TWO ESSAYS ON THE INVESTMENT OF INSTITUTIONAL INVESTORS

A Dissertation

by

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ABSTRACT

This dissertation consists of two essays on the investment of institutional investors. The first essay focuses on managers' choice on ESG investing, and examines whether mutual fund managers' pecuniary benefits can affect their decisions on ESG investment. Firstly, I find that stocks with higher ESG scores are associated with lower returns, which implies a trade-off between mutual fund ESG investment and financial performance. Next, using fund flow as an implicit incentive factor, I show that funds with greater flow-performance sensitivity invest less in high ESG firms, while funds with greater flow-ESG score sensitivity invest more in high ESG firms. Moreover, using hand-collected data of manager compensations, I provide evidence that mutual funds whose managers' compensations are explicitly linked to fund financial performance have lower ESG investment. Taken together, these findings suggest that pecuniary benefits can play a significant role in managerial decisions on ESG investment.

The second essay, coauthored with Yong Chen, examines investors' attitude toward tail risk in investment decision-making. Based on a large sample of mutual funds, we show that investor flows are significantly sensitive to tail risk in the cross-section, even after controlling for fund performance and characteristics. Using terrorist attacks and the COVID-19 as exogenous shocks to investors' fear level, we find that fund flows become increasingly sensitive to tail risk following the shocks, suggesting that fear can be a driving force of the tail risk aversion. In particular, the flow-tail risk sensitivity during the onset of the COVID-19 is about 4.5–10 times as large as that in other periods. In addition, tail risk is associated with the activeness of mutual fund investment strategies. The results are robust to alternative measures of tail risk. Overall, our findings suggest that investors care about tail risk beyond traditional risks.

DEDICATION

To my family.

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1. INTRODUCTION

This dissertation includes two essays that study the investment of institutional investors. In the first essay, “Why Do Good? ESG Investment in Mutual Funds", I examine whether fund managers’ pecuniary benefits can affect managerial decisions on ESG investment. To set up the stage for mutual fund-level analysis, I first investigate the relation between ESG score and stock returns. Using a portfolio sorting analysis, I find that low ESG stocks outperform high ESG stocks by approximately 25 basis points per month after adjusting for Fama-French 5-factor model. This result is consistent with the theoretical prediction of Pástor, Stambaugh, and Taylor (2020) in which “green" stocks have lower expected returns than “brown" assets in equilibrium. In addition, it is consistent with many empirical findings such as Hong and Kacperczyk (2009) who find that “sin" stocks outperform their industry comparables. Thus, the stock-level finding suggests a trade-off between mutual fund ESG investment and financial performance. Based on the inference, I next use fund flow as an implicit incentive factor and construct two implicit manager compensation measures − flow-performance sensitivity and flow-ESG score sensitivity, which capture the sensitivity of investor flow to fund past performance and portfolio ESG scores, respectively. Consistent with my hypothesis that manager compensation can be a driving force of managerial decisions on ESG investment, I find that mutual funds with larger flow-performance sensitivity have lower subsequent fund ESG scores, and funds with greater flow-ESG score sensitivity are associated with higher subsequent fund ESG scores. Moreover, I construct an explicit manager compensation measure based on hand-collected data, and find that fund managers whose compensations are explicitly linked to fund performance have lower ESG investment, which provides further evidence that supports my hypothesis. In sum, this essay studies institutions’ ESG choice from the perspective of fund manager compensation, and reveals that fund managers’ pecuniary benefits, embedded in manager compensation contracts, can have a significant impact on fund ESG investment.

