
	All Proposals	Contentious	Non-contentious
Family Does Not Hold Actively	1.31***	8.12**	0.72*
	(0.52)	(3.91)	(0.40)
Contentious	Absorbed	Yes	No
Proposal Category Controls	Absorbed	Absorbed	Absorbed
Firm Controls	Absorbed	Absorbed	Absorbed
Fund Controls	Yes	Yes	Yes
Family Controls	Yes	Yes	Yes
Proposal Fixed Effects	Yes	Yes	Yes
Observations	6,325,036	451,969	5,873,067
Adj. R-squared	0.398	0.234	0.152

Table 1.8: The Effect of Index Opposition on Election Outcomes

This table presents regression results relating a proposal's failure to index and active fund voting opposition on contentious proposals. Panel A presents descriptive statistics and Panel B presents the regression specification as defined in Equation (1.4) of the text. The dependent variable is an indicator variable for a proposal failure (multiplied by 100). The unit of observation is a company proposal. Index (Active) Oppose % is calculated as the number of votes submitted by index (active) funds in opposition to a proposal divided by the total number of votes submitted by index (active) funds on that proposal, where a fund's vote is how the fund voted on a proposal across all its shares of the company. Ind. Opp.% − Act. Opp.% is the difference between Index Oppose % and Active Oppose %. All variables are defined in Appendix A. Standard errors, presented in parentheses under coefficient estimates, are clustered at the fund level. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels.

Panel A: Descriptive Statistics

	Median	Mean	SD	P5	P25	P75	P95
Fail	0	0.01	0.10	0	0	0	0
Contentious	0	0.11	0.31	0	0	0	1
Fail if Contentious	0	0.06	0.23	0	0	0	1
Index Oppose %	0.02	0.09	0.18	0	0	0.07	0.53
Active Oppose %	0.01	0.09	0.20	0	0	0.07	0.63
Ind. Opp.% − Act. Opp.%	0	-0.01	0.11	-0.17	-0.02	0.01	0.14

Panel B: Proposal failure and differences in opinion				
	(1)	(2)	(3)	(4)
	Cont.	Non-cont.	Cont.	Non-cont.
Ind. Opp.% − Act. Opp.%	9.97***	5.85***	11.07***	7.18***
	(1.19)	(0.58)	(1.12)	(0.44)
Active Oppose %	20.38***	4.08***	18.74***	5.63****
	(1.60)	(0.63)	(1.42)	(0.48)
Ln(Market Value)	0.49**	-0.04		
	(0.22)	(0.03)		
Ln(Book Assets)	-0.13	0.06***		
	(0.19)	(0.02)		
ROA	0.04	-0.03		
	(3.31)	(0.46)		
Book to Market	-0.00	-0.00		
	(0.05)	(0.01)		
Leverage	0.00	-0.00		
	(0.04)	(0.00)		
Excess Return	-2.21***	0.03		
	(0.63)	(0.08)		
Proposal Category Controls	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	No	No	Yes	Yes
Observations	15,535	151,506	24,722	234,416
Adj. R-squared	0.256	0.070	0.398	0.112

Table 1.9: The Effect of Index Opposition on Abnormal Returns

This table presents regression results relating a company's abnormal returns to index and active fund voting support. The regression specification is defined in Equation (1.5) of the text. Panel A presents summary statistics for the dependent and independent variables. *Alpha* is the Fama-French four-factor alphas on the day of a shareholder election, in percent. *Index (Overall) %* For is the percentage of votes by index funds (all funds) in favor of a proposal. Pass is an indicator equal to one if the proposal passes. *ISS For* is an indicator equal to one if ISS supports the proposal. Panel B presents the regression results. The dependent variable is the Fama-French four-factor alpha on the day of the shareholder election, in decimal form. The sample consists of "close votes" where proposals have between 45 and 55% support by funds in Columns 1 and 2 and between 40 and 60% support in Columns 3 and 4. Standard errors, presented in parentheses under coefficient estimates, are robust. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels.

Panel A: Descriptive Statistics

	Median	Mean	SD	P5	P25	P75	P95
Alpha (percent)	0.01	0.01	0.17	-0.25	-0.07	0.09	0.28
Index % For	0.46	0.49	0.26	0.08	0.31	0.63	1
Pass	1	0.89	0.32	0	1	1	1
Overall % For	0.40	0.44	0.24	0.11	0.29	0.53	0.99
ISS % For	0	0.14	0.35	0	0	0	1

Panel B: Abnormal returns around close votes				
	(1)	(2)	(3)	(4)
	Cont.	Non-cont.	Cont.	Non-cont.
Pass × Index % For	0.20***	0.51***	0.09**	0.34***
	(0.08)	(0.13)	(0.05)	(0.08)
Index % For	-0.20***	-0.39***	-0.11***	-0.29***
	(0.07)	(0.09)	(0.04)	(0.06)
Pass	-0.08***	-0.06*	-0.02	0.00
	(0.03)	(0.03)	(0.02)	(0.02)
Pass × ISS For		-0.05		-0.10**
		(0.07)		(0.04)
ISS For		0.02		0.02*
		(0.02)		(0.01)
Overall % For		0.27*		0.27***
		(0.16)		(0.09)
Pass × Overall % For		-0.42**		-0.38***
		(0.18)		(0.11)
Vote Level of Support Threshold	45 to 55	45 to 55	40 to 60	40 to 60
Observations	1,390	1,390	3,022	3,022
Adj. R-squared	0.011	0.015	0.004	0.007

Figure 1.1: The Growth of Index Ownership

This figure presents U.S. equity mutual and exchange-traded fund assets under management as a percentage of total U.S. equity market capitalization from 2000 to 2018. The data on active fund and index fund total net assets is from the Investment Company Institute's 2019 Investment Company Factbook. Total U.S. market capitalization is sourced from World Bank.

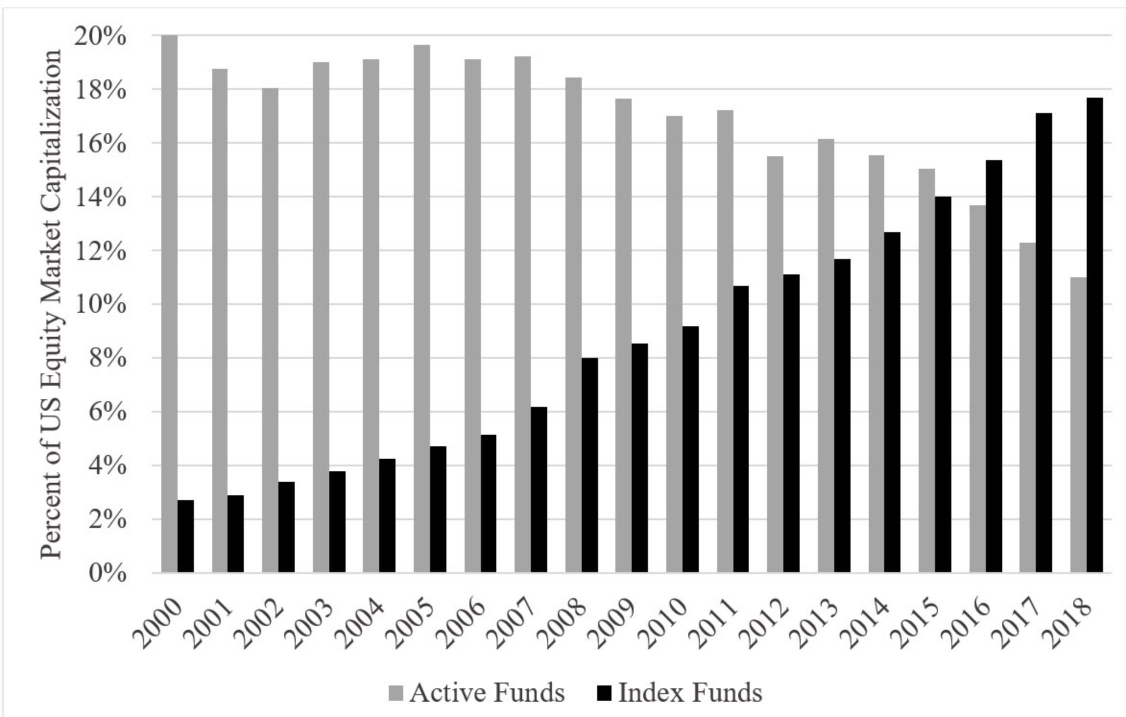


Figure 1.2: Overlapping Holdings and *Family Does Not Hold Actively* Shares

This figure presents a hypothetical institutional fund family consisting of two index funds A and B and three actively managed funds X, Y, and Z. The unshaded circles represent shares held only by active funds that are not held by index funds within this fund family, or *Family Holds Only in Active Funds* shares. The hashed circles represent shares that are held by both index and active funds within this fund family, or *Family Holds in Index & Active* shares. The dark black circles are shares held only by index funds within this fund family, or *Family Does Not Hold Actively* shares. *Family Does Not Hold Actively shares* may be held by active funds in other fund families or in multiple index funds within the same family.

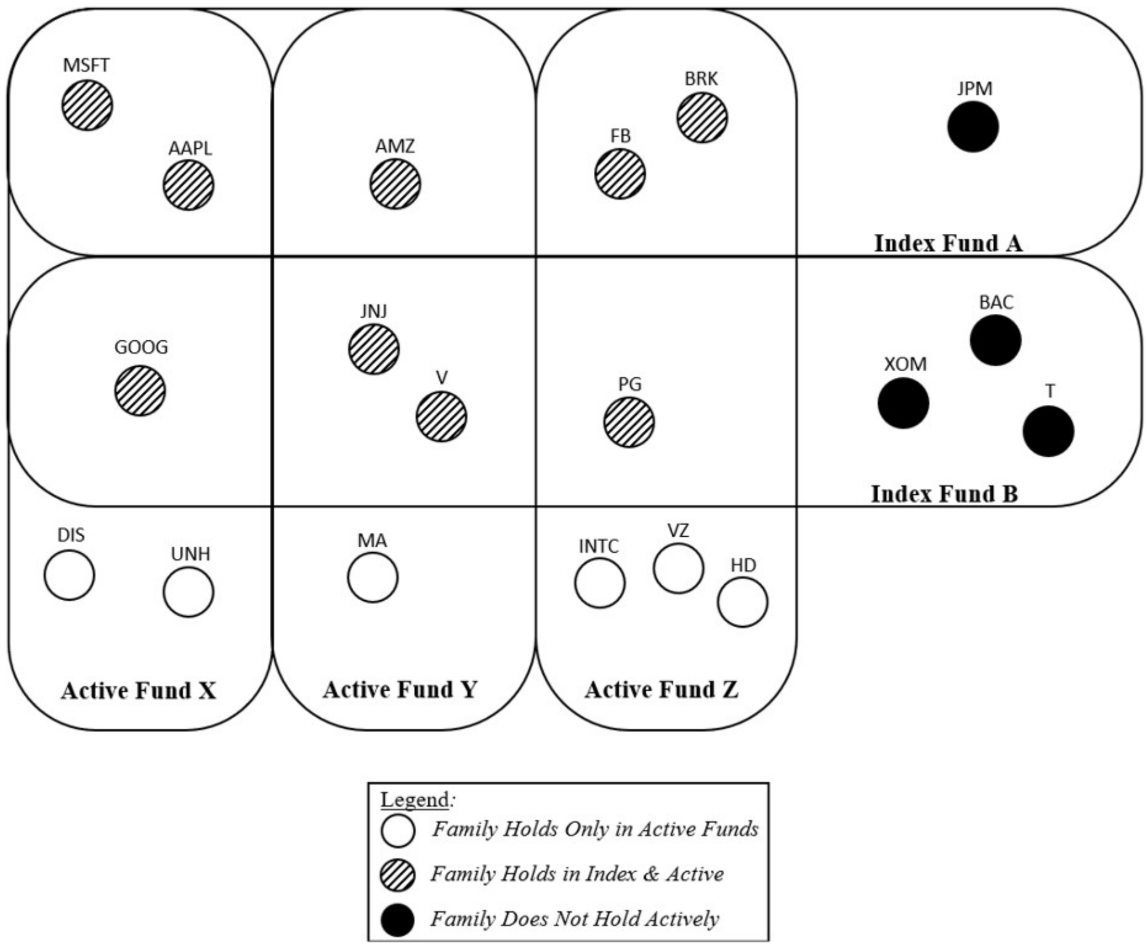
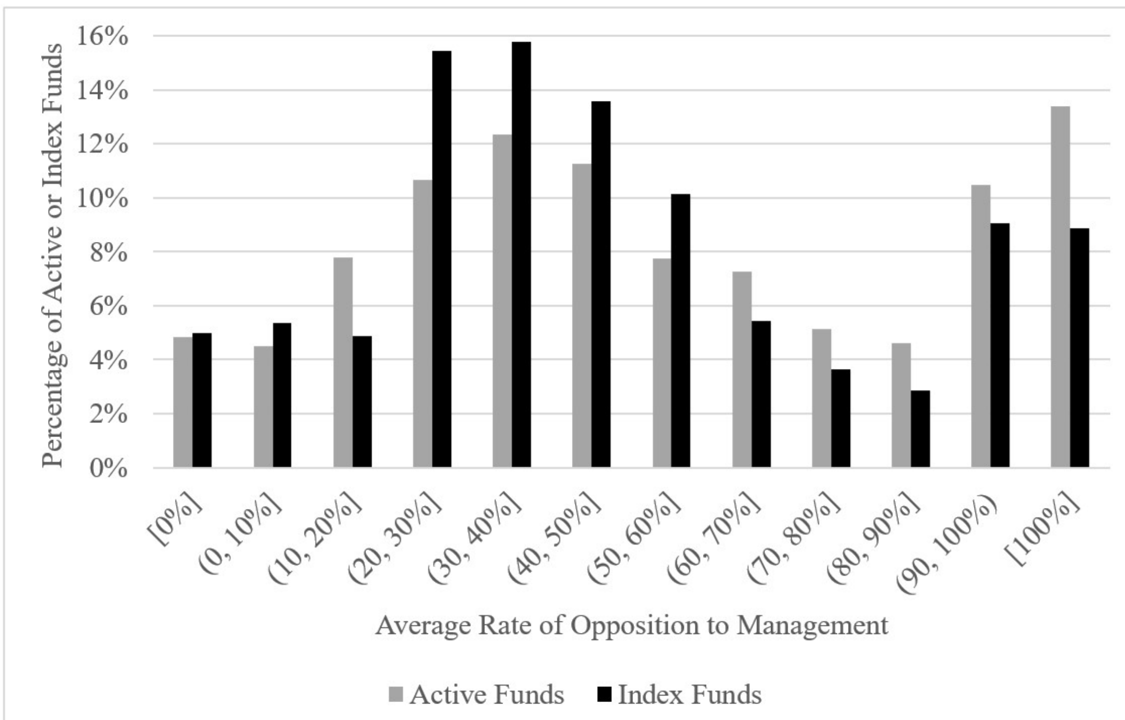


Figure 1.3: Distribution of Funds by their Overall Rate of Opposition to Management

This histogram presents the distribution of index funds and active funds based on their overall level of opposition to management on contentious proposals. Contentious proposals are those proposals where ISS recommends a vote against management. The sample is all index and active funds in the ISS Voting Analytics database from 2006 to 2016. For each fund, I divide the number of times the fund voted in opposition to a management proposal by the total number of times the fund submitted a vote on a management proposal for its life in the sample. A fund's vote is how the fund voted on a proposal across all its shares of the company. A fund is then sorted into deciles based on this average rate of opposition, as depicted on the horizontal axis. The vertical axis presents the percentage of active funds (lighter vertical bars) and the percentage of index funds (darker vertical bars) that fall into each decile.



Chapter 2 Misconduct and Fraud by Investment Managers

2.1 Introduction

Fraud and misconduct by investment managers is an important and justified concern for investors. During the period 2001-2016 the Security and Exchange Commission (SEC) successfully prosecuted 981 cases of fraud committed by investment managers, which collectively caused more than $40 billion in direct losses. In addition, these frauds also cause indirect harm; Gurun, Stoffman, and Yonker (2018) show that fraud by investment managers has significant spillover effects, resulting in reduced stock market participation and investment even by those not directly victimized. Further, this harm is not limited to a single category of investment manager. Zitzewitz (2006) estimates that the mutual fund late trading scandal cost shareholders $400 million per year from 1998 to 2003. Hedge funds, with their non-traditional holdings and less regulatory scrutiny, have also suffered from fraud. Capco (2003) finds that nearly half of hedge fund failures are due to fraud, mainly from misappropriation of investor funds and misrepresentation of investments.[1] Practitioners also recognize the potential harm from fraud and misconduct by investment managers (e.g., Scharfman (2009) and Swensen (2000)). This issue has become increasingly relevant in recent years, as investors have shifted away from direct holdings and into indirect investments through investment managers (e.g., see French (2008), Table I)).

Despite the significant economic consequences of fraud by investment managers, academics have produced relatively little research on this topic until recently. In part, this is because detailed data on investment managers and fraud has only recently become publicly available in a format that permits rigorous academic study. Indeed, one of the purposes of this chapter is to detail the available data and to stimulate research in the area by making available the data used in this study (https://doi.org/10.13023/nsjd-rk62). In addition to stimulating research in this area, our results provide useful information for regulators and policymakers concerned with preventing fraud and provide guidance for investors when selecting investment managers.