In the second essay, “Do Investors Care About Tail Risk? Evidence from Mutual Fund Flows", coauthored with Yong Chen, we investigate investors’ attitude toward tail risk by examining the relation between investor flows and tail risk in the context of equity mutual funds. We define our fund-level tail risk measure as the difference between the fund's market exposure in distressed months and the fund's average market exposure in other months over a rolling-window period, and the distressed months are periods when the stock market experiences the 5% left-tail realizations. Based on the measure, we first document a large heterogeneity in tail risk across individual mutual funds. Second, we find that investors allocate less capital to funds with greater tail risk even after we control for fund performance and characteristics, which provides strong evidence that investors do care about fund tail risk. Finally, we explore the potential economic mechanism for the observed flow-tail risk relation. Motivated by the finding of Guiso, Sapienza, and Zingales (2018) that the time variation of investors' risk aversion can be explained by fear, we use terrorist attacks and the COVID-19 pandemic as shocks to investors' fear level, and find that fund flows become more sensitive to tail risk following these shocks, which provides evidence that the observed flow-tail risk relation can be driven by fear-induced risk aversion. To summarize, this essay shows that investors care about mutual fund tail risk when they make capital allocation decisions, and it advances our understanding of how untraditional beta risks (e.g., tail risk) can drive investor flows in mutual funds.

The rest of the dissertation is organized as follows. Section 2 includes the first essay, "Why Do Good? ESG Investment in Mutual Funds". Section 3 contains the second essay, "Do Investors Care About Tail Risk? Evidence from Mutual Fund Flows". Section 4 summarizes the dissertation.

2. WHY DO GOOD? ESG INVESTMENT IN MUTUAL FUNDS

2.1 Introduction

Investors' demand for socially sustainable and responsible investing has been growing in the past couple of decades. According to a 2020 survey, the Forum for Sustainable and Responsible Investment reports that approximately $17.1 trillion of total assets in the US are managed by professional managers who take into consideration Environmental, Social, and Governance (ESG) criteria when they make portfolio allocation decisions at the beginning of 2020. The number represents a 97% increase from $8.7 trillion in 2016, and accounts for almost one third of the $51.4 trillion of total assets under professional management at the start of 2020. Meanwhile, ESG investment has drawn increasing attention from institutional investors who attempt to meet clients' heightened demand for sustainable and responsible investing. For instance, Blackrock, the world's largest asset manager, has been constantly pushing for public awareness of ESG investing in recent years. Its Chairman and CEO, Laurence Fink, has been emphasizing the importance of ESG factors to firm's long-term growth in his annual letters to firm CEOs since 2016. In addition, fund managers of Blackrock are required to consider ESG factors when they make investment decisions since 2018.[1] Therefore, with the substantial amount of assets managed by institutional investors and the rapid growth of ESG investing, it is of great importance to study how institutional investors make their decisions on ESG investment.

In this paper, I explore how compensations of mutual fund managers affect funds' ESG investment. I focus on mutual fund industry because of its importance in the economy. According to the Investment Company Institute, 46.4% of the US households invest in mutual funds, and the total assets managed by the US mutual fund industry exceed $21 trillion as of 2019. Thus, as one of the major institutional investors and investment vehicles, mutual funds offer an ideal setting to study

[1] Laurence Fink's most recent letter to CEOs is available at `https://www.blackrock.com/corporate/investor-relations/larry-fink-ceo-letter`. Blackrock ESG Integration Statement is accessible at `https://www.blackrock.com/corporate/literature/publication/blk-esg-investment-statement-web.pdf`.

the relation between manager compensation and fund ESG choice.

Before examining the impacts of manager compensation on fund ESG investment, I first set up the stage by investigating the relation between ESG score and stock returns. Specifically, I perform time-series regressions of a high-minus-low portfolio that long high ESG stocks and short low ESG stocks, on risk factors from conventional asset pricing models, and find that high ESG stocks tend to yield worse financial performance. On average, the high-minus-low portfolio delivers a return of -25.2 basis points per month after adjusting for Fama-French 5-factor model. The result that high ESG stocks are associated with low returns is consistent with the theoretical model of Pástor, Stambaugh, and Taylor (2020) in which "green" stocks have lower expected returns in equilibrium due to both investor preference and risk hedging purpose. It is also consistent with many empirical findings, such as Hong and Kacperczyk (2009) who document that "sin" stocks generate higher returns than their industry comparables, and Di Giuli and Kostovetsky (2014) who find that improvement in firm corporate social responsibility ratings is associated with poor future stock returns. Thus, the stock-level finding suggests that mutual funds with more portfolio allocation to high ESG stocks should deliver lower returns, which implies a trade-off between mutual fund ESG investment and financial performance.