In this chapter, we provide a systematic examination of all detected fraud cases committed by registered investment advisors during the period 2001-2016. We document the type and extent of fraud and show the relation between fraud and various characteristics that investment management firms disclose in their Form ADV filings. These firm characteristics fall into three categories. First, firms with prior regulatory, civil law, or criminal violations are significantly more likely to subsequently commit fraud. Although these prior violations are frequently for minor issues, they have strong predictive power. Second, conflicts-of-interest predict fraud; fraud is significantly more likely to occur at firms that buy securities from or sell securities to their clients. Third, there is a strong relation between monitoring and fraud. Firms

[1] Capco (2003) find that 54% of hedge fund failures are caused by operational issues, and 46% are caused by operational issues that can be classified as forms of fraud.

with a dedicated Chief Compliance Officer, an indicator of the strength of internal monitoring, are less likely to commit fraud. External monitoring by clients is also important; firms with large clients are less likely to commit fraud, but firms whose clients are primarily themselves agents are more likely to commit fraud. These results are consistent with the findings of Dimmock and Gerken (2012) and suggest the prior paper captured long lived predictive factors.

The economic magnitude of the predictability of fraud is large. An investor who avoided the 5% of firms with the highest predicted risk of fraud, would successfully avoid 27.1% of fraud cases and 28.6% of the dollar losses from fraud. We conduct K-fold cross-validation tests, and show that these results are robust in out-of-sample data. As an additional test of the predictive ability of the data, we divide the sample into newly initiated fraud cases and continued fraud cases (cases that were initiated in a previous year but continue into the subsequent year). We find that our model can successfully predict 29.8% of newly initiated frauds.

We further divide the sample of frauds into firm-wide frauds, committed by the firm's senior executives, and rogue employee fraud, committed by non-executive employees without the knowledge of senior executives. We find that rogue employee fraud is much more predictable – avoiding the 5% of firms with the highest fraud risk would allow an investor to avoid 61.8% of rogue employee frauds. Firm-wide fraud is less predictable, but our model continues to successfully predict an economically meaningful proportion of such fraud.

The final empirical results presented in this paper are a true out-of-sample test of the predictability of investment manager fraud. Dimmock and Gerken (2012) predict fraud using mandatory disclosures made by investment managers during the 2001-2006 period. We take the coefficient estimates from Dimmock and Gerken (2012) and use these to predict fraud detected post-publication. The results show that the model continues to perform well out-of-sample, although not as well as during the in-sample period.

2.2 Related Research

This handbook chapter is closely related to Dimmock and Gerken (2012) who use Form ADV data for the years 2001 to 2006 to predict fraud by investment managers. They find that disclosures of prior misconduct, conflicts of interest, and monitoring all have power to predict fraud. Using their model, an investor who avoided the 5% of firms with the highest fraud risk would have avoided 29.4% of fraud cases and $4 billion in losses. Other studies that predict fraud by investment managers include Zitzewitz (2006) and Bollen and Pool (2012). Zitzewitz (2006) examines mutual fund late trading, and shows it can be predicted based on fund-level correlations between daily mutual fund flows and market returns. Bollen and Pool (2012) show that suspicious patterns in the reported returns of hedge funds can predict hedge fund fraud. Gregoriou and Lhabitant (2009) provide a case study of the infamous Ponzi scheme committed by Bernie Madoff, highlighting operational red flags that hinted at the potential for fraud.

Instead of predicting fraud, Gurun et al. (2018) focus on how fraud by investment managers affects investor behavior. They find that fraud results in investors withdrawing assets from investment managers. However, this effect is mitigated by trust building activities. Gurun et al. (2018) also highlight an important spillover effect from fraud by investment managers: In addition to direct losses financial losses, fraud causes a decline in trust that results in reduced stock market participation, which has potentially large welfare losses due to forgone investment opportunities.

The mutual fund late trading scandal motivated multiple academic studies of fraud by investment managers. Houge and Wellman (2005), Choi and Kahan (2007), Chapman-Davies, Parwada, and Tan (2014), and Wu (2018) examine investors' reactions to the revelation of mutual fund scandals, and find that the fund families implicated in these scandals suffered large outflows. Goetzmann, Ivković, and Rouwenhorst (2001) and Zitzewitz (2003) propose pricing methods that prevent the possibility of late-trading arbitrage.

Another branch of the literature on fraud by investment managers examines return misreporting by hedge funds.[2] Bollen and Pool (2008) find evidence of conditional return smoothing in the returns reported by hedge funds; hedge funds appear to quickly report positive returns, but smooth out the reporting of bad returns over multiple months. Bollen and Pool (2009) show the returns reported by hedge funds exhibit a strong discontinuity around zero; hedge fund are nearly twice as likely to report a small positive return as a small negative return. Further, this discontinuity does not occur in the months when the hedge fund is audited. Agarwal, Daniel, and Naik (2011) show that hedge funds report significantly higher returns in the last month of their fiscal year (i.e., the month when the hedge fund manager's annual incentive fee is calculated). Ben-David, Franzoni, Landier, and Moussawi (2013) show that hedge funds manipulate stock prices at quarter ends, and this is affected by incentive fees and relative performance considerations. Cici, Kempf, and Puetz (2016) show direct evidence of valuation misreporting by hedge funds. They compare the individual stock valuations reported by hedge funds in their 13F filings with the stock prices in the CRSP database, and find that 7% of all equity positions reported by hedge funds are misvalued. Further, stock value misreporting is correlated with hedge funds' incentives to misreport, and with the return misreporting patterns documented by Bollen and Pool (2009) and Agarwal et al. (2011).

Following the discovery of these patterns of return misreporting by hedge funds, various authors studied different mechanisms that can reduce misreporting. Cumming and Dai (2010a) and Cumming and Dai (2010b) show that across-country variation in legal restrictions on hedge fund is related to return misreporting, and Cumming and Dai (2009) show that hedge fund regulation is related to capital flows. Cumming, Dai, and Johan (2015a) show that hedge funds subject to Delaware state law are different than funds incorporated in other states. Dimmock and Gerken (2016) use changes in hedge fund registration requirements in the U.S. to evaluate how regulatory oversight affects return misreporting. They find that return misreporting decreased following

[2] Agarwal, Mullally, and Naik (2015, Section 3.3) provide an excellent review of studies on operational risk and fraud in hedge funds.

a mandatory registration requirement, but then increased again following the reversal of this requirement. A later study, Honigsberg (2019), independently replicates the finding of Dimmock and Gerken (2016). Cassar and Gerakos (2011) show that stronger internal control systems by hedge fund managers reduce the occurrence of return misreporting. Jylha (2011) shows that misreporting is significantly greater when hedge fund managers have stronger financial incentives to misreport. Clifford, Ellis, and Gerken (2018) study the relation between hedge fund fraud and boards of directors. They find that hedge funds with independent directors on their boards are significantly less likely to engage in fraud, and the economic magnitudes of this effect are large. Finally, in a cross-country study Kang, Kim, and Jun Oh (2016) examine the relation between national cultures and return manipulation by hedge funds, and find more manipulation in cultures with greater individualism, masculinity, and power distance.

Brown, Goetzmann, Liang, and Schwarz (2008) and Brown, Goetzmann, Liang, and Schwarz (2009) examine the relation between information disclosed in Form ADV filings and operational risk of hedge funds. Brown et al. define operational risk as any fund managed by an advisor who has disclosed any past legal or regulatory violation (committed either by the hedge fund adviser itself, any non-hedge fund advisory part of the firm, or by any affiliated firm). They show that this measure of operational risk is correlated with various organizational features of the hedge fund adviser. They also show their measure of operational risk is correlated with fund performance and survival, but is not correlated with hedge fund flows. Brown, Goetzmann, Liang, and Schwarz (2012) find similar results using due diligence reports rather than Form ADV disclosures.

This chapter is also related to a recent, but growing literature on misconduct by individual financial advisors employed by investment advisory firms. Charoenwong, Kwan, and Umar (2017) provide evidence that the identity of the regulator influences misconduct committed by individual advisors at regulated firms. Dimmock, Gerken, and Graham (2018a) show there are peer effects in misconduct by financial advisors; individual advisors are significantly more likely to commit misconduct if they are exposed to co-workers who commit misconduct. Egan, Matvos, and Seru (2019) explore how misconduct affects the labor market for financial advisors. They find that misconduct frequently results in financial advisors being fired, but many are subsequently rehired and certain firms seem to specialize in misconduct. Egan, Matvos, and Seru (2017) study gender differences in the punishment for misconduct by financial advisors, finding that women are more likely to be fired and less likely to be rehired following misconduct. Dimmock, Gerken, and Van Alfen (2019) study exogenous shocks to financial advisors' wealth caused by real estate price changes during the financial crisis, and find that advisors are significantly more likely to commit misconduct following a negative wealth shock.

2.3 The Investment Advisers Act of 1940 and Mandatory Disclosures

Our data about investment managers come primarily from mandatory disclosures required by the Investment Advisers Act of 1940 (IAA).[3] The IAA authorizes the SEC to regulate investment advisers, and requires investment advisers to comply with detailed anti-fraud provisions, to register with the SEC, and to disclose certain information.

The IAA requires advisers to register with the SEC if the adviser has 15 or more U.S. clients and more than a certain level of assets under management (AUM). The level of AUM requiring registration was increased from $25 million to $100 million on January 1, 2012. Advisers not required to register with the SEC are generally required to register with state regulators (for further information on registration requirements see Charoenwong et al. (2017)). The IAA defines an investment adviser as an individual or legal entity that is compensated for providing advice regarding investment securities. Historically, some hedge fund advisers avoided the registration requirement by counting each fund as a client, rather than counting the fund's investors. In 2004, the SEC passed Rule IA-2333 requiring hedge funds to count investors instead of funds for the purpose of determining whether registration was necessary. In 2006, a Federal Court overruled Rule IA-2333 and some hedge funds deregistered. The Dodd-Frank Act included a provision requiring hedge fund advisors to count investors and not funds, forcing many hedge fund advisors to register beginning in 2011 (see Cumming et al. (2015a) for further discussion of the effects of Dodd-Frank on hedge funds).

Registration with the SEC requires an investment advisor to comply with strict recordkeeping requirements, prohibits certain types of fees, and imposes some other restrictions on behaviors. Most importantly, for the purposes of this chapter, registered investment advisors are required to disclose certain information by filing Form ADV.[4] Registered investment advisors must file Form ADV at least annually, but must also refile if there are any material changes to the disclosed information. Form ADV reports a large amount of information about the investment advisor's business, conflicts of interest, and past legal and regulatory violations.

2.4 Data

In this chapter, we employ two primary types of data: SEC filings regarding investment fraud by U.S. registered investment advisors and disclosures made by these investment advisors in their Form ADV filing. We combine the two data sources by matching on the firms' Central Registration Depository (CRD) number;[5] if the CRD

[3]For a detailed explanation of the Investment Advisers Act of 1940 and its provisions, see https://www.sec.gov/divisions/investment/iaregulation/memoia.htm.

[4]There are six distinct versions of Form ADV over our sample period. While the vast majority of disclosures are the same throughout, Form ADV has expanded reporting for certain types of information (e.g., AUM by clientele).

[5]The CRD number is a unique identification number that identifies an investment management firm. It is similar to the permco variable in CRSP.

number is not available in the SEC fraud filings, we match using full legal names.

2.4.1 Investment Fraud

We collect investment fraud data by searching two sources on the SEC's enforcement action website: administrative proceedings[6] and litigation releases[7] for the period August 1, 2001 to December 31, 2016. We mechanically search the filings for phrases related to "fraud" and "investment adviser" (or "investment advisor"). From these subset of documents, we then identify by hand all case filings that involve violations of the anti-fraud provisions in the Investment Advisers Act of 1940. We do not include types of fraud or misconduct committed by an investment advisor that do not directly affect investment advisor clients (e.g., defrauding brokerage clients), nor do we include misconduct that potentially benefits the investment advisor's clients (e.g., insider trading).

Many fraud cases occur over multiple years and are often detected years after initiation. In our sample, we read all legal filings for each fraud case and identify the period when fraud occurred. We then assign the fraud case to the year(s) when it was committed, not the year when it was detected. To illustrate, Figure 2.1 shows an example of one fraud case. In 2012, Veros Partners solicited clients to invest in a new fund that would provide short-term operating loans to farmers; Veros made loans to farmers, but the loans were not repaid. In the spring of 2013 and again in the spring of 2014, Veros solicited clients to invest in a new fund that would provide short-term financing for farmers, but instead used the proceeds to repay investors in the earlier funds (and to pay Veros managers undisclosed "success fees"). The SEC filed civil charges against Veros and its management in April 2015. In September of 2016, the SEC signed a consent agreement in which the Veros management team agreed to sanctions and repayment. A criminal trial was scheduled for February 2017. We classify this as a single fraud case occurring in 2013 and 2014, with detection occurring in 2015.

The SEC administrative proceedings and litigation releases include investment fraud committed by both registered and unregistered investment advisors. Although our empirical tests use only the sample of registered advisors, Panel A of Table 2.1 summarizes fraud by both registered and unregistered advisors. There are 639 fraud cases committed by registered advisors and 342 cases by non-registered advisors. Columns (2) and (3) divide the fraud cases into "firm-wide" versus "rogue employee" fraud. Firm-wide frauds are either committed by senior executives or occurs with their knowledge and, at the very least, implicit acceptance. Rogue employee frauds are committed by non-executive employees who evade their firms' internal control systems. The vast majority of fraud is firm-wide fraud, comprising 95.9% and 82.8% of cases at unregistered and registered advisors, respectively.

The final column of Panel A shows the aggregate losses to investors during this period were $45.6 billion, which almost certainly understates losses as we are unable to determine a dollar amount in 22.4% of the cases. Panel B of Table 2.1 summarizes

[6] See https://www.sec.gov/litigation/admin.shtml.

[7] See https://www.sec.gov/litigation/litreleases.shtml.

the distribution of losses for fraud committed by registered advisors. The average loss was $78.8 million, with losses for firm-wide fraud substantially larger than for rogue employee fraud. Panel B also summarizes the duration of fraud cases. The median fraud persists for three years, but this is positively skewed as a small number of cases persist for over a decade.

Figure 2.2 shows the number of *detected* fraud cases by year. For each year, the dark bars show the number of initiated frauds and the light bars show the number of ongoing frauds for the firms in the ADV sample. The figure includes only fraud cases that were ongoing during the 2001-2016 sample period. Thus, the reported cases for 1984-2000 include only those frauds initiated prior to 2001 that continued into the sample period. The number of initiated frauds is stable early in the sample, but rises during the financially crisis and then declines. The number of ongoing frauds shows a similar pattern. The rise during the financial crisis suggests that investment advisors may be more likely to commit fraud when asset markets perform poorly. The decline in both initiated and ongoing fraud cases towards the end of the sample highlights an important feature of fraud data. Although it is possible that investment fraud has become much less frequent in recent years, another important factor is that fraud is detected with a significant lag. Thus, the low rates of fraud in 2014 onward likely reflect, at least in part, that recent frauds have not yet been detected rather than a decrease in the actual commission of fraud.

Table 2.2 summarizes the types of fraud committed by registered investment advisors. *Direct theft* occurs when an advisor directly steals money from clients (but does not include theft through related party transactions nor Ponzi schemes). *Misrepresentation* occurs when an advisor makes material misrepresentations to a client, and does not commit other acts that would fall under another category (all fraud involves an element of misrepresentation). This includes cases in which an advisor lies about assets under management or past returns, or lies about past misconduct (e.g., falsely denies prior sanctions by regulators). *Self-dealing* includes a wide-range of behaviors that involve transactions between clients and parties related to the investment advisor. Examples include: front-running, in which the advisor purchases securities ahead of client orders and then resells them at slightly higher prices; trading between client accounts and a proprietary trading desk at prices unfavorable to the client; brokerage fraud, in which the advisor trades through an affiliated broker at terms that are unfavorable to the client and have not been adequately disclosed; and ex post allocation of trades, in which the advisor purchases securities but delays assigning them to a specific account, and instead waits to assign winners to the proprietary trading desk and losers to clients. *Overstating assets* occurs when an advisor overstates the value of assets under management, and charges advisory fees based on these inflated values. A *Ponzi scheme* occurs when an advisor uses investment inflows to meet investment outflows. *Mutual fund late trading* occurs when an advisor allows some investors to transact shares after a fund's net asset value has been calculated for the day.

The summary statistics in Table 2.2 show that *Direct theft* is the most common type of fraud, followed by *Misrepresentation* and *Self-dealing*, with *Overstate assets*, *Ponzi scheme*, and *Mutual fund late trading* being relatively less common. However, the losses per case are particularly large for Ponzi scheme and Mutual fund late trading. We also report in parentheses summary statistics that exclude the sizable Madoff Ponzi scheme which represents over 65% of total Ponzi scheme losses. The percent of total losses and the average loss per case remain highest for Ponzi schemes regardless of this exclusion.

2.4.2 Form ADV Data and Variables

The SEC website allows the public to view the information disclosed in an investment advisor's most recent Form ADV filing.[8] The SEC also provides access to monthly historical snapshots of Form ADV filings. These publicly available files do not include Schedules A, B, or C, or the DRP filings that detail past misconduct. Also, detailed data on free response fields such as the private fund information in Section 7.B. are also not available. For filings prior to November 2009, the snapshots include only a limited summary of select Form ADV variables (and no data of any type is available for filings prior to June 2006). For this study, we obtained the complete set of historical Form ADV variables through a Freedom of Information Act request. Another complication for researchers using these data is that Form ADV has been altered multiple times changing the mapping of variable names to form questions across different versions of the forms. To facilitate access to the complete Form ADV data for other researchers, we have made these data available at https://doi.org/10.13023/nsjd-rk62.

Following Dimmock and Gerken (2012) and Dimmock, Gerken, and Marietta-Westberg (2015), we use Form ADV data to construct an annual panel of registered investment advisors. Table 2.3 summarizes the Form ADV variables from each firm's first Form ADV filed from 2000 to 2015. Panel A summarizes the continuous variables and Panel B summarizes the binary variables.

Employee ownership is the percentage of the firm that is owned by employees and is calculated following the methodology in Dimmock et al. (2015). This variable accounts for indirect employee ownership through trusts and pass-through entities. The majority of firms in the sample are wholly employee owned. We include this variable because ownership affects both the incentives and the oversight of the firm. Owners receive the benefits of committing fraud, but also bear the full reputational penalty if fraud is detected. More generally, employee ownership eliminates the principal-agent problem between the managers and owners (although the agency conflict between clients and the firm remains). *Firm age* (in years) is included in all regressions as a control for the firm's reputational capital that would be at risk if the firm committed fraud.

Assets under management (AUM) is the total market value of the assets managed by the advisory firm. AUM is highly skewed; in 2015, the largest 1% of advisors managed more than half of the industry's total AUM. *Average account size* is the firm's AUM divided by the number of clients. The definition of client includes both people and investment vehicles (i.e., an investment company with multiple investors is counted as a single client). *Average account size* is also highly skewed. *Percent*

[8]The filings of individual firms are available at https://www.adviserinfo.sec.gov/. Bulk downloads of some of the information in historical filings are available at https://www.sec.gov/help/foiadocsinvafoiahtm.html.

client agents is the percentage of the firm's clients that are agents rather than direct beneficiaries of the invested funds (e.g., pension funds or other investment advisors). All of these variables are related to monitoring and oversight. There is likely greater investor oversight when total AUM and AUM per client are higher. Clients who are themselves agents have weaker incentives, but possibly greater expertise, than principals.

Panel B of Table 2.3 summarizes the binary independent variables, and includes univariate significance tests comparing fraud firms and clean firms (firms that do not commit fraud during the sample period). The first group of variables measure disclosures of past misconduct. *Past fraud* identifies firms that a prior SEC filing identifies as having committed investment management fraud (it does not include other forms of fraud that did not affect the firm's investment advisory clients). *Past fraud* includes only fraud cases that have already been publicly identified and that have ended. *Past affiliated fraud* identifies firms that have an affiliated firm that has previously committed investment management fraud. (Affiliated firms are any firm that controls, is controlled by, or is under common control.) *Past regulatory* identifies firms that disclose past regulatory violations. *Past civil or criminal identifies* firms that disclose past civil or criminal violations. For the regulatory, civil, and criminal violations, we include disclosures related to the firm as well as disclosures related to employees of the firm. As shown by the paired t-test results, firms with past misconduct are more likely to subsequently commit fraud.

The next group of variables are disclosures of potential conflicts of interest. *Referral fees* identifies firms that pay a third party for referring clients to the firm. This practice creates a potential conflict of interest for the third party, and could facilitate the flow of funds to asset managers who commit fraud. *Interest in transaction* identifies firms that trade directly with their clients, or recommend securities in which the firm has an ownership or any other type of sales interest. *Soft dollars* identifies firms that receive research or other products or services from a broker in connection with clients' securities transactions. *Broker in firm* identifies firms that employ registered representatives of a broker-dealer. *Interest in transactions*, *Soft dollars*, and *Broker in firm* can all create conflicts of interest and provide mechanisms for self-dealing through related parties. The univariate t-tests show that firms with *Interest in transactions*, *Broker in firm*, and *Soft dollars* all have higher rates of fraud.

The final group of variables measure oversight and monitoring. *Investment Company Act* identifies firms that manage funds on behalf of an investment company registered under the Investment Company Act of 1940 (e.g., mutual funds); this Act requires certain disclosures and monitoring by independent directors, among other requirements. *Custody* identifies firms that have direct custody of their clients' assets. *Custody* facilitates many types of fraud, although firms with custody of clients' assets are subject to more stringent audit requirements including at least one "surprise" audit each year.[9] *Dedicated CCO* identifies firms whose Chief Compliance Officer (CCO) has no other formal role at the firm. All registered investment ad-

[9]SEC Rule IA-2968 became effective on March 12, 2010 and enhanced the regulatory safeguards to prevent misconduct when the investment advisor and custodian are related parties, including requiring use of an auditor registered with and following the standards of the Professional Company

visors are required to designate a CCO, who is responsible for ensuring compliance with all regulatory requirements. At many firms, however, the CCO also holds other roles within the firm. *Hedge fund clients* identifies firms at which 75% or more of the clients are "pooled investment vehicles (other than investment companies)," as this indicates a relatively sophisticated client base.

2.5 Predicting Fraud and Misconduct

In this section, we test whether it is possible to use the disclosure information summarized above to predict fraud by investment managers. The purpose of these regressions is to show variables that predict fraud; as such, these regressions provide potentially useful information to investors selecting asset managers or to regulators allocating monitoring resources. We do not claim that these regressions show causality. Investment managers jointly choose organizational structures and business practices along with the decision of whether to commit fraud. Thus, our results should not be interpreted to imply it would be desirable to change or prohibit practices that are correlated with misconduct.

As noted in the data section, our dependent variable is *detected* fraud. It is highly likely that there are undetected fraud cases committed by firms in our sample. Thus, any significant relation between an independent variable and fraud measures both that variable's relation with the actual commission of fraud and the variable's relation with the probability of detection conditional upon commission. Investment advisors who intend to commit fraud should select business practices that hinder the detection of fraud, which will bias towards zero the coefficient estimates in empirical tests.

This handbook chapter provides novel insights into how undetected fraud affects predictive tests of fraud by investment managers. This chapter builds heavily upon Dimmock and Gerken (2012), who run predictive tests within the sample period 2001-2006. This current chapter includes a significantly longer time period, and includes fraud cases that occurred during the period 2001-2006 but were not detected until after the publication of Dimmock and Gerken (2012), allowing us to examine how the subsequent detection of these cases alters the inference in the earlier article. Additionally, it also allows for a true out-of-sample (post-publication) test of the models in Dimmock and Gerken (2012).

2.5.1 Predicting Fraud by Investment Managers

Panel A of Table 2.4 shows the results of probit regressions that predict fraud by investment managers. In column (1), the sample is a cross-section of the investment management firms with one observation per firm. The independent variables are taken from each firm's first Form ADV filing, and the dependent variable equals one if the firm ever commits fraud during the sample period. In columns (2)-(5), the sample is a panel of firm-year observations. The independent variables are based on the Form

Accounting Oversight Board (see Bedard, Cannon, and Schnader (2014) for more details).

ADV data as of the firm's most recent filing before the beginning of the calendar year, and the dependent variable equals one if the firm commits fraud during the subsequent year. Columns (2) and (3) include all firm-years with valid data. Column (4) excludes firms with a prior history of fraud. Column (5) excludes firms that have, or are affiliated with another firm that has, any prior legal or regulatory violations. In column (1), the reported standard errors are robust. In columns (2)-(5), the reported standard errors are clustered by firm. The model χ^2 at the bottom of each column shows the significance of the overall model.

Past fraud and *Past affiliated fraud* are both insignificant predictors of future fraud. There are very few (surviving) firms with a history of past fraud, so the power for these coefficients is quite low. This finding is identical to that of Dimmock and Gerken (2012), who estimated a similar relation over a much shorter time-period. Indeed, Panel A of Table 2.4 contains more than twice as many firm-year observations as in the earlier study. Despite the large expansion of the sample size, the results are similar. Given the similarity of the results, for the remaining independent variables we compare with the results of Dimmock and Gerken (2012) only for those results that differ.

Past regulatory and *Past civil or criminal* violations both have a strong positive relation with fraud. Such prior violations are likely indicative of poor internal controls, unethical management, or other underlying problems within a firm. Prior violations, may also increase scrutiny by regulators and investors, increasing the rate of detection conditional upon the occurrence of fraud. Form ADV requires advisors to disclose their own past violations as well as all violations by affiliated firms, thus prior violations are generally higher for firms that are affiliated with more firms. Such affiliations may increase conflicts of interest or create a mechanism for fraudulent self-dealing, resulting in fraud.

Investment advisors that pay *Referral fees* to third parties for client recommendations have significantly higher rates of fraud. *Referral fees* represent a potential conflict of interest and may indicate a general lack of ethics in a firm. Fraudulent firms may also be more willing to pay referral fees because they may find acquiring clients relatively difficult, as they cannot survive standard due diligence procedures. Further, frauds such as Ponzi schemes require a constant inflow of investors, creating a strong incentive to pay for referrals.

The coefficient estimate on *Interest in transaction* is highly significant. Firms that trade directly with their own clients have higher rates of fraud. Trading directly with clients is an obvious conflict of interest and may indicate a lack of ethics. Client transactions also provide a mechanism for committing fraud. For example, front-running clients' trades or pump-and-dump schemes depend on trading directly with the client.

Soft dollars is not significantly related to fraud. The use of soft dollars is a potential conflict of interest, and soft dollar abuse can rise to the level of fraud. However, prior to the beginning of our sample period the SEC aggressively cracked down on soft dollar abuse, following a series of inspections in 1998 that found 28% of investment advisors misused soft dollars.[10] This result is suggestive that the regulatory changes made in response to the 1998 report were successful.

Broker in firm is not significantly related to fraud (except in column (1)). Trading through an affiliated brokerage firm enables certain types of fraud (e.g., ex post allocation of trades or front-running) and removes one possible source or external oversight. However, brokerages must register with the SEC and are subject to additional regulatory requirements (e.g., SEC and FINRA broker-dealer examinations and inspections) and auditing requirements, which may discourage the commission of fraud. Alternatively, it may be more difficult to detect fraud committed through an affiliated brokerage firm, reducing the detection of fraud rather than its occurrence.

There is a positive, albeit weak, relation between fraud and *Investment Company Act*. This result is mainly driven by the mutual fund late trading scandal, and the coefficient estimates are considerably smaller than in Dimmock and Gerken (2012), suggesting this finding may reflect past practices and may not be predictive of future misconduct.

Custody of client assets is negatively related to fraud. Although custody potentially facilitates fraud, it also increases regulatory scrutiny and comes with enhanced audit and regulatory requirements. There are two possible interpretations of this result. First, the increased audit requirements are sufficient to outweigh any effect through which custody facilitates fraud. Second, even with the increased audit requirements, custody allows fraudulent advisors to avoid detection, and thus the weakly negative relation reflects a difference in the detection rate. Dimmock and Gerken (2012) did not find a relation between *Custody* and fraud, and the regulatory requirements were made more stringent since the end of the sample used in that paper, suggesting that it is more likely that the enhanced regulatory requirements reduce the occurrence of fraud.

Dedicated CCO and *Majority employee owned* both measure types of internal governance. *Dedicated CCO*, indicating firms with a Chief Compliance Officer who has no other formal role, is negatively associated with fraud. This can be interpreted as a signal of how seriously a firm takes compliance issues, and is thus related to a reduced propensity to commit fraud. Alternatively, it is possible that *Dedicated CCO* causes a reduction in fraud via internal monitoring and oversight. *Majority employee owned* is not significantly related to fraud.

There is a negative relation between fraud and the logarithm of the average account size. This is consistent with monitoring and due diligence by large investors. Large investors have more resources for screening investment advisors, greater familiarity with best practices, and stronger incentives to monitor advisors. *Percent client agents*, on the other hand, is positively related with fraud. Clients who are agents (e.g., pension funds or charitable trusts), have weaker incentives to screen and monitor investment advisors relative to clients who invest their own funds. *Hedge fund clients* is not significantly related to fraud.

Neither *Log(AUM)* nor *Log(firm age)* are consistently associated with fraud. Dimmock and Gerken (2012) found a positive relation between fraud and *Log(AUM)*, but

[10] For more details see https://www.sec.gov/news/studies/softdolr.htm#sweep.

this relation appears to have been driven primarily by the mutual fund later trading scandal in the early part of the sample and does not persist in the later part of the sample.

2.5.2 Interpreting the Predictive Content of the Models

The χ^2 test results at the bottom of each column in Panel A of Table 2.4 show that the fraud prediction models are highly statistically significant. These results do not provide, however, the economic meaning of the predictability in an easily interpretable form. In this section, we examine the economic interpretation of the probit regression results. Figure 3 shows the receiver operating characteristic (ROC) curve for the probit regression in column (3) of Table 2.4. Predicting fraud involves a tradeoff between correctly identifying fraud cases (sensitivity) versus false positives from incorrectly classifying clean firms as fraudulent (1-specificity). The ROC curve visually displays this tradeoff. The y-axis displays the proportion of fraud cases correctly predicted and the x-axis displays the proportion of false positives. If the model has no predictive power, and thus classifies fraud firms essentially at random, the ROC curve will be a 45-degree line. The ROC curve in Figure 2.3 rises steeply at first, indicating that a sizeable fraction of frauds can be predicted with a low false positive rate. The relatively flat slope in the upper right portion of the graph indicates that a small fraction of frauds are very difficult to detect.

As an alternative means of displaying the tradeoff between predicting fraud versus false positives, Panel B of Table 2.4 summarizes the within-sample predictive performance of the model. Following Dechow, Ge, Larson, and Sloan (2011), we select the cutoff point that produces a false positive rate of 5% and summarize the model's predictive accuracy (i.e., we set the cutoff level by taking the predicted value from the probit regression such that 5% of clean firms have a predicted value equal or higher, and 95% of clean firms have a lower predicted value). We then summarize the number and proportion of fraudulent firms with a predicted value equal to or higher than the cutoff point.

In the full sample results, shown in column (3), the model successfully predicts 27.1% of frauds with a false positive rate of 5%. In column (4), in which the sample is limited to include only firms with no prior fraud cases, the model successfully predicts 26.2% of frauds. The predictive accuracy is substantially lower in column (5), in which the sample is limited to exclude all firms with any prior legal or regulatory violation. In this restricted sample, the model predicts 13.2% of frauds with a false positive rate of 5%. This highlights the importance of past legal and regulatory disclosures in predicting fraud. Indeed, although only 19.8% of firm-year observations have a past violation, these firm-years contain 46.6% of fraud observations. The comparison between the final column and the earlier columns shows the importance of the mandatory disclosures in Form ADV. Although many of the disclosures are for minor issues, any prior misconduct is a strong predictor of future fraud.

The last row in Panel B shows the proportion of total dollar losses from fraud that could have been avoided based on the prediction model (assuming the investor avoided all firms with a predicted probability of committing fraud equal to or higher than the cutoff level that produces a 5% false positive rate). In all columns, the proportion of dollar losses avoided is similar to the proportion of fraud cases predicted. That is, the models seem to predict large and small fraud cases with equal accuracy. This differs from Dimmock and Gerken (2012) who found more accurate predictions for larger frauds.

2.5.3 K-Fold Cross-Validation Tests

A common concern for predictive models is overfitting – that the within-sample prediction rate overstates out-of-sample performance. In this section, we perform model assessment using k-fold cross-validation (see James, Witten, Hastie, and Tibshirani (2014, Chapter 5) for an excellent introduction to both model assessment and k-fold cross-validation). For these tests, we randomly assign each firm to one of 10 groups. Importantly, we randomize at the firm (and not firm-year) level to avoid across-time dependence within firm observations. We then designate one of the groups as the hold-out sample, estimate the model using observations from the other nine groups, and use these coefficient estimates to predict fraud in the hold-out sample. We repeat this procedure for each of the 10 groups. We then repeat this procedure 20 times, resulting in 200 separate out-of-sample comparison groups, and report the average number of fraud cases successfully predicted.

The k-fold cross-validation results in Panel C of Table 2.4 show that the out-of-sample performance of the models is very similar to the in-sample performance. For the baseline model, shown in column (3), on average we predict only 0.2 fewer frauds out-of-sample. The standard deviation of the number of frauds predicted, along with the minimum and maximum numbers, show the results are very stable across iterations of the cross-validation tests. Finally, the results at the bottom of the panel show that the false positive rate is not substantially larger out-of-sample than in-sample. Overall, these results support that the validity of the predictive models.

2.6 Predicting the Initiation vs. the Continuance of Fraud

In the baseline mode, the dependent variable includes frauds that are newly initiated in the next year as well as frauds that were previously initiated and continue into the next year. Predicting fraud prior to initiation is potentially more valuable than predicting continued frauds. Additionally, ongoing fraud can alter the predictive ADV variables, obscuring the distinction between predicting new acts of fraud and detection of ongoing cases. Both are potentially interesting, but differentiating them could reveal offsetting effects (e.g., if some variable is positively related to initiation of fraud, but causes the fraud to be detected earlier shorting its continuation). In this section, we separate newly initiated and continued fraud cases and estimate a sequential logit model of initiation and continuance of fraud (see Buis (2011) for further discussion of the sequential logit model).