Next, I conduct tests to examine the relation between manager compensation and fund ESG choice. Fund managers care about fund flows because their compensation primarily depends on fund size. As a result, fund flows can have a great impact on the asset allocation decisions of fund managers. For example, Dou, Kogan, and Wu (2020) show that mutual fund flows obey a strong factor structure, with the common fund flows comoving negatively with economic uncertainty. Mutual fund managers, motivated by their hedging motives, tilt their portfolios away from stocks with higher common flow betas (i.e., stocks that have more negative returns when the mutual fund sector experiences a larger common outflow). Exploiting its connection with manager compensation, I use mutual fund flows as an implicit incentive factor and generate two implicit manager compensation variables. Referred to as flow-performance sensitivity and flow-ESG score sensitivity, the two variables are estimated as the sensitivity of investor flow to fund returns and

ESG scores, respectively. The flow-performance sensitivity measure is motivated by the convex relation observed between investor flow and fund performance (e.g., Brown, Harlow, and Starks, 1996; Chevalier and Ellison, 1997; Sirri and Tufano, 1998). The flow-ESG score sensitivity measure is motivated by the finding of Hartzmark and Sussman (2019) that mutual funds with higher Morningstar sustainability ratings could attract more investor flows. The flow sensitivity measures reflect investors' response to fund performance and ESG profiles, as a result, fund managers are expected to adjust portfolio holdings accordingly in order to attract new investors and/or retain existing investors for higher compensation. A larger value of flow-performance sensitivity indicates more investor flow after good fund performance. Given the inferred negative relation between fund returns and ESG investment, I hypothesize that mutual funds with greater flow-performance sensitivity should have lower fund ESG scores. On the other hand, mutual funds with high flow-ESG score sensitivity should maintain or increase their ESG investment due to the positive response of their investors to fund ESG scores, which leads to the second hypothesis that mutual funds with greater flow-ESG score sensitivity should have larger fund ESG scores. I perform both portfolio sorting and panel regression analyses, and the results are consistent with my hypotheses.

In addition to the implicit variables, I use an explicit manager compensation variable, *Performance-based pay*, to further examine the impact of manager compensation on fund ESG investment. Hand-collected from fund filings in the SEC EDGAR (Electronic Data Gathering, Analysis, and Retrieval) database, *Performance-based pay* is an indicator variable that equals one if manager's compensation is explicitly linked to fund investment performance, and zero otherwise. If a fund manager's compensation is directly linked to fund returns, ceteris paribus, I expect the fund manager to be more incentivized to deliver good performance. Consequently, the fund should have low ESG scores due to the observed negative relation between stock returns and ESG investment. Consistent with this hypothesis, I find that mutual funds with managers' compensation explicitly linked to investment performance indeed exhibit smaller ESG investment. Overall, the findings show that how fund managers are compensated has an significant impact on fund ESG investing.

Furthermore, motivated by Starks, Venkat, and Zhu (2018) who suggest that institutional investors with long investment horizon prefer ESG investment, I examine whether the observed relation between manager compensation and ESG choice can be explained by fund's short-termism. Using portfolio turnover ratio as a proxy for short-termism (i.e., a larger value of turnover ratio indicates greater extent of fund short-termism), I first observe a significantly negative relation between fund short-termism and ESG choice, which is consistent with the finding of Starks, Venkat, and Zhu (2018). Moreover, repeating the analysis by interacting fund short-termism with manager compensation variables, I find that my inference on the relation between manager compensation variables and ESG investing remains unchanged. These results suggest that investment horizon cannot entirely explain the observed relation between manager compensation and fund ESG investment.