Panel A of Table 2.5 presents the regression results. Column (1) predicts the initiation of fraud in the subsequent year, while column (2) predicts whether a firm that had already initiated a fraud will continue this fraud case in the subsequent year. Standard errors are clustered by firm. In general, the coefficient estimates in column (1) are larger than those presented in Table 4. In contrast, the coefficient estimates in column (2) are smaller than those presented in Table 4. The overall pattern of results suggests that the Form ADV variables are better at predicting the initiation of fraud than at predicting which initiated fraud cases will continue. There is, however, a change in both sign and significance for *Past fraud* and *Past affiliated fraud* in column (2) relative to the full model in Table 2.4. The negative coefficient on *Past Fraud* is consistent with past offenders having new instances of fraud detected sooner and thus being unable to continue the scheme, consistent with the firm's past actions attracting greater regulatory scrutiny. The positive and significant loading on *Past affiliated fraud* indicates that past instances of fraud at affiliated firms predict the continuance of fraud at a firm.

Panel B of Table 2.5 shows that at a false positive rate of 5% the model correctly predicts 29.8% of fraud cases initiated in the next year.[11] This is slightly higher than the baseline model prediction rate (27.1%), suggesting the Form ADV data can be used to predict the initiation of fraud and not just the continuation of previously initiated cases.

2.7 Firm-Wide Fraud vs. Fraud by a Rogue Employee

Investment management fraud can be "firm-wide" as in the Madoff Ponzi scheme, where the firm's owners and senior managers were actively involved in perpetrating the fraud. In such cases, the same individuals who choose to commit fraud also choose the firm's organizational structure and business practices. Thus, firm-wide fraud may be correlated with practices that are deliberately chosen to enable fraud. Investment management fraud can also be committed by a rogue employee, who must evade the firm's oversight procedures and who cannot alter the firm's policies to enable the fraud. Thus, rogue employee fraud may be correlated with weak internal controls. In this section, we examine the distinction between these two types of frauds.

Panel A of Table 2.6 presents the results of a multinomial probit regression predicting fraud. The dependent variable in column (1) is equal to one if the firm commits a firm-wide fraud in the subsequent year. The dependent variable in column (2) is equal to one if a rogue employee commits fraud in the subsequent year. The coefficient estimates in both columns are generally similar with a few exceptions. *Past civil or criminal* is significant only for rogue employee fraud, suggesting that firms with prior civil violations or who hire criminals likely have relatively weak internal control systems. Rogue employee fraud is significantly less common at *Majority employee owned* firms, which suggests managerial ownership improves monitoring incentives. *Percent client agent* has a significant positive relation with firm-wide fraud; this is likely an endogenous relation with fraudulent firms targeting a client base with reduced incentives for monitoring. Firm-wide fraud is significantly lower at older firms,

[11] We do not report the proportion of continued fraud cases predicted, because for continued frauds it is only possible to make predictions conditional upon knowing with certainty which firms were committing fraud in the prior year, which is not a reasonable assumption.

consistent with the argument that reputational capital provides a disincentive for fraud.

Panel B of Table 2.6 shows the proportion of fraud cases that can be predicted at a false positive rate of 5%. Firm-wide fraud is considerably more difficult to predict; the model successfully predicts 20.5% of firm-wide frauds versus 61.8% of rogue employee frauds. With firm-wide fraud, the senior management can choose policies and procedures that decrease the probability that fraud is detected, and the fraud is unlikely to be detected by internal monitoring procedures. Thus, firm-wide fraud is more difficult to detect.

2.8 Out-of-Sample Prediction and Model Stability

The true test of a predictive model (and the value of its inputs – in this case the SEC's mandated disclosures via Form ADV) is its out-of-sample performance. In this chapter we revisit the tests of Dimmock and Gerken (2012), which allows us an opportunity to evaluate the out-of-sample performance of the models in that paper by applying the predictions to post-publication data. We graphically display this out-of-sample performance in Figure 2.4. This figure uses the model estimates from column (3) of Table 3 of Dimmock and Gerken (2012), which was estimated on fraud data for the period 2001-2006. For each year from 2001-2015, we show both the sensitivity (proportion of fraud cases correctly predicted) and 1 specificity (proportion of clean firms incorrectly labelled as fraud firms) for the model. The cutoff for classifying a firm as a fraud firm is set so that 1 specificity within sample is equal to 5%. The prediction sample for Figure 2.4 includes two types of out-of-sample fraud cases. First, we use frauds that were initiated in the 2001-2006 period, but which were not detected until after the data were collected for the 2012 article. Second, we use frauds that were initiated and detected after 2006. Before proceeding to discuss the results in Figure 2.4, it is worth revisiting the findings in Figure 2.2, which show the fraud cases in our sample by year. As Figure 2.2 shows, there are relatively few fraud cases in the later years of our sample, with particularly few cases in 2014 and 2015. This likely reflects the fact that fraud is detected with a lag, and thus the later years of the sample likely contain many fraud cases that have not yet been detected.

Figure 2.4 shows that the proportion of fraud cases correctly identified was highest in the early years of the estimation sample. This period had a large number of mutual fund late trading cases, which the model does an excellent job of predicting. Moving to the out-of-sample period, the model predicts approximately 20% of fraud cases during the period 2007-2011, and does so with a false prediction rate that is lower than 5% (fewer false predictions out-of-sample than in-sample). The model's out-of-sample performance becomes more volatile in the period 2012-2015 as the sample of fraud cases becomes smaller. Unfortunately, the time-series evidence is unable to disentangle alternative explanations for the relative drop in model performance. Model performance could decline post-publication because regulators (and investment managers) could shift behavior (i.e., a form of the Lucas critique). Specifically, the SEC significantly increased access to Form ADV data in line with the suggestions of Dimmock and Gerken (2012), which could have increased the deterrence effects of these disclosures. Another confounding factor is that there were other significant regulatory changes due to the implementation of the Dodd–Frank Wall Street Reform and Consumer Protection Act during this period. The decrease in model power in the later years, due to fewer fraud observations, also means we cannot dismiss the possibility that the decrease is due simply to chance. Overall, the model continues to perform well out-of-sample, although apparently not as well as in-sample, suggesting that the mandated disclosures still contain useful information to predict fraudulent activity.

2.9 Policy Implications and Conclusions

Consistent with Dimmock and Gerken (2012), we find that mandatory disclosures related to past regulatory and legal violations, conflicts of interest, and monitoring are significant predictors of fraud by investment managers. Further, these variables can predict both the initiation and continuation of fraud, as well as firm-wide and rogue-employee fraud. The predictions perform well both in- and out-of-sample. The results clearly show that the mandatory disclosures made by investment managers contain useful and relevant information for the investing public. Until 2011, the SEC did not provide public access to historical Form ADV data through its website. Shortly after the initial public circulation of the working paper version of Dimmock and Gerken (2012), the SEC began to provide access to monthly snapshots of historical Form ADV data.[12] However, those publicly available files on the SEC website do not contain all of the information provided in Form ADV filings, and these data are severely limited prior to 2010 reducing their usefulness to researchers.[13]

We believe that improving public access to comprehensive historical disclosures could increase the benefits these disclosures were meant to provide. Our models incorporate only a fraction of the data available through the Form ADV and its schedules. Future work could incorporate a richer set of variables based on recent research (e.g. Clifford et al. (2018) and Cumming, Leung, and Rui (2015b) shows board characteristics – which are available via Form ADV Schedule A – are related to hedge fund fraud). Accordingly, in conjunction with writing this handbook chapter, we have created a publicly available data set that contains the complete set of SEC Form ADV filings we obtained including the data used in our tests. These data are available at https://doi.org/10.13023/nsjd-rk62. It is our hope that easier data access will spur additional research on the topic of fraud by investment managers and provide investors with important information regarding their choice of investment manager.

[12] See https://www.sec.gov/help/foiadocsinvafoiahtm.html for data downloads, or visit https://www.adviserinfo.sec.gov/IAPD/InvestmentAdviserData.aspx to search for firms.

[13] Due to data requirements, the study is limited to U.S. based investment advisors. Nevertheless, the fraud predictors identified in this paper should provide useful information to investors and regulators in a global setting. However, further research in an international context would be valuable.

Table 2.1: Summary of Investment Fraud

This table summarizes cases of investment fraud committed by investment advisors between 1984 and 2016 as reported on SEC administrative proceedings and litigation releases filed from 2001 to 2016. Registered denotes firms that file a Form ADV with the SEC. Firm-wide fraud is committed by high level executives, or at the very least, with the firms' implicit acceptance. Rogue employee fraud is committed by individuals who evade their firms' internal control systems and the firms do not knowingly benefit.

Panel A: Registered versus non-registered advisors

	Total	Firm-wide	Rogue employee	Investor losses ($ billions)
Non-registered	342	328	14	6.5
Registered	639	529	110	39.1
Total	981	857	124	45.6

Panel B: Fraud characteristics

		Investor losses ($ million)				Duration (years)		
	Obs.	Mean	Median	Max	Missing	Mean	Median	Max
Firm-wide	529	93.5	3.2	18,000.0	122	4.2	3	20.8
Rogue employee	110	11.7	1.3	300.0	21	4	3	15
Total	639	78.8	2.7	18,000.0	143	4.1	3	20.8

Table 2.2: Summary of Fraud Types

This table summarizes the types of investment fraud committed by registered investment advisors between 1984-2016 as reported on SEC administrative proceedings and litigation releases filed from 2001 to 2016. Direct theft occurs when an investment advisor directly steals money from a client. Misrepresentation occurs when an advisor makes material misrepresentations to clients. Self-dealing occurs when an advisor siphons off clients' money through related party transactions. Overstating assets occurs when an advisor overstates the amount of assets under management to increase fees. A Ponzi scheme occurs when an advisor steals clients' money, and uses new investments to repay old investments. Mutual fund late trading occurs when an advisor allows some investors to transact shares after a fund's net asset value has been calculated. The numbers in parentheses exclude Bernie Madoff's 2008 Ponzi scheme.

	Number of cases	Percent of total cases	Investor losses ($ billions)	Percent of total losses	Average loss per case ($ millions)
Direct theft	212	33.20%	5.21	13.3% (24.7%)	24.56
Misrepresentation	161	25.20%	2.8	7.2% (13.3%)	17.39
Self-dealing	145	22.70%	0.87	2.2% (4.1%)	5.98
Overstate assets	49	7.70%	0.98	2.5% (4.7%)	20.04
Ponzi scheme	37	5.80%	27.5	70.30%	743.24
	(36)	(5.6%)	(9.50)	(45.0%)	(263.89)
MF late trading	35	5.50%	1.74	4.5% (8.3%)	49.8

Table 2.3: Summary of Investment Advisory Firms

This table summarizes information from each firm's first Form ADV filing from 2000 to 2015. There are 24,536 unique firms in the sample. Employee ownership is the aggregate employee ownership of the firm. Percent client agents is the percentage of clients that are agents for the owners of the assets. Past fraud equals one if the firm is identified as committing fraud in a previous SEC filing. Past affiliated fraud equals one if the firm's affiliates have been identified as committing fraud in a previous SEC filing. Past regulatory equals one if the firm reports past regulatory violations. Past civil or criminal equals one if the firm reports past civil or criminal violations. Referral fees equals one if the firm compensates any party for client referrals. Interest in transaction equals one if the firm recommends securities in which it has an ownership interest, serves as an underwriter, or has any other sales interest. Soft dollars equals one if the firm receives benefits other than execution from a broker-dealer in connection with clients' trades. Broker in firm equals one if the firm employs registered representatives of a broker-dealer. Investment Company Act equals one if the firm is registered under the Investment Company Act of 1940. Custody equals one if the firm has custody of clients' cash or securities. Dedicated CCO equals one if the chief compliance officer has no other job title. Hedge fund clients equals one if more than 75% of the firm's clients are hedge funds. The column Clean (Fraud) summarizes firms in which a fraud is not committed (is committed) from first filing through December 2015. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels based on Fisher's exact test.

Panel A: Firm characteristics					
	Mean	SD	25th	50th	75th
Employee ownership	62.10%	38.6	15	87.5	92.5
Avg. acct. size ($ thousand)	65,285	610,636	158	895	24,115
Percent client agents	25.70%	34.8	0	10	35
Assets under mgmt. ($ million)	1,307	11,304	3	50	228
Firm age (years)	3.3	5.8	1	1	1

Panel B: Firm disclosures			
	All	Clean	Fraud
Past fraud	0.1	0.1	1.3***
Past affiliated fraud	1.10%	1.1	2.6**
Past regulatory	9.80%	9.4	29.6***
Past civil or criminal	2.80%	2.6	11.3***
Referral fees	33.60%	33.2	50.0***
Interest in transaction	28.80%	28.5	46.5***
Soft dollars	51.10%	50.9	56.3**
Broker in firm	50.40%	50.2	60.1***
Investment Company Act	8.90%	8.7	17.2***
Custody	18.20%	18.2	17.9
Dedicated CCO	15.50%	15.6	11.7**
Hedge fund clients	10.70%	10.7	8.3*

Table 2.4: Predicting Fraud

The full sample consists of 128,468 firm-year observations. In the first column, the sample includes only each firm's first Form ADV filed during the sample period. In the remaining columns, the independent variables are taken from each firm's Form ADV filing for each year from 2000 to 2015. In the second and third columns, the full sample is included. In the fourth column, the sample excludes firms with a previously disclosed fraud. In the fifth column, the sample excludes all firms that disclose in Item 11 of Form ADV any type of prior legal or regulatory violation, either by the firm itself or an affiliated firm. Refer to Table 2.2 for variable definitions. Column (1) of Panel A shows the results of a cross-sectional probit regression predicting fraud. The dependent variable equals one if the firm commits fraud in any subsequent year through 2015. Standard errors are robust. Columns (2)–(5) show the results of pooled probit regressions predicting fraud. The dependent variable equals one if the firm commits fraud in the subsequent year. Standard errors are clustered by firm and year. In the interest of brevity, the constants are not reported. Standard errors are reported in square brackets. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The columns in Panels B and C correspond to the columns in Panel A. Panel B shows the proportion of fraud that could be predicted within-sample. Panel C shows the results from k-fold cross-validation tests.

Panel A: Predictors of fraud					
	Cross Section	Full sample	Full sample	No prior fraud	No prior violat.
Past fraud	0.213		0.136		
	[0.28]		[0.14]		
Past affiliated fraud	-0.209		-0.1	-0.099	
	[0.14]		[0.11]	[0.12]	
Past regulatory	0.318***	0.321***	0.323***	0.329***	
	[0.06]	[0.05]	[0.05]	[0.05]	
Past civil or criminal	0.310***	0.195***	0.205***	0.200***	
	[0.09]	[0.06]	[0.06]	[0.07]	
Referral fees	0.037	0.128***	0.130***	0.124**	0.134**
	[0.05]	[0.05]	[0.05]	[0.05]	[0.06]
Interest in transaction	0.239***	0.316***	0.317***	0.319***	0.361***
	[0.06]	[0.05]	[0.05]	[0.05]	[0.07]
Soft dollars	-0.067	-0.025	-0.023	-0.02	-0.013
	[0.05]	[0.04]	[0.04]	[0.04]	[0.05]
Broker in firm	0.203***	0.083	0.085	0.084	0.033
	[0.05]	[0.07]	[0.07]	[0.07]	[0.08]
ICA of 1940	0.117	0.122	0.126	0.139*	0.156*
	[0.07]	[0.08]	[0.08]	[0.08]	[0.09]
Custody	-0.103	-0.071	-0.07	-0.084*	-0.114
	[0.07]	[0.04]	[0.04]	[0.05]	[0.07]
Dedicated CCO	-0.048	-0.154***	-0.154***	-0.140**	-0.026
	[0.08]	[0.06]	[0.06]	[0.06]	[0.06]
Majority emp. owned	-0.053	-0.069	-0.075	-0.068	-0.077
	[0.05]	[0.07]	[0.07]	[0.07]	[0.07]
Log(avg. acct. size)	-0.061***	-0.080***	-0.080***	-0.075***	-0.037**
	[0.02]	[0.01]	[0.01]	[0.01]	[0.02]
Percent client agents	0.001	0.002***	0.002***	0.002***	0.002**
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Hedge fund clients	0.091	0.162*	0.163*	0.149*	0.153*
	[0.10]	[0.08]	[0.08]	[0.08]	[0.09]
Log(AUM)	0.082***	0.062***	0.062***	0.059***	0.009
	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]
Log(firm age)	0.015	-0.062**	-0.062**	-0.062**	-0.071***
	[0.03]	[0.03]	[0.03]	[0.03]	[0.03]
Model chi-square	315.4***	279.1***	265.8***	258.6***	86.38***
Observations	15,848	128,468	128,468	127,646	102,704

Panel B: Within-sample predictions

	Cross Section	Full sample	Full sample	No prior fraud	No prior violat.
# Fraud	389	1,260	1,260	1,224	673
Fraud predicted	111	339	341	321	89
	28.50%	26.90%	27.10%	26.20%	13.20%
# Clean firms	15,459	127,208	127,208	126,422	102,031
Clean firm false pos.	772	6,360	6,360	6,321	5,101
	5.00%	5.00%	5.00%	5.00%	5.00%
Prop. $ losses avoided	28.80%	28.50%	28.60%	24.10%	13.50%

Panel C: K-fold cross-validation hold-out sample predictions

	Cross Section	Full sample	Full sample	No prior fraud	No prior violat.
Avg # fraud predicted	104.2	336.25	340.8	317.8	87.7
Avg % fraud predicted	26.80%	26.70%	27.00%	26.00%	13.00%
Stdv # fraud predicted	3.8	2.1	2.1	3.1	3.9
Min # fraud predicted	98	332	336	311	78
Max # fraud predicted	110	339	344	322	93
Avg # false positives	766.9	6,352.00	6,367.70	6,316.80	5,106.70
Avg % false positives	5.00%	5.00%	5.00%	5.00%	5.00%
Stdv false positives	33.2	54.6	69.1	80.8	114.3
Min # false positives	723	6,258	6,266	6,164	4,900
Max # false positives	852	6,482	6,482	6,471	5,288

Table 2.5: Initiation versus Continuance of Fraud

The sample consists of 129,465 firm-year observations. The independent variables are taken from each firm's Form ADV filings from 2000 through 2015. Panel A shows the results of a sequential logit regression predicting fraud. The first column shows estimates of the probability that a firm initiates a fraud in the subsequent year. The second column shows estimates of the probability that a firm with a preexisting fraud continues that fraud into the subsequent year. Refer to Table 2.3 for variable definitions. In the interest of brevity, the constants are not reported. All significance tests are based on standard errors clustered by firm. Standard errors are reported in square brackets. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Panel B shows the proportion of initiated fraud cases that could be predicted within-sample.