Finally, I investigate whether mutual fund ESG investment comes at the cost of fund performance. To this end, I sort mutual funds into deciles based on their ESG scores and then check subsequent fund returns of the ten groups. The portfolio sorting result reveals a somewhat negative relation between fund ESG scores and financial performance. However, the difference in portfolio returns and Fama-French 5-factor alpha between the two extreme ESG groups are approximately 11 and 7 basis points per month respectively, which are neither statistically nor economically significant. In addition, I perform cross-sectional regressions of return performance measures on fund ESG scores, and find an insignificant relation between fund returns and ESG investment. This finding is consistent with the equilibrium of Berk and Green (2004) who argue that performance-induced investor flow eliminates fund outperformance due to decreasing returns to scale.[2]

My paper is related to the growing literature that explores potential factors contributing to the ESG choice of institutional investors. One strand of the literature examines investor preference or social norm as one factor (e.g., Hong and Kacperczyk, 2009; Chava, 2014; Riedl and Smeets, 2017). These studies generally document that stocks exhibiting weakness in certain ESG area(s) are held less by norm-constrained institutions. Another strand of the literature points to economic incentives as an alternative factor. For example, from the perspective of fund flows, existing lit-

[2]Similarly, Hartzmark and Sussman (2019) find a generally insignificant return difference between low and high ESG funds using Morningstar sustainability ratings as fund-level ESG performance measure.

erature documents that investors are willing to allocate more capital to mutual funds with good sustainability ratings (Hartzmark and Sussman, 2019), and that investor flow becomes less sensitive to past poor returns for socially responsible investment funds in the US (Bollen, 2007; Benson and Humphrey, 2008) and around the globe (Renneboog, Ter Horst, and Zhang, 2011). In terms of financial performance, many studies report that ESG investing tends to underperform in different asset classes (e.g., Renneboog, Ter Horst, and Zhang, 2008; Hong and Kacperczyk, 2009; Di Giuli and Kostovetsky, 2014; El Ghoul and Karoui, 2017; Luo and Balvers, 2017; Baker, Bergstresser, Serafeim, and Wurgler, 2018; Zerbib, 2019; Barber, Morse, and Yasuda, 2020). On the other hand, various papers find contrasting evidence that ESG stocks or funds can outperform in the long run (e.g., Edmans, 2011; Eccles, Ioannou, and Serafeim, 2014) or deliver better financial performance during stock market crises (e.g., Cornett, Erhemjamts, and Tehranian, 2016; Lins, Servaes, and Tamayo, 2017; Albuquerque, Koskinen, Yang, and Zhang, 2020; Ding, Levine, Lin, and Xie, 2020; Pástor and Vorsatz, 2020). Distinct from existing studies, I focus on economic incentives of fund managers and investigate how manager compensation affects mutual fund ESG choice, which is novel in the literature. My emphasis on fund managers is important in the sense that they are agents who make portfolio allocation decisions. My study complements existing studies by showing that pecuniary benefits, embedded in manager compensation contracts, can play a significant role in managers' decisions on ESG investment.

My paper also contributes to the literature on managerial incentives in mutual fund industry. The majority of existing studies focus on the advisory contracts of mutual fund investment advisors. Due to the restriction of the Investment Advisers Act of 1940 that asymmetric incentive fees are prohibited, most of the advisory contracts specify an advisory fee that is a percentage of fund assets (Elton, Gruber, and Blake, 2003; Golec and Starks, 2004). However, this restriction does not apply to the compensation contracts of portfolio managers. Therefore, I focus on the compensation contracts of fund managers, who make investment decisions, rather than the contracts of investment advisors. My hand-collected data from mutual fund filings reveal that manager compensation contracts, explicitly linked to investment performance, are widely applied among US equity mutual funds, which is consistent with the finding of Ma, Tang, and Gómez (2019). This finding also highlights the importance of manager compensation contracts in studying mutual fund managerial incentives in ESG investment.

The rest of the paper proceeds as follows. Section 2.2 describes the data and provides sample summary statistics. Section 2.3 presents results on the relation between manager compensation and fund ESG investment. In Section 2.4, I examine whether fund's ESG investment is related to future fund performance. Section 2.5 provides robustness checks and additional analyses. Finally, Section 2.6 concludes.