Panel A: Predicting initiation versus continuance of fraud		
	Initiate	Continue
Past fraud	0.246	-0.801*
	[0.30]	[0.47]
Past affiliated fraud	-0.292	0.831***
	[0.20]	[0.29]
Past regulatory	0.803***	0.046
	[0.13]	[0.18]
Past civil or criminal	0.474***	-0.328
	[0.15]	[0.21]
Referral fees	0.374***	-0.266*
	[0.12]	[0.15]
Interest in transaction	0.821***	0.047
	[0.14]	[0.16]
Soft dollars	-0.039	0.078
	[0.12]	[0.14]
Broker in firm	0.258**	0.067
	[0.12]	[0.17]
Investment Company Act	0.22	-0.183
	[0.16]	[0.25]
Custody	-0.187	0.003
	[0.12]	[0.18]
Dedicated CCO	-0.431***	0.378**
	[0.13]	[0.19]
Majority emp. owned	-0.207*	0.129
	[0.12]	[0.17]
Log(avg. acct. size)	-0.208***	-0.034
	[0.03]	[0.04]
Percent client agents	0.005***	0.007**
	[0.00]	[0.00]
Hedge fund clients	0.386*	0.389
	[0.23]	[0.34]
Log(AUM)	0.175***	-0.001
	[0.03]	[0.04]
Log(firm age)	-0.140***	0.018
	[0.05]	[0.06]
Model chi-square	352.16***	291.11***

Panel B: Within-sample predictions	Initiate
# Fraud	228
Fraud predicted	68
	29.80%
# Clean firms	129,237
Clean firm false positives	6,411
	5.00%

Table 2.6: Firm-wide versus rogue employee fraud

The sample consists of 129,465 firm-year observations. The independent variables are taken from each firm's Form ADV filings from 2000 through 2015. Panel A shows the results of a multinomial probit regression predicting fraud. In the first column, the dependent variable equals one for firms that experience a firm-wide fraud in the subsequent year. In the second column, the dependent variable equals one for firms that experience a rogue employee fraud in the subsequent year. The excluded category is clean firms. Refer to Table 2.3 for variable definitions. In the interest of brevity, the constants are not reported. All significance tests are based on standard errors clustered by firm. Standard errors are reported in square brackets. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The columns in Panel B correspond to the columns in Panel A. Panel B shows the proportion of fraud that could be predicted within-sample.

Panel A: Predicting firm wide versus rogue employee fraud		
	Firm	Rogue
Past fraud	0.067	0.363
	[0.19]	[0.28]
Past affiliated fraud	-0.003	-0.063
	[0.10]	[0.22]
Past regulatory	0.425***	0.520***
	[0.08]	[0.15]
Past civil or criminal	0.15	0.433***
	[0.09]	[0.14]
Referral fees	0.139**	0.215
	[0.06]	[0.14]
Interest in transaction	0.453***	0.287*
	[0.07]	[0.17]
Soft dollars	0.005	-0.08
	[0.06]	[0.14]
Broker in firm	0.120*	0.252
	[0.06]	[0.16]
Investment Company Act	0.224**	0.158
	[0.09]	[0.18]
Custody	-0.072	-0.206
	[0.07]	[0.13]
Dedicated CCO	-0.113*	-0.154
	[0.07]	[0.16]
Majority emp. owned	-0.023	-0.294*
	[0.07]	[0.16]
Log(avg. acct. size)	-0.080***	-0.192***
	[0.02]	[0.03]
Percent client agents	0.003***	-0.001
	[0.00]	[0.00]
Hedge fund clients	0.181	-0.135
	[0.12]	[0.28]
Log(AUM)	0.049***	0.205***
	[0.02]	[0.04]
Log(firm age)	-0.099***	0.068
	[0.03]	[0.06]
Model chi-square	212.85***	198.81***

Panel B: Within-sample predictions	Firm	Rogue
# Fraud	1,133	249
Fraud predicted	232	154
	20.50%	61.80%
# Clean firms	128,332	129,216
Clean firm false positives	6,404	6,404
	5.00%	5.00%

Figure 2.1: Timeline for Fraud Committed by Veros Partners

This figure shows a simplified timeline of a Ponzi fraud committed by Veros Partners. Veros began operations in 2006. In March 2012, Veros initiated a Ponzi scheme in which clients were promised a high guaranteed rate of return for a 12-month investment. When repayment came due, Veros used the proceeds from new investments to repay outstanding amounts or convinced the client to "roll over" their investment.

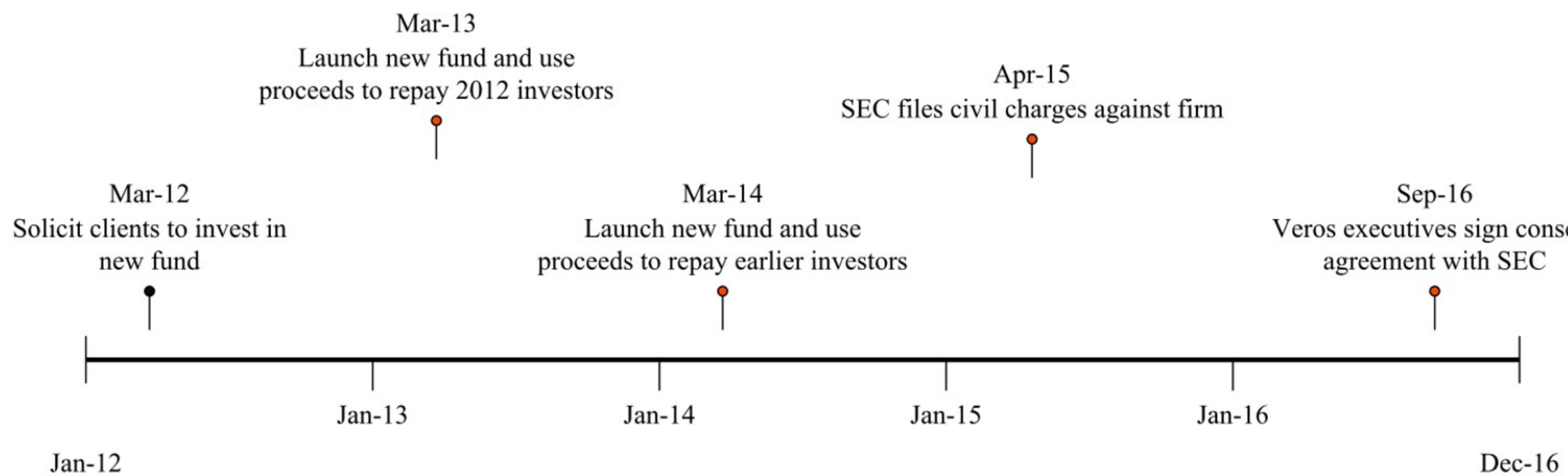


Figure 2.2: Fraud Cases over Time

This figure shows fraud initiations (darker bars) and ongoing fraud cases (lighter bars) by calendar year for all detected cases disclosed in the SEC litigation releases or administrative proceedings for firms in the sample. The beginning and ending dates for each fraud case is disclosed in the SEC releases. The figure includes only fraud cases that were ongoing during the 2001-2016 sample period and were committed by firms filing Form ADV during the sample period. Thus, the reported cases for 1984-2000 include only those fraud cases initiated prior to 2001, but which continued into the sample period. Fraud cases initiated prior to 2001, but which were detected or discontinued prior to 2001 are not included.

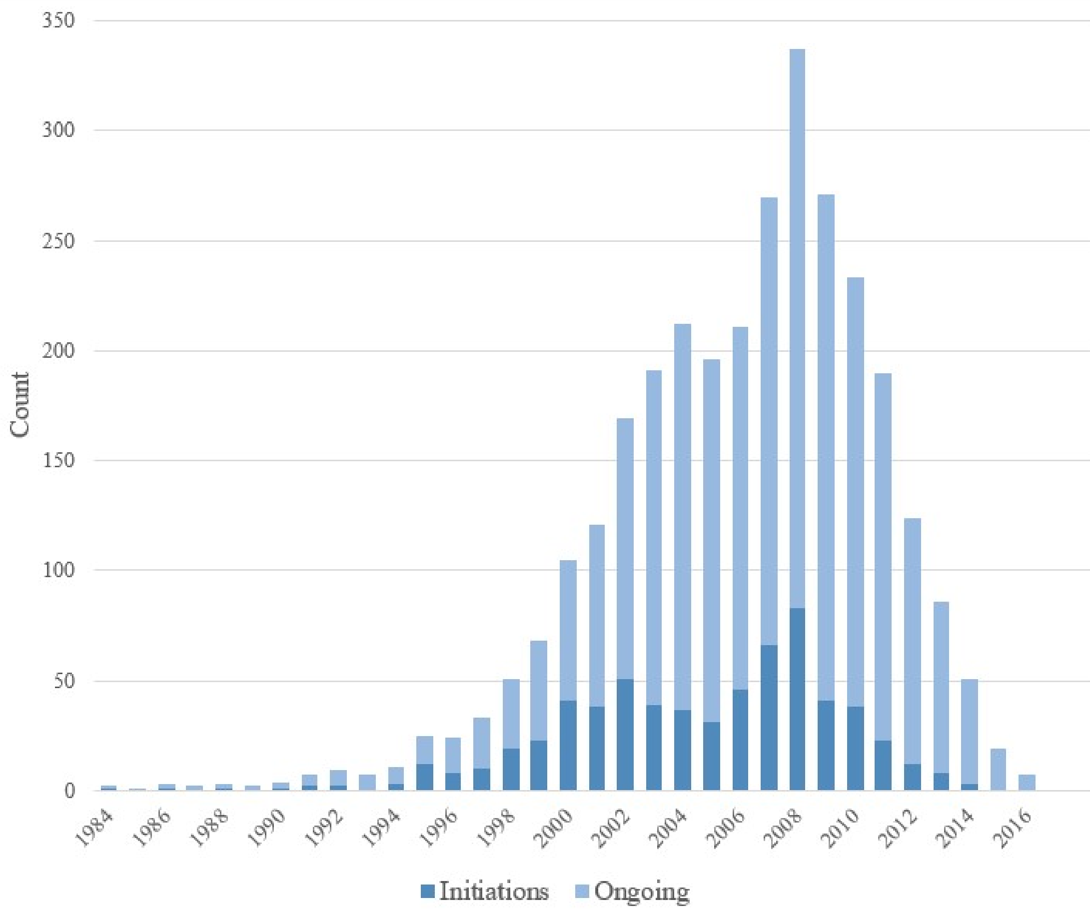


Figure 2.3: Model Diagnostic Performance

TThis figure shows the receiver operating characteristic (ROC) curve for the probit mode specification from column (3) of Table 2.4. The sample consists of 128,468 firm-year observations. The ROC curve plots the relation between the proportion of fraud detected and the proportion of false positives for all possible classification cut-points. The ROC curve is generated by taking each observation's estimated fraud probability and computing the sensitivity and specificity using that observation as a cut-point.

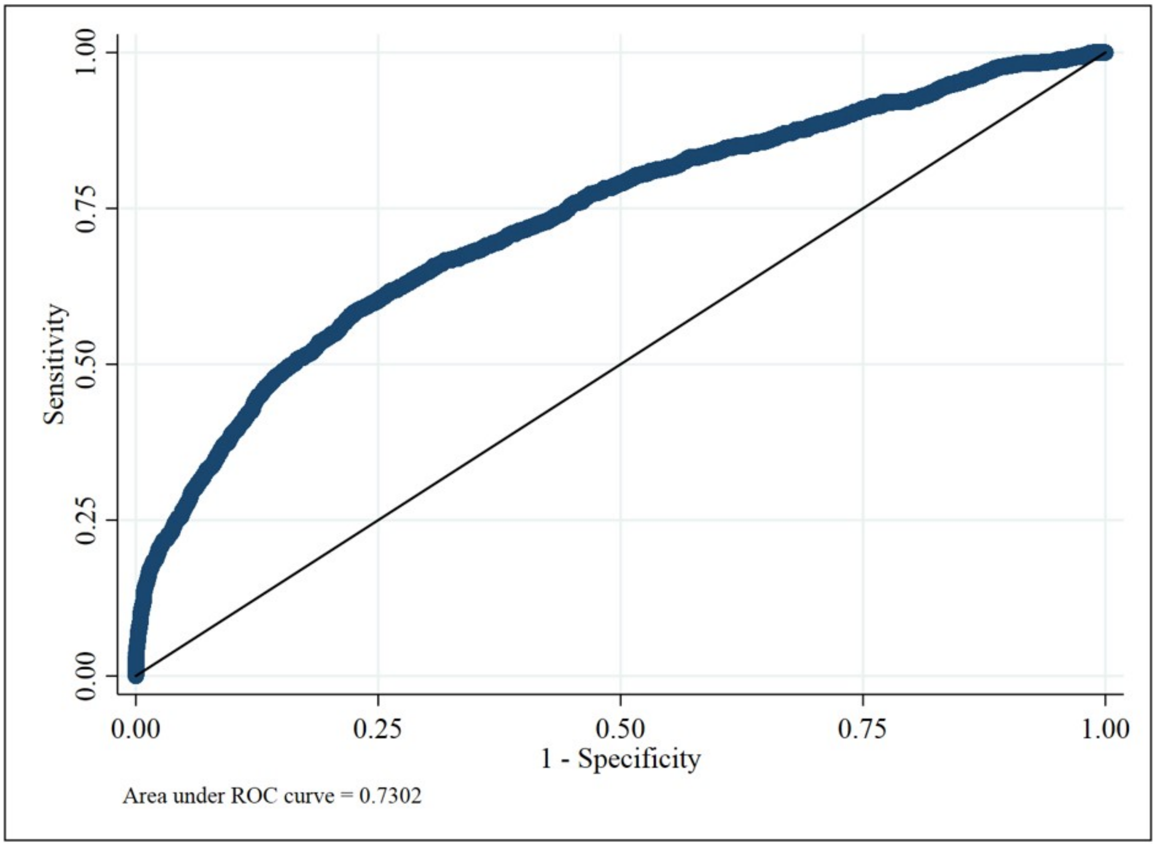
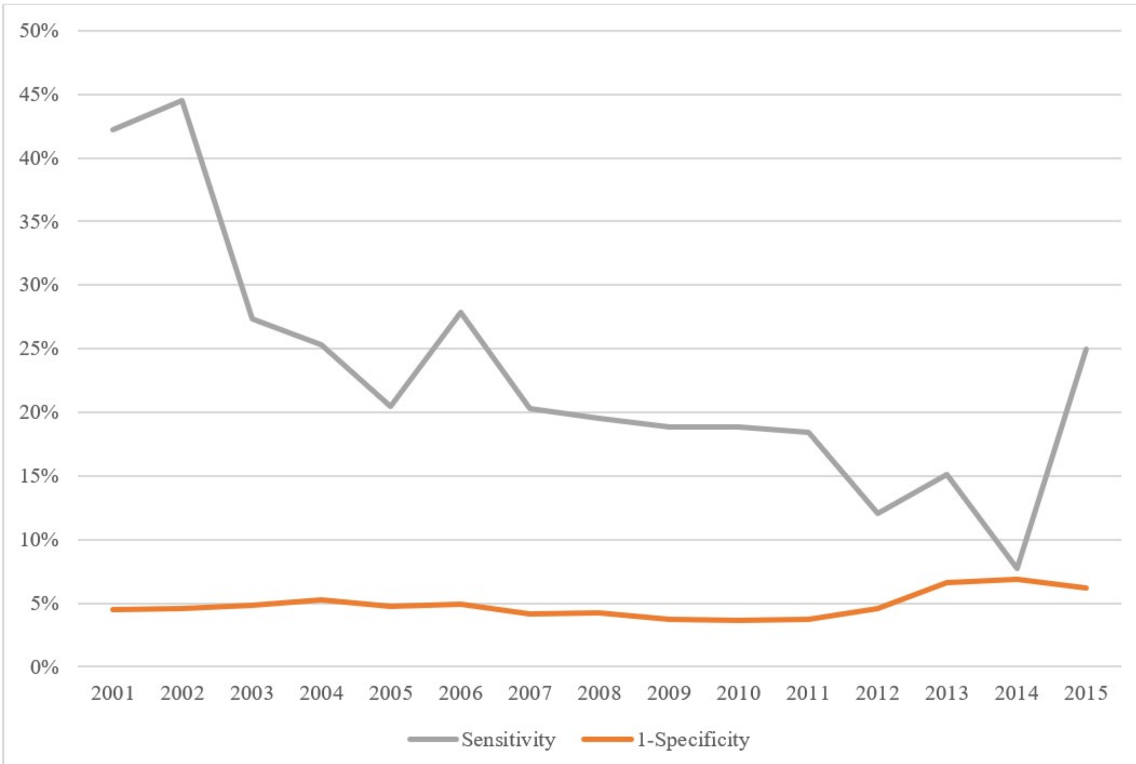


Figure 2.4: Model Performance over Time

This figure shows model prediction statistics (sensitivity and specificity) by calendar year. The model uses the coefficient estimates from column (3) of Table 3 of Dimmock and Gerken (2012), who estimated a prediction model using data from 2001-2006. The inputs of the model are obtained from Form ADV filings from 2001-2015.