2.2 Data and sample summary

2.2.1 Data sources on mutual fund ESG profiles

I construct my sample from multiple data sources. Data on firms' Environmental, Social, and Governance (ESG) performance are obtained from the MSCI ESG KLD STATS database. Compiled annually by Morgan Stanley Capital International (MSCI), the database classifies ESG-related issues into seven main categories: community, diversity, employee relations, environment, human rights, product, and corporate governance. Within each category, the database contains a set of binary indicators assessing both positive and negative ESG performance of publicly traded firms.[3] The positive and negative indicators are referred to as "strengths" and "concerns", respectively. An ESG indicator is equal to one if its assessment criteria are met and zero otherwise.[4] Each year, aggregate strengths and aggregate concerns are obtained by separately summing positive and negative indicators for all seven categories. The net ESG score is then calculated as the difference between aggregate strengths and aggregate concerns, which is used as firm-level ESG performance measure in later analyses. The MSCI ESG KLD STATS database is available from 1991 to 2018,

[3] According to the manual, MSCI collects ESG-related data from academic, government, and non-governmental organization datasets, company disclosures, media, and other sources. The database also includes six additional categories, namely alcohol, gambling, firearms, military, nuclear, and tobacco. Following existing studies (e.g., Starks, Venkat, and Zhu, 2018; Cao, Titman, Zhan, and Zhang, 2020; Chen, Dong, and Lin, 2020, among others), I exclude the six additional categories when calculating firm-level ESG ratings as they each include only a limited number of negative indicators.

[4] If a company has not been researched for a particular indicator, this indicator is then left blank.

and only common stocks traded on NYSE, AMEX, and NASDAQ are included in my analysis. Similar to Cao, Titman, Zhan, and Zhang (2020), I use firm-level ESG scores of each calendar year to calculate mutual fund ESG-related measures of the next calendar year (i.e., 1992-2019), since the MSCI publishes its data around the end of each calendar year. My empirical analyses focus on the period from 2004 onward, and I choose 2004 as the starting year of my sample for two considerations: 1) the MSCI database begins to cover the largest 3,000 US firms since 2003, and 2) the ESG investing in the US does not start to pick up the pace until the mid 2000s. With regard to the coverage of the MSCI database, the solid blue and red lines in Panel A of Figure A.1 plot the number of firms covered by the MSCI and the total number of common stocks in the CRSP, respectively. The dashed yellow line in Panel A plots the ratio of number of stocks covered by the MSCI to number of common stocks in the CRSP. On average, the MSCI database covers approximately 2,500 stocks per year since 2003, which represents approximately 60% of the entire CRSP universe in terms of firm number. Additionally, the solid blue and red lines in Panel B of Figure A.1 represent the aggregated market value (USD in trillions) of firms covered by the MSCI and the total market value of the CRSP respectively, and the dashed yellow line in Panel B plots the percentage of market value of firms covered by the MSCI relative to all stocks in the CRSP universe, which shows that the percentage of market value remains relatively stable around 80% since 2003. The results suggest that firms covered by the MSCI ESG KLD STATS database are arguably representative of the overall stock market since its coverage of the top 3,000 US firms by market capitalization in 2003. Furthermore, some anecdotal evidence suggests that the ESG investing does not receive much attention from investors until the mid 2000s. For example, Figure A.2 plots the size of the US ESG investing since 1995, and it shows that the ESG investment starts to accelerate around 2005.[5] Due to these two reasons, I start my sample from 2004.