Chapter 3 Mutual Fund Voting Divergence and Performance

3.1 Introduction

Over the past several decades, ownership of US equities has shifted from direct holdings by individual investors to indirect holdings through investment management companies. As much as 90% of the stock market was held directly at the end of the World War II; by the year 2000, direct ownership had fallen by more than half as individuals increasingly held their financial assets in mutual funds and pension funds.[1] Today, these investment companies hold about 31% of the equity market.[2]

With such large holdings by investment companies, the landscape of corporate governance has changed. Voting rights attached to common shares are now concentrated within a few hundred fund complexes rather than spread across millions of proxy-voting individuals. This has implications for the outcome of proposals up for a vote at company meetings. Morgan et al. (2011) demonstrate that the proposals mutual funds support more than other investors[3] are more likely to pass. Additionally, implementation of non-binding shareholder proposals are higher when mutual funds provide greater support. Thus, how mutual funds govern their portfolio companies is of particular relevance to the investor.

Mutual funds are bound by their fiduciary duty to cast their votes in a manner consistent with a shareholder's best interest. Perhaps surprisingly, mutual funds within the same family can and do cast votes differently on the same proposal. As in Morgan et al. (2011), I call such within-family voting differences "divergence." Table 3.1 presents the divergence ratio for several well-known fund families in my sample. Consider first the largest 5 mutual fund families as of December 2016: BlackRock, Vanguard, State Street, Fidelity, and JPMorgan. Their divergence ratio on all proposals is 3.7%, 0.1%, 5.1%, 9.7%, and 3.6%, respectively, considerable variation among just the top 5 funds. Put another way, funds within the BlackRock family vote differently on the same proposal and average of 3.7% of the time. Funds within the Vanguard family rarely vote differently on the same proposal: their divergence ratio is 0.1%. The divergence ratio on contentious management sponsored director elections, the variation in the divergence ratio is even greater for these otherwise similar families.

Given that the funds within a family will have access to the same information in evaluating proposals, it may come as a surprise that funds would ever vote differently. Further, as Malenko and Shen (2016) demonstrate, many institutional investors rely on the recommendation of outside proxy advisors who make the same recommendation on how a vote should be cast to all funds within a family. Previous papers, however, have documented varying levels of cooperation among mutual funds within

[1] "Households Own More of the Stock Market These Days" *The Wall Street Journal*. October 3, 2016.

[2] "2017 Investment Company Fact Book." *The Investment Company Institute*. 57$^{\text{th}}$ edition.

[3] International, individual, and hedge funds to name a few.

a family. Differences in voting patterns among funds within the same complex is therefore not altogether extraordinary. Evans et al. (2017) show that some families encourage competition among their individual fund managers while others encourage cooperation. They find that funds at families that offer incentives to encourage competition have higher average performance. Kempf and Ruenzi (2007) show that funds within a family adjust their risk based on their performance and size rank within the family. The authors conclude that funds of a family should be seen as competitors, rather than as coordinated entities.

Several studies have considered the consequences of opposing management on fund returns, flows, and business ties. Iliev and Lowry (2014) find a significantly positive relationship between active voting and fund alphas: funds that more frequently oppose proxy advisors perform better. Dimmock, Gerken, Ivković, and Weisbenner (2018c) show that funds more frequently opposing management have greater future net flows, providing evidence that such active voting behavior is valued by investors. Davis and Kim (2007) demonstrate that there is a positive relationship between business ties (through 401(k) and pension account servicing) and the propensity to vote with management.

While the consequences of mutual fund voting patterns have been widely studied in the literature, no paper to my knowledge has considered the relationship between the divergence ratio and fund performance. The main finding of this paper is that mutual funds in families with a higher divergence ratio outperform those with a lower level of divergence. That is, fund families that allow for managers at individual funds to vote their own shares achieve a statistically significant net alpha between 60 and 104 basis points higher than funds in families with a lower level of divergence.

The conclusion of Iliev and Lowry (2014) holds here: "the types of funds that invest more resources in voting also differ along other dimensions, perhaps more diligent picking of stocks, which contribute to higher returns." Clearly, the divergence ratio alone cannot explain higher returns of the stocks held by the fund. At the very least the higher risk-adjusted returns of funds in the top divergence quintile is an interesting relationship and a previously unobserved phenomenon.

The remainder of this paper proceeds as follows. In the next section, I discuss the data sources and the sample. Section 3.3 describes in greater detail the calculation of the divergence measure as well as the regression procedures and multifactor pricing models. Section 3.4 presents the main results of the study, and Section 3.5 concludes.

3.2 Data

Summary statistics for the data are presented in Table 3.2. The data comes from Institutional Shareholder Services (ISS- formerly RiskMetrics) and the Center for Research in Secuirty Prices (CRSP). For performance regressions, factor realizations are obtained from Ken French's and Yu Yuan's websites.

3.2.1 CRSP

The data on mutual fund characteristics and their returns comes from the CRSP Survivor-Bias-Free U.S. Mutual Fund database. The focus of this study is on domestic long-only U.S. equity funds. In order to limit the sample to just these funds, I drop any that CRSP labels as a variable annuity, index fund, or ETF.[4] I identify any international, sector, balanced, buy-write, enhanced, leveraged, long/short, and commodity funds based on the CRSP fund name using the list of keywords of Jordan and Riley (2016). Those funds are then removed from the sample. As in Jordan and Riley (2016), I require that all funds be at least 2 years old and have at least $20 in assets under management (AUM) to correct for the incubation bias as identified in Evans (2010). Once a fund achieves this AUM threshold, it remains in the sample until it is no longer listed in CRSP. All share classes of a fund within CRSP are collapsed at the class group identifier. The AUM of the fund is the sum of all assets in each share class. Other fund characteristics are calculated as a asset weighted average across share classes.

Panel A of 3.2 presents summary statistics for the sample of mutual funds in this study. The sample runs from June 2012 to July 2016. There are 1,160 funds across 116 families, with a median size of $530 million and an average expense ratio of 1.07%. On average, there are 12 unique funds within a family. The calculation of a fund family's divergence requires that a family have at least two funds that meet the criteria above, so no family has only one fund in sample.

3.2.2 Factor Realizations

In accessing the performance of funds within families of varying divergence ratios, I use several multifactor pricing models. For these performance regressions, daily factor realizations of *SMB*, *HML*, *UMD*, *RMW*, and *CMA* are obtained from Ken French's website.[5] Daily factor realizations of $SMB_{S\&Y}$, $MGMT$, and $PERF$ are obtained from Yu Yuan's website.[6]

3.2.3 ISS Voting Analytics

As of August 31, 2004, all mutual funds and registered management investment companies are required to report how they vote their proxies on equity shares held in the prior year. These vote records are disclosed on the SEC Form N-PX. Each fund must file this form with the SEC by the end of August, covering all votes submitted in the previous N-PX reporting year, from July 1st through June 30th.

The data on these forms is collected and maintained by ISS. Included in the data are the fund family and mutual fund, type of proposal, a brief description of the proposal, the company the proposal pertains to, the company management's

[4]Index funds and ETFs are included in the calculation of a fund family's divergence. Performance regressions will not include index or passive funds and ETFs.

[5]$http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html$

[6]$http://www.saif.sjtu.edu.cn/facultylist/yyuan/$

recommendation, who proposed the vote (shareholder or management), and how each fund voted.

ISS is the largest proxy advisory firm, covering nearly 40,000 meetings in 117 markets and executing 8.5 million proxy ballots for its 1700 institutional clients. The data includes ISS's recommendation for each proposal on the ballot of all Russell 3000 companies, which is provided to each of its institutional clients. The importance of these recommendations is well documented in the literature. Malenko and Shen (2016) find that a negative ISS recommendation on say-on-pay proposals leads to a 25 percentage point reduction in support. Morgan et al. (2011) find that an ISS recommendation in favor of a proposal increases the probability a fund will vote in favor of that proposal by 43.6%.

Panel C of Table 3.2 summarizes the voting data. The funds vote on over 38 million items, nearly 26 million of which are management sponsored director elections (MSDEs). Funds cast a vote in favor of the proposal on the ballot some 91.6% of the time and in favor of MSDEs 93.3% of the time. The approval rate on the 3.7 million contentious proposals in the sample is significantly lower at 45%. Contentious management sponsored director elections (cMSDEs), where ISS opposes management's voting recommendation, are approved by the funds in sample only about half of the time.

There is no unique identifier that maps the ISS and CRSP databases. In order to link fund characteristics, family characteristics, and fund performance data of CRSP to the divergence ratio obtained from ISS, I match based on the family name. Each record is checked for accuracy. I allow any family that is acquired to be stand-alone in the years up until acquisition, at which point the family's funds are subsumed by the acquiring family.

3.3 Methodology

3.3.1 The Divergence Measure

The divergence measure is calculated at the family-year level. For each year, I divide the number of times funds within a family vote differently on the same proposal by the number of proposals that a family has the opportunity to vote on more than once. For family i in N-PX year t:

$$Divergence_{i,t} = \frac{\#\ Proposals\ Voted\ Differently_{i,t}}{\#\ Overlapping\ Proposals_{i,t}} \tag{3.1}$$

This measure is calculated for all 116 families that map from the CRSP to ISS database for all years in which data is available. In calculating divergence, I allow all index and passively managed funds to remain within the sample. If Fidelity votes one way on a proposal for a company held in its active Magellan Fund and another way on that same proposal in its passive Spartan S&P 500 fund, such a vote would be included in that year's divergence calculation.

The primary analysis of this paper will use the divergence ratio on cMSDE proposals. For both the numerator and denominator, only those votes that are contentious management-sponsored director elections will be tallied. This limits the sample to those votes where opposing management is potentially value increasing, as in Dimmock et al. (2018c).

3.3.2 Regression Procedure

I follow a procedure similar to Iliev and Lowry (2014) and Jordan and Riley (2016) in evaluating the performance of the funds. On the left hand side will be either the equally weighted-average net-of-fee or gross-of-fee returns across all mutual funds on a day within the sample, less the risk-free rate. The regressions all have 1,133 observations corresponding to the number of trading days from the end of N-PX year 2012 to the end of N-PX year 2016, with the average return on the left and the factors on the right. The intercept of these regressions is the alpha that would be obtained by holding an equally-weighted portfolio of all mutual funds across the sample period, rebalanced at the beginning of each N-PX year.

For each of the factor models, I regress the average daily return of a portfolio of funds formed on the previous year's divergence. Funds are sorted into quintiles based on their family's prior N-PX year cMSDE divergence ratio. The top quintile includes those funds in a family-year with the highest divergence ratio; the bottom quintile includes funds in a family-year with the lowest divergence ratio. In differencing columns, I subtract the average daily returns from the top and bottom quintile funds for each day and then regress this difference on the factors.

I consider several factor models in assessing performance, each of which are discussed in greater detail below.[7] These models are the Capital Asset Pricing Model (CAPM), the Fama-French and Carhart four-factor model, a six-factor model including investment and profitability factors, the Stambaugh and Yuan (2017) mispricing factor model and the four- and six-factor models supplemented with the size premium as calculated in Stambaugh and Yuan (2017). I consider each of these models as robustness checks to ensure that any perceived over- or under-performance (positive or negative alpha) is not a result of an inadequate pricing model. For example, earlier studies tend to use the CAPM to calculate alpha. Later studies, such as Carhart (1997), Fama and French (1993), and Fama and French (2015) demonstrate that what was previously perceived as alpha as calculated by the CAPM may actually be explained by common factors in stock returns. Cremers, Petajisto, and Zitzewitz (2012) show that even the four-factor model can have biased alphas because the intercept term in the four-factor regressions is non-zero for index and passively managed funds. Regardless, the four-factor model is perhaps the most commonly used model in the evaluation of mutual fund alphas.

3.3.3 The Capital Asset Pricing Model

The Capital Asset Pricing Model (CAPM), which relates the expected return of a risky asset to the systematic risk of the market, arose from the seminal, independent,

[7]See Jordan and Riley (2016) for further discussion on these models

and contemporaneous works of Sharpe (1964), Lintner (1965), and Mossin (1966). The model is presented as:

$$E(R_i) - R_f = \beta_i(E(R_M) - R_f) + \alpha_i \tag{3.2}$$

where $E(R_i)$ is the expected return of asset i, R_f is the risk-free rate,[8] and $E(R_M)$ is the return of the value-weighted market portfolio of risky assets. $E(R_M) - R_f$, then, represents the "market risk premium", or the excess return of the market portfolio over the risk-free rate. Alpha, α, is the abnormal rate of return above or below which the model predicts. The key measure in this model is β_i (beta) which represents the systematic, or non-diversifiable, risk.

3.3.4 The Four-Factor Model

Fama and French (1992) demonstrate that the relationship between beta and expected returns practically disappears from 1963-1990. Their tests do not support the simple intuition of the CAPM, that average stock returns are related to market betas. However, the addition of two factors that capture the effects of asset size and value capture the cross-sectional variation of stock returns. These findings led to the development of the size and value factors SMB and HML in Fama and French (1993). As discussed in Jordan and Riley (2016), Carhart (1997) supplements the new Fama and French (1992) three-factor model with a momentum pricing factor (UMD) motivated by the findings of Jegadeesh and Titman (1993). This results in the widely used four-factor model:

$$E(R_i) - R_f = \beta_{i1}(E(R_M) - R_f) + \beta_{i2}(SMB) + \beta_{i3}(HML) + \beta_{i4}(UMD) + \alpha_i \tag{3.3}$$

Carhart (1997) shows that by using this model to control for common factors of size, value, and persistence in stock returns, the misattributed risk-adjusted performance of the CAPM is eliminated.

3.3.5 The Six-Factor Model

Additional works have introduced new factors that seek to further explain the cross section of expected returns. Fama and French (2015) construct factors that capture the effects of profitability (RMW) and capital investments (CMA). Jordan and Riley (2016) find that the addition of these RMW and CMA factors to the four-factor model reveals that mutual fund managers have risk-adjusted skill, and as many as 15% of mutual fund managers have persistent skill in excess of the fees they charge their clients. The six-factor model is:

$$\begin{aligned} E(R_i) - R_f = \beta_{i1}(E(R_M) - R_f) + \beta_{i2}(SMB) + \beta_{i3}(HML) + \\ + \beta_{i4}(UMD) + \beta_{i5}(RMW) + \beta_{i6}(CMA) + \alpha_i \end{aligned} \tag{3.4}$$

[8] The return on a 90-day US Treasury bill is generally used as a proxy for the risk-free rate of return.

3.3.6 The Stambaugh & Yuan Mispricing Factors Model

The above factor models have generally followed a simple pattern: add a factor for each new pricing anomaly that is uncovered empirically. In a departure from this simple procedure, Stambaugh and Yuan (2017) develop two new "mispricing" factors used in addition to the market factor beta and a newly-calculated SMB factor.[9] These two new factors, MGMT and PERF each capture several anomalies each. The $MGMT$ factor includes six anomalies uncovered in the literature: net stock issues, composite equity issues, accruals, net operating assets, asset growth, and investment to assets. These factors can be more or less directly impacted by firm's management. The $PERF$ factor includes five anomalies: distress, O-score, momentum, gross profitability, and return on assets. These factors are related to performance. This model is presented as:

$$E(R_i) - R_f = \beta_{i1}(E(R_M) - R_f) + \beta_{i2}(SMB_{S\&Y}) + \beta_{i3}(MGMT) + \beta_{i4}(PERF) + \alpha_i \tag{3.5}$$

Additionally, I consider the $SMB_{S\&Y}$ factor within the context of the 4- and 6-factor models of Fama and French (1993), Carhart (1997), and Fama and French (2015) to determine if the calculated alphas are sensitive to the size factor employed. These supplemented models are:

$$\begin{aligned} E(R_i) - R_f = \beta_{i1}(E(R_M) - R_f) + \beta_{i2}(SMB_{S\&Y}) + \beta_{i3}(HML) + \\ + \beta_{i4}(UMD) + +\alpha_i \end{aligned} \tag{3.6}$$

and

$$\begin{aligned} E(R_i) - R_f = \beta_{i1}(E(R_M) - R_f) + \beta_{i2}(SMB_{S\&Y}) + \beta_{i3}(HML) + \\ + \beta_{i4}(UMD) + \beta_{i5}(RMW) + \beta_{i6}(CMA) + \alpha_i \end{aligned} \tag{3.7}$$

3.4 Results

In this section, I run the regressions as discussed in the previous subsections and Equations 3.2 through 3.7, from the Capital Asset Pricing Model to the Stambaugh & Yuan mispricing factors model. In all cases, the alphas are annualized and reported in percent.

3.4.1 The CAPM and Four Factor Models

Table 3.3 presents the regression results for the CAPM and four-factor models for both net and gross returns. Consider first the net regressions of Panel A. The results in

[9] The Stambaugh & Yuan size premium $SMB_{S\&Y}$, unlike the Fama & French size premium, is calculated using only those stocks that are least likely to be mispriced. Across all 1,113 days in my sample, the correlation between SMB and $SMB_{S\&Y}$ is approximately 0.87.

Columns (1) and (2) indicate that both the top and bottom quintile funds, as sorted based on their prior N-PX year's cMSDE divergence ratio, achieve a statistically significant and negative alpha. The test for differences between these alphas is shown to be statistically significant in Column (3) at the 5% level. That is, holding a portfolio of funds within a family in the top-quintile of the past N-PX year divergence ratio will deliver a CAPM alpha 1.04% greater than a portfolio of funds within a family in the bottom-quintile. Upon the inclusion of the SMB, HML, and UMD factors, some of the under-performance is "explained away" by common factors: the alphas drop in magnitude yet maintain their negative sign and statistical significance. The differences in the loading on the SMB is the greatest, with top quintile funds having a significantly lower small cap exposure.

The gross regressions presented in Panel B show that alphas are generally indistinguishable from zero before fees, results that mirror Fama and French (2010) and Jordan and Riley (2016). Additionally, as Fama and French (2010) argue, gross returns are better when evaluating skill because the varitaion in the expense ratios charged by funds has little effect on the ability to deliver alpha. In spite of the lack of significant alpha in gross returns, the difference in alpha between the top and bottom quintiles for both the CAPM and four-factor models is positive with meaningful magnitude.

3.4.2 The Six-Factor Model

The inclusion of the Fama and French (2015) firm profitability and investment factors, RMW and CMA, to the traditional four-factor model provides an additional test. Table 3.4 presents these results. As in Jordan and Riley (2016), the addition of RMW and CMA reduces the magnitude of the net and gross alphas relative to the four-factor model. Notice also that the magnitude and significance falls for the value factor HML, which is found to be redundant for describing average returns in the sample examined in Fama and French (2015).

While the magnitudes for alphas fall with the inclusion of these factors, the conclusion that top quintile funds outperform bottom quintile funds does not change. The difference in alphas between the top and bottom quintile funds is positive and significant for the net regressions in Panel A. In Panel B, the difference in gross alphas is insignificant but still positive with a sizable magnitude of 54 basis points. Consistent with prior research, average mutual fund alphas are zero before expenses and negative upon reducing returns by the expense ratio.

3.4.3 The Stambaugh & Yuan Model

I now abandon the traditional "x minus y" factors of Fama and French (2015) and Carhart (1997), instead considering the mispricing factors of Stambaugh and Yuan (2017). The mispricing factors PERF and MGMT, coupled with beta and the recalculated SMB factor, are shown to better explain the cross-section of returns in Stambaugh and Yuan (2017) by reducing the magnitude and significance of alpha. Table 3.5 tests if my previous CAPM, four-factor, and six-factor results are robust to this model. The net regressions of Panel A show that the negative alpha remains statistically significant at the 99% level for both the top and bottom quintile funds. The difference in alpha between the top and bottom quintile funds remains statistically significant, with a meaningful magnitude of 75 basis points.

The difference between the top and bottom quintiles is also the same for the gross return regression in Panel B. Here again, the alpha in the top and bottom quintile funds is either insignificant or marginally significant. Regardless, the difference of 69 basis points between the alphas is determined by the t-test to be greater than zero.

In both the net and gross regressions for the Stambaugh & Yuan model, the difference in the SMB factor is the largest among the factors. Funds in the bottom quintile have greater exposure to small stocks. The SMB of Stambaugh and Yuan (2017) is calculated using only those stocks that are determined by their models to be least likely mispriced. Nonetheless, the loadings on this size factor are similar in magnitude and significance to the traditional four- and six- factor models. Likewise, the difference on the loading between top and bottom quintile funds is virtual identical across models. Top quintile funds also have less exposure to the performance anomalies captured by PERF and greater exposure to the management anomalies capture by MGMT, but these differences are quite small despite their statistical significance.

3.4.4 The Stambaugh & Yuan Four- and Six- Factor Models

As a final test, I consider the SMB factor as constructed in Stambaugh and Yuan (2017) as a supplement to the traditional four- and six- factor models. These results are presented in Table 3.6. Panel A (Panel B) provides the net (gross) estimates for the four- and six- factor model. Relative to the traditional models of Tables 3.4 and 3.5, the alphas and differences in alphas increase in magnitude slightly. Panel B shows that the gross alphas in the four factor regression are now significantly negative for the four-factor model. This indicates that mispriced stocks in the calculation of the Fama-French SMB factor lead to the conclusion that funds on average provide no risk-adjusted return when in fact the risk-adjusted return is negative. Otherwise, the magnitude of the loading on the size factor is similar to the traditional models.

3.4.5 Summary of Results

Table 3.7 presents the differencing columns from the previous four tables. Panel A (Panel B) shows that for net (gross) returns in all models, the alpha is higher for the top quintile of funds than the bottom quintile of funds. For the net regressions of Panel A, the magnitude of the difference in alpha varies from 0.60% to 1.04%. In all cases, the difference is statistically significant and positive: an investor can achieve between 60 and 104 additional basis points of risk-adjusted return by holding a portfolio of funds with higher past divergence ratios. From the previous four tables, however, it is clear that the risk-adjusted performance is not positive, regardless of which portfolio is held.

The results are somewhat abated for the gross regressions presented in Panel B. While the differences in alpha for all models is positive, the level of significance is generally lower, and some differences are insignificant. The generally smaller magnitude of the differences relative to the net returns highlights the effect that the variation in expense ratios has on the results.

3.5 Conclusion

Funds allowed to vote at the fund level perform better than funds at families who assign the voting decision to member funds. Alphas are 60 to 104 basis points higher for funds with the highest divergence ratio- a measure that captures voting disparity within a family. The divergence ratio is uncorrelated with size and the expense ratio, as well as the number of active and index funds within the family.

The performance results are stronger for net returns than gross returns. Additionally, the average net alpha is consistently negative, regardless of the divergence quintile. No significantly positive risk-adjusted returns are realized for any portfolio of funds based on the divergence ratio. Consistent with prior literature, the gross alphas are frequently indistinguishable from zero. The results provide evidence of competition within fund families as identified in Kempf and Ruenzi (2007). These findings are also consistent with the separating equilibirium of Evans et al. (2017), who find that managers of competitive fund families have higher average performance.

There is no direct link between the divergence ratio of fund families and the performance of the shares their mutual funds hold. Further, funds within a family submitting opposing votes on the same proposal cannot both be making the optimal voting choice. The divergence ratio therefore proxies for active engagement in corporate governance at the fund level and reveals whether the family encourages competition or coordination among its member funds. Consistent with prior research, such active involvement in the governing of portfolio companies has benefits, realized through higher risk-adjusted returns.

Table 3.1: Divergence Ratios

This table presents divergence ratios for a group of the 116 mutual fund families in the 2012 through 2016 N-PX reporting periods that make up the sample. The divergence ratio is the number of times within an N-PX year that funds within a family vote differently on a proposal divided by the number of times funds within a family vote on the same item. The first two columns present the divergence ratio for all items voted on by a family, as well as each family's average number of overlapping votes per N-PX year. The next two columns present the same, but only for contentious management sponsored director elections (cMSDEs), where contentious is defined as ISS submitting a recommendation different than management's recommendation.

	All Proposals		Contentious MSDE Proposals	
	Divergence	# Overlapping	Divergence	# Overlapping
AIG SunAmerica	5.9%	14,793	12.5%	559
AIM Invesco	5.4%	10,006	16.0%	295
Allianz Global Investors	14.3%	13,562	49.6%	484
American Beacon Advisors	5.7%	2,641	19.4%	67
Blackrock	3.7%	24,132	6.3%	1,341
Bank of New York Mellon	0.0%	2,940	0.0%	66
Charles Schwab	0.1%	22,900	0.1%	1,230
Columbia	0.0%	10,518	0.2%	308
Deutsche DWS Scudder	0.1%	6,441	0.3%	214
Dimensional Fund Advisors	3.8%	18,651	13.3%	1,017
Dreyfus	1.0%	7,002	0.5%	191
Fidelity	9.7%	25,720	46.8%	1,543
GE Asset Management	4.7%	9,872	28.2%	285
Goldman Sachs	4.2%	9,835	13.5%	375
Hartford Mutual Funds	3.4%	8,519	7.4%	312
HSBC	0.0%	1,023	0.0%	34
ING Voya	2.1%	17,282	3.0%	724
Janus Capital Management	5.9%	6,998	11.3%	195
John Hancock	8.5%	19,559	36.7%	991
JPMorgan Funds	3.6%	14,924	10.3%	573
Legg Mason	8.3%	6,705	47.2%	183
Morgan Stanley	0.0%	5,326	0.0%	156
Nationwide Gartmore	10.7%	17,560	42.8%	947
Oppenheimer Funds	0.3%	5,753	0.1%	174
State Street	5.1%	21,155	4.0%	1,082
T. Rowe Price Associates Inc	0.6%	16,349	3.1%	635
TIAA-CREF	0.1%	24,667	0.4%	1,443
Transamerica	9.0%	8,952	41.1%	281
UBS	4.2%	2,093	26.0%	49
USAA	4.9%	12,411	51.0%	481
Vanguard Group Inc	0.1%	25,419	0.5%	1,515
Wells Fargo	0.3%	9,410	0.5%	241

Table 3.2: Descriptive Statistics

This table presents descriptive statistics on the funds (Panel A), the divergence ratio (Panel B), and the voting sample (Panel C). The divergence ratio is the number of times within an N-PX year that funds within a family vote differently on a proposal divided by the number of times funds within a family vote on the same item. Contentious MSDEs (cMSDEs) are management sponsored director elections where ISS recommends a vote against the director up for election. *Diverg., cMSDE* is the divergence ratio as calculated by considering only contentious management sponsored director election proposals in the vote count. *TNA* is the total net assets of the fund family in a year. *Exp. Ratio* is the weighted average expense ratio of all funds in the family-year. *# Funds*, *# Active*, and *# Index* are the number of total, active, and passive funds within a family-year.

Panel A: Funds				
Unique Funds				1,160
Unique Families				116
	Mean	**Median**	**Min**	**Max**
TNA (millions)	2,065	530	1	111,797
Exp. Ratio (%)	1.06	1.07	0.12	2.44
Unique Funds per Family	12	9	2	91

Panel B: Divergence				
	Mean	**Median**	**Min**	**Max**
Overall Divergence (%)	3.35	0.7	0	29.24
Contentious MSDEs Divergence (%)	13.48	4.91	0	60.64

Panel C: Voting		
	n	**Approval Rate**
Proposals	38,154,945	91.60%
Management Sponsored Proposals	25,914,529	93.33%
Contentious Proposals	3,707,756	44.99%
Contentious MSDE Proposals	1,467,327	50.74%

Table 3.3: CAPM and Four-Factor Models

This table shows the average risk-adjusted performance of an equally weighted portfolio of mutual funds formed on each day from June 2012 to July 2016. The CAPM and four-factor models are presented in equations 3.2 and 3.3. Alpha is annualized and reported in percent. The dependent variable is the average equally-weighted mutual fund return for a calendar day. Panel A (Panel B) displays the results when the dependent variable is net (gross) of fees. Columns (1), (2), (4) and (5) in each panel is for the sample of top and bottom quintile funds, respectively, as ranked by their previous N-PX year cMSDE divergence ratio. Columns (3) and (6) test for differences between the top and bottom quintile portfolios. Robust standard errors are used to calculate the t-statistics presented in brackets below coefficient estimates. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: CAPM and Four Factor Regressions, Net						
	(1)	(2)	(3)	(4)	(5)	(6)
	Top Quintile	Bottom Quintile	Top-Bottom	Top Quintile	Bottom Quintile	Top-Bottom
Beta	1.06***	1.06***	-0.00*	1.02***	1.01***	0.01***
	[181.54]	[141.00]	[-1.68]	[270.69]	[220.61]	[6.52]
SMB				0.20***	0.29***	-0.09***
				[34.94]	[40.18]	[-20.25]
HML				-0.01	-0.02**	0.01**
				[-1.07]	[-2.01]	[2.58]
UMD				0.01	-0.00	0.01***
				[1.12]	[-0.50]	[3.08]
Alpha	-2.43***	-3.48***	1.04**	-1.62***	-2.23***	0.60*
	[-2.66]	[-2.74]	[2.12]	[-2.86]	[-3.13]	[1.65]
Observations	1,133	1,133	1,133	1,133	1,133	1,133
R-squared	0.987	0.976	0.004	0.995	0.993	0.453

Panel B: CAPM and Four Factor Regressions, Gross						
	(1)	(2)	(3)	(4)	(5)	(6)
	Top Quintile	Bottom Quintile	Top-Bottom	Top Quintile	Bottom Quintile	Top-Bottom
Beta	1.06***	1.06***	-0.00*	1.02***	1.01***	0.01***
	[181.55]	[141.00]	[-1.68]	[270.71]	[220.63]	[6.52]
SMB				0.20***	0.29***	-0.09***
				[34.94]	[40.19]	[-20.24]
HML				-0.01	-0.02**	0.01***
				[-1.06]	[-2.01]	[2.58]
UMD				0.01	0.00	0.01***
				[1.12]	[-0.50]	[3.08]
Alpha	-1.38	-2.37*	0.99**	-0.57	-1.12	0.55
	[-1.51]	[-1.87]	[2.01]	[-1.00]	[-1.57]	[1.50]
Observations	1,133	1,133	1,133	1,133	1,133	1,133
R-squared	0.987	0.976	0.004	0.995	0.993	0.453

Table 3.4: Six-Factor Model

This table shows the average risk-adjusted performance of an equally weighted portfolio of mutual funds formed on each day from June 2012 to July 2016. The Six Factor model is presented in equation 3.4. Alpha is annualized and reported in percent. The dependent variable is the average equally-weighted mutual fund return for a calendar day. Panel A (Panel B) displays the results when the dependent variable is net (gross) of fees. Columns (1) and (2) in each panel is for the sample of top and bottom quintile funds, respectively, as ranked by their previous N-PX year cMSDE divergence ratio. Column (3) tests for differences between the top and bottom quintile portfolios. Robust standard errors are used to calculate the t-statistics presented in brackets below coefficient estimates. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Six Factor Regressions, Net			
	(1)	(2)	(3)
	Top Quintile	Bottom Quintile	Top-Bottom
Beta	1.02***	1.00***	0.01***
	[253.58]	[209.47]	[6.02]
SMB	0.19***	0.28***	-0.09***
	[31.87]	[37.90]	[-19.11]
HML	0.00	0.01	0.00
	[0.13]	[0.49]	[-0.80]
UMD	0.01	0.00	0.01**
	[1.13]	[-0.14]	[2.24]
CMA	-0.05***	-0.08***	0.03***
	[-3.59]	[-4.44]	[3.26]
RMW	-0.04***	-0.02	-0.02***
	[-3.76]	[-1.62]	[-2.78]
Alpha	-1.55***	-2.15***	0.60*
	[-2.78]	[-3.07]	[1.65]
Observations	1,133	1,133	1,133
R-squared	0.995	0.993	0.464

Panel B: Six Factor Regressions, Gross			
	(1)	(2)	(3)
	Top Quintile	Bottom Quintile	Top-Bottom
Beta	1.02***	1.00***	0.01***
	[253.63]	[209.49]	[6.03]
SMB	0.19***	0.28***	-0.09***
	[31.86]	[37.90]	[-19.11]
HML	0.00	0.01	0.00
	[0.13]	[0.49]	[-0.80]
UMD	0.01	0.00	0.01**
	[1.13]	[-0.14]	[2.24]
CMA	-0.05***	-0.08***	0.03***
	[-3.58]	[-4.44]	[3.27]
RMW	-0.04***	-0.02	-0.02***
	[-3.76]	[-1.62]	[-2.78]
Alpha	-0.49	-1.04	0.54
	[-0.89]	[-1.48]	[1.49]
Observations	1,133	1,133	1,133
R-squared	0.995	0.993	0.464

Table 3.5: Stambaugh & Yuan Model

This table shows the average risk-adjusted performance of an equally weighted portfolio of mutual funds formed on each day from June 2012 to July 2016. The Stambaugh & Yuan model is presented in equation 3.5. Alpha is annualized and reported in percent. The dependent variable is the average equally-weighted mutual fund re- turn for a calendar day. Panel A (Panel B) displays the results when the dependent variable is net (gross) of fees. Columns (1) and (2) in each panel is for the sample of top and bottom quintile funds, respectively, as ranked by their previous N-PX year cMSDE divergence ratio. Column (3) tests for differences between the top and bottom quintile portfolios. Robust standard errors are used to calculate the t-statistics presented in brackets below coefficient estimates. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Stambaugh & Yuan Regressions, Net

	(1)	(2)	(3)
	Top Quintile	Bottom Quintile	Top-Bottom
Beta	1.01***	0.99***	0.02***
	[259.50]	[201.52]	[7.16]
SMBSY	0.18***	0.27***	-0.09***
	[31.44]	[37.74]	[-19.49]
PERF	0.01	0.01**	-0.01***
	[1.60]	[2.57]	[-2.66]
MGMT	-0.08***	-0.10***	0.03***
	[-9.66]	[-10.19]	[5.45]
Alpha	-1.58***	-2.34***	0.75**
	[-2.81]	[-3.23]	[1.99]
Observations	1,133	1,133	1,133
R-squared	0.995	0.992	0.420

Panel B: Stambaugh & Yuan Regressions, Gross			
	(1)	(2)	(3)
	Top Quintile	Bottom Quintile	Top-Bottom
Beta	1.01***	0.99***	0.02***
	[259.52]	[201.53]	[7.16]
SMBSY	0.18***	0.27***	-0.09***
	[31.43]	[37.74]	[-19.49]
PERF	0.01	0.01**	-0.01***
	[1.60]	[2.57]	[-2.67]
MGMT	-0.08***	-0.10***	0.03***
	[-9.66]	[-10.19]	[5.44]
Alpha	-0.54	-1.23*	0.69*
	[-0.96]	[-1.70]	[1.85]
Observations	1,133	1,133	1,133
R-squared	0.995	0.992	0.42

Table 3.6: Stambaugh & Yuan Four- and Six-Factor Models

This table shows the average risk-adjusted performance of an equally weighted portfolio of mutual funds formed on each day from June 2012 to July 2016. The Stambaugh & Yuan Four- and Six-Factor models are presented in equation 3.6 and 3.7. Alpha is annualized and reported in percent. The dependent variable is the average equally-weighted mutual fund return for a calendar day. Panel A (Panel B) displays the results when the dependent variable is net (gross) of fees. Columns (1), (2), (4) and (5) in each panel is for the sample of top and bottom quintile funds as ranked by their previous N-PX year cMSDE divergence ratio. Columns (3) and (6) test for differences between the top and bottom quintile portfolios. Robust standard errors are used to calculate the t-statistics presented in brackets below coefficient estimates.***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Stambaugh & Yuan 4- and 6-Factor Regressions, Net						
	(1)	(2)	(3)	(4)	(5)	(6)
	Top Quintile	Bottom Quintile	Top-Bottom	Top Quintile	Bottom Quintile	Top-Bottom
Beta	1.02***	1.01***	0.01***	1.01***	0.99***	0.02***
	[259.88]	[202.41]	[6.98]	[242.91]	[190.84]	[7.08]
SMBSY	0.19***	0.28***	-0.09***	0.18***	0.26***	-0.08***
	[31.15]	[34.64]	[-18.76]	[28.15]	[32.81]	[-17.92]
HML	-0.04***	-0.07***	0.03***	-0.04***	-0.06***	0.02***
	[-5.51]	[-7.14]	[5.93]	[-4.42]	[-4.75]	[2.83]
UMD	0	-0.02**	0.01***	-0.00	-0.02***	0.01***
	[-0.49]	[-2.46]	[4.43]	[-0.87]	[-2.66]	[4.01]
CMA				-0.03**	-0.06***	0.02**
				[-2.19]	[-2.81]	[2.39]
RMW				-0.07***	-0.07***	-0.00
				[-6.82]	[-5.11]	[-0.24]
Alpha	-2.07***	-2.87***	0.80**	-1.92***	-2.71***	0.78***
	[-3.42]	[-3.72]	[2.12]	[-3.29]	[-3.60]	[2.08]
Observations	1,133	1,133	1,133	1,133	1,133	1,133
R-squared	0.995	0.991	0.42	0.995	0.992	0.425

Panel B: Stambaugh & Yuan 4- and 6- Factor Regressions, Gross						
	(1)	(2)	(3)	(4)	(5)	(6)
	Top Quintile	Bottom Quintile	Top-Bottom	Top Quintile	Bottom Quintile	Top-Bottom
Beta	1.02***	1.01***	0.01***	1.01***	0.99***	0.02***
	[259.89]	[202.42]	[6.98]	[242.96]	[190.86]	[7.08]
SMBSY	0.19***	0.28***	-0.09***	0.18***	0.26***	-0.08***
	[31.14]	[34.64]	[-18.76]	[28.15]	[32.82]	[-17.92]
HML	-0.04***	-0.07***	0.03***	-0.04***	-0.06***	0.02***
	[-5.51]	[-7.14]	[5.93]	[-4.42]	[-4.75]	[2.82]
UMD	-0.00	-0.02**	0.01***	-0.00	-0.02***	0.01***
	[-0.49]	[-2.46]	[4.43]	[-0.88]	[-2.66]	[4.01]
CMA				-0.03**	-0.06***	0.02**
				[-2.19]	[-2.81]	[2.39]
RMW				-0.07***	-0.07***	-0.00
				[-6.81]	[-5.11]	[-0.23]
Alpha	-1.01*	-1.76**	0.74**	-0.87	-1.60**	0.73*
	[-1.67]	[-2.28]	[1.97]	[-1.49]	[-2.12]	[1.93]
Observations	1,133	1,133	1,133	1,133	1,133	1,133
R-squared	0.995	0.991	0.42	0.995	0.992	0.425

Table 3.7: Differencing Columns

This table presents the differencing columns from the six pricing models presented in the previous four tables. Panel A (Panel B) displays the results when the dependent variable is net (gross) of fees. The alpha in each column is the additional alpha achieved by funds in the top quintile over funds in the bottom quintile as ranked by the previous year's cMSDE divergence ratio. Robust standard errors are used to calculate the t-statistics presented in brackets below coefficient estimates. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Differencing Columns for Net Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
	CAPM	Four Factor	Six Factor	S&Y	S&Y 4 Factor	S&Y 6 Factor
Beta	-0.00*	0.01***	0.01***	0.02***	0.01***	0.02***
	[-1.68]	[6.52]	[6.02]	[7.16]	[6.98]	[7.08]
SMB		-0.09***	-0.09***			
		[-20.25]	[-19.11]			
HML		0.01**	-0.00		0.03***	0.02***
		[2.58]	[-0.80]		[5.93]	[2.83]
UMD		0.01***	0.01***		0.01***	0.01***
		[3.08]	[2.24]		[4.43]	[4.01]
CMA			0.03***			0.02**
			[3.26]			[2.39]
RMW			-0.02***			-0.00
			[-2.78]			[-0.24]
SMBSY				-0.09***	-0.09***	-0.08***
				[-19.49]	[-18.76]	[-17.92]
PERF				-0.01***		
				[-2.66]		
MGMT				0.03***		
				[5.45]		
Alpha	1.04**	0.60*	0.60*	0.75**	0.80**	0.78**
	[2.12]	[1.65]	[1.65]	[1.99]	[2.12]	[2.08]
Observations	1,133	1,133	1,133	1,133	1,133	1,133
R-squared	0.004	0.453	0.464	0.420	0.420	0.425

Panel B: Differencing Columns for Gross Regressions						
	(1)	(2)	(3)	(4)	(5)	(6)
	CAPM	Four Factor	Six Factor	S&Y	S&Y 4 Factor	S&Y 6 Factor
Beta	-0.00*	0.01***	0.01***	0.02***	0.01***	0.02***
	[-1.68]	[6.52]	[6.03]	[7.16]	[6.98]	[7.08]
SMB		-0.09***	-0.09***			
		[-20.24]	[-19.11]			
HML		0.01**	-0.00		0.03***	0.02***
		[2.58]	[-0.80]		[5.93]	[2.82]
UMD		0.01***	0.01***		0.01***	0.01***
		[3.08]	[2.24]		[4.43]	[4.01]
CMA			0.03***			0.02**
			[3.27]			[2.39]
RMW			-0.02***			-0.00
			[-2.78]			[-0.23]
SMBSY				-0.09***	-0.09***	-0.08***
				[-19.49]	[-18.76]	[-17.92]
PERF				-0.01***		
				[-2.67]		
MGMT				0.03***		
				[5.44]		
Alpha	0.99**	0.55	0.54	0.69*	0.74*	0.73*
	[2.01]	[1.50]	[1.49]	[1.85]	[1.97]	[1.93]
Observations	1,133	1,133	1,133	1,133	1,133	1,133
R-squared	0.004	0.453	0.464	0.420	0.420	0.425

Appendix A: Variable Definitions for Chapter 1

Family Does Not Hold Actively	An indicator variable with a value of 1 if a proposal is voted on only by index funds within an institutional fund family and a value of 0 if a proposal is voted on by both index funds and active funds within an institutional fund family.	Institutional Shareholder Services Voting Analytics Database
Family Holds in Index & Active	A firm an index fund votes on that is held by both index funds and active funds within its institutional fund family.	Institutional Shareholder Services Voting Analytics Database
Contentious	An indicator variable with a value of 1 if Institutional Shareholder Services recommends a vote against management's recommendation for that proposal, and 0 otherwise.	Institutional Shareholder Services Voting Analytics Database
Market Value	The logarithm of the firm's previous quarter market value.	Compustat Daily Updates-Fundamentals Quarterly variable mkvaltq.
Book Assets	The logarithm of the firm's previous quarter book assets.	Compustat Daily Updates-Fundamentals Quarterly variable atq.
ROA	The firm's previous quarter net income divided by the firm's previous quarter total assets.	Compustat Daily Updates-Fundamentals Quarterly variable niq divided by atq.
Book to Market	The firm's previous quarter Book to Market ratio, calculated as the book value of stockholders' equity divided by market value.	Compustat Daily Updates-Fundamentals Quarterly variable teqq divided by mkvaltq.

Leverage	The firm's previous quarter total long-term debt divided by the firm's previous quarter market value.	Compustat Daily Updates-Fundamentals Quarterly variable dlttq divided by mktvaltq.
Excess Return	The firm's three-month return prior to the shareholder election minus the value weighted market return over the same period.	CRSP Monthly Stock File variable ret minus vwretd.
Director Elections	Management sponsored proposals to elect members to the board of directors.	Institutional Shareholder Services Voting Analytics Agenda ID 201
Compensation	Management sponsored proposals regarding executive pay, bonuses, and incentive plans.	Institutional Shareholder Services Voting Analytics Agenda IDs 219-220, 501, 503, 506-507, 509-510, 512, 514, 516, 522, 524-526, 528, 530, 534-535, 537-538, 541, 547-550, 552, 554-556, 558-559, 564-566, 568, 570, 581, 588, 592-593, and 595-599.
Accounting	Management sponsored proposals regarding auditors and financial statements.	Institutional Shareholder Services Voting Analytics Agenda IDs 101, 104-105, 109, 136, 155, 173, and 280.

General	Management sponsored proposals regarding general business and other annual meeting items. In all specifications where proposal categories are excluded, this is the base case (or omitted) category from the regression.	Institutional Shareholder Services Voting Analytics Agenda IDs 10, 20, 40, 50, 60, 102-103, 106, 111, 113-115, 119, 122, 125-127, 131, 135, 137, 146, 148, 151, 159, 163, 168, 175-176, 179, 198-199, 301-302, 304-310, 312-316, 319-321, 323, 325, 328-334, 338-339, 342-343, 353, 373-375, 377-379, 401, 404-407, 409-415, 418-419, 452-454, 456-457, 470, 601-603, 605-606, 609, 611-618, 620-624, 627, 653, 658, and 660-661.
Board	Management sponsored proposals relating to the board of directors, excluding director elections.	Institutional Shareholder Services Voting Analytics Agenda IDs 110, 178, 196, 202-209, 212-217, 223, 225-227, 229-235, 250, 255, 260-262, 264-265, 267, 271, 273, 276, 292, 296, 298-299, 604, and 607-608.
Payout	Management sponsored proposals regarding dividends, repurchases, and other payout plans.	Institutional Shareholder Services Voting Analytics Agenda IDs 107-108, 152, 318, 335, and 346-348.
Family TNA	The sum of the total net assets across all funds within a quarter for an institutional fund family.	CRSP Survivor-Bias Free Mutual Fund Database variable tna_latest.
Fund TNA	The sum of the total net assets within for a fund, across all share classes.	CRSP Survivor-Bias Free Mutual Fund Database variable tna_latest summed at the crsp_cl_grp level.

S&P 500 Fund	An indicator variable with a value of 1 if a fund is an S&P 500 index fund, and 0 otherwise.	CRSP Survivor-Bias Free Mutual Fund Database variable lipper_class equal to "SPSP".
Fund Age	The age (in years) of the oldest share class of a fund.	CRSP Survivor-Bias Free Mutual Fund Database variable caldt minus the first_offer variable, using the minimum first_offer across a fund's share classes.
Family Age	The age (in years) of the oldest fund in an institutional fund family.	CRSP Survivor-Bias Free Mutual Fund Database variable caldt minus the first_offer variable, using the minimum of first_offer across all of a mgmt_cd's funds.
Number of Funds	The number of unique funds offered by an institutional fund family in a quarter.	CRSP Survivor-Bias Free Mutual Fund Database, using the unique crsp_cl_grps within a mgmt_cd for a given quarter.

Appendix B: Variable Definitions for Chapter 2

Variable name	Definition	Data Source
Past fraud	The firm committed a previously detected fraud	SEC administrative proceeding or litigation release was filed for firm prior to firm-year observation
Past affiliated fraud	An affiliate of the firm committed a previously detected fraud	SEC administrative proceeding or litigation release was filed for affiliated firm prior to firm-year observation and Form ADV Schedule D Section 7.A reports fraud firm as affiliate
Past regulatory	Filed a regulatory disclosure reporting page (DRP)	One of more of: Items 11c1-3, 11d1-5, 11e-4
Past civil or criminal	Filed a criminal or civil DRP	One of more of: Items 11a1-2, 11b1-2, 11h1a, 11h1b, 11h1c, 11h2
Referral fees	Do you or any related person, directly or indirectly, compensate any person for client referrals?	Item 8f
Interest in transaction	Do you or any related person: buy (or sell) securities from advisory clients; recommend securities in which you have an ownership interest or serve as underwriter, general or managing partner or have any other sales interest?	One of more of: Items 8a1, 8a3, 8b2, 8b3
Soft dollars	Do you or any related person receive research or benefits other than execution from a broker-dealer or a third party in connection with client securities transactions?	Item 8e, Item 8g1 beginning in 2012
Broker in firm	Employs registered representatives of a broker-dealer	Item 5b240

Investment Company Act	Investment adviser (or sub-adviser) to an investment company registered under the Investment Company Act	Item 2a4
Custody	Do you or any related person have custody of any advisory clients' cash or securities?	One of more of: Items 9a1-2, 9b1-2
Dedicated CCO	CCO has no other stated role within firm	CCO on Schedule A has no other "Title or Status"
Majority employee owned	Over 50% aggregate employee ownership	Imputed using Dimmock, Gerken, and Marietta-Westberg (2015) method
Log (avg. acct. size)	Logarithm of assets under management per client	Log (Item 5f2c/(Item 5f2f + 1) + 1)
Percent client agents	Percent of banking, mutual, pension, charitable, corporate, and government clients	Sum of items: 5d3, 5d4, 5d5, 5d7, 5d8, 5d9 imputed using Dimmock, Gerken, and Marietta-Westberg (2015) method
Hedge fund clients	Primarily hedge fund clients	Item 5d6 greater than or equal to 75%
Log (AUM)	Logarithm of assets under management	Log (Item 5f2c + 1)
Log (firm age)	Logarithm of firm age in years	Log (years since date registered with the SEC)

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Vita

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Education

M.S., Finance, Louisiana State University 2013
B.S., Finance, Louisiana State University 2011

Working Papers

(Black)Rock the Vote: Index Funds and Opposition to Management

- Presented at the SEC Department of Economic and Risk Analysis PhD Student Symposium (2013); Eastern Finance Association Annual Meeting (2019), Financial Management Association Annual Meeting (2019); Financial Management Association Doctoral Student Consortium (2019), the University of Kentucky, the University of South Carolina, The College of New Jersey, Towson University, Salisbury University, the University of Richmond, and The Citadel.

Misconduct and Fraud by Investment Managers

- With Stephen G. Dimmock and William C. Gerken.
- SSRN link
- Forthcoming chapter in the handbook in *Corruption and Fraud in Financial Markets: Malpractice, Misconduct, and Manipulation*.
- Data employed by SEC Commissioner Robert J. Jackson, Jr. in his *Statement on Final Rules Governing Investment Advice*.

Mutual Fund Voting Divergence and Performance

- Presented at the University of Kentucky.

Teaching Experience

University of Kentucky

- FIN 300: Introduction to Corporate Finance — Summer 2018
  - Average evaluation: 4.9/5.0
- B&E 105: Technology for Business Solutions — 2018-2019
  - Hybrid online/in-person mass lecture
- Python for Finance (MSF) — 2019
  - Two-day seminar

Awards, Participation, and Fellowships

Competitive Awards

- American Finance Assocation Travel Grant Award 2019
- UK Research Excellence Team Grant ($8,000) 2017

Presentations and Discussions

- SEC DERA PhD Student Symposium 2018
- Eastern Finance Association Annual Meeting 2019
- Financial Management Association Annual Meeting 2019
- Financial Management Association Doctoral Student Consortium 2019

Fellowships

- Block Award 2018-2019
- Steckler Fellowship 2017-2019
- Gatton Fellowship 2015-2018
- Luckett Fellowship 2015-2016

Certifications, & Programming Skills

Certifications

- Licensed Louisiana Property & Casualty Insurance Agent
- Licensed Louisiana Life & Health Insurance Agent
- Bloomberg Market Concepts

Programming Skills

- Stata, Python, Javascript