The mutual fund sample is from the CRSP Survivor-Bias-Free US Mutual Fund database and the Thomson Reuters s12 database. The CRSP database provides share-class-level data of fund returns and characteristics. Share classes of a mutual fund are tailored to the needs of different

[5] Data source: US SIF Trends Report 2020, which is available at https://www.ussif.org/files/US%20SIF%20Trends%20Report%202020%20Executive%20Summary%20Final.pdf.

clients, but they generally hold identical investment portfolios. Therefore, for each mutual fund with multiple share classes in the sample, its share-class-level data (e.g., retail and institutional share classes) are aggregated to the fund level, and value-weighted fund returns and characteristics are computed accordingly. In addition, data on quarterly mutual fund holdings are obtained from the Thomson Reuters s12 database. As fund-level ESG performance measure, the mutual fund ESG score is calculated as the value-weighted ESG scores of all the stocks held by each fund according to its quarterly holdings data. I restrict my sample to actively managed US equity mutual funds, and exclude global funds, bond funds, money market funds, balanced funds, index funds, exchange-traded funds, and sector funds. To mitigate data biases associated with new funds (e.g., incubation bias, Evans, 2010), I further restrict my sample to funds with total net assets (TNA) of at least $10 million and age of more than two years.

2.2.2 Hand-collected data on manager compensation

Information on manager compensation structure of each mutual fund is retrieved from the Statement of Additional Information (SAI), which is one section of Form N-1A filed by open-end management investment companies. In 2004, the SEC imposes a new regulation that requires each mutual fund, starting from March 2005, to disclose in SAI the compensation structure of its portfolio managers. For this reason, I obtain Form N-1A from the SEC EDGAR database and manually collect the annual information on manager compensation for all actively managed US equity mutual funds from 2006 to 2018.[6] In addition, I collect fund name and fund ticker/CUSIP (if available) in order to match the dataset to the CRSP Mutual Fund database.

There are two major reasons why I focus on manager compensation contracts in this study. The first reason is due to its asymmetric nature, which is different from the majority of advisory contracts of investment advisors. Figure A.3 plots simplified organizational structure of a mutual fund. The board of directors, elected by shareholders of a mutual fund, hire the investment advisor to handle daily management of the fund. Regulated by the Investment Advisers Act of 1940, asymmetric incentive fees are not allowed in the advisory contracts of investment advisors.

[6] I choose 2006 as the starting year because the number of funds in 2005 is approximately 64% of that in 2006.

However, this restriction does not apply to compensation contracts of portfolio managers who are employees of the investment advisor, which allows greater heterogeneity among manager compensation contracts. The other reason is that fund managers are agents who make day-to-day portfolio investment decisions, therefore, it is crucial to concentrate on manager compensation structure to investigate its impact on mutual fund ESG investment.

2.2.3 Sample summary

After combining the above-mentioned datasets, my final sample consists of 217,288 fund-month observations with 2,430 unique actively managed US equity mutual funds, which covers the period from 2004 to 2018. Panel A of Table A.1 reports the summary statistics of mutual fund ESG scores and other fund characteristics for all fund-month observations. The average fund has an ESG score of 1.01 with a standard deviation of 1.79. Moreover, the variation in mutual fund ESG score is substantial, as indicated by its 10th and 90th percentiles, which are -0.96 and 3.76 respectively. The wide range of fund ESG scores provides a solid foundation for the later cross-sectional analysis on manager compensation and fund ESG investment. Based on mutual fund filings, I construct fund-level variables of manager compensation and report summary statistics of those variables in Panel B of Table A.1 for a total of 19,505 fund-year observations.[7] The summary statistics show that approximately 96% of funds in my sample disclose that their managers receive variable compensations in addition to a fixed salary, and the majority of funds (85.26%) link manager compensation explicitly to investment performance. In addition, 31.70% of funds tie manager compensation to advisor profits, and 31.67% of the sample include some arrangement of deferred compensation. Finally, only 9.80% of the sample funds explicitly link manager compensation to their assets under management (AUM). The summary statistics of manager compensation variables are generally consistent with Ma, Tang, and Gómez (2019), although their sample covers more types of mutual funds.[8] Panel C of Table A.1 presents summary statistics of fund-related

[7]For detailed examples on how the variables of manager compensation are generated, please refer to the Appendix A.2 of the dissertation.

[8]Similar to Ma, Tang, and Gómez (2019), I exclude funds with multiple investment advisors as the compensation structure generally differs across investment advisors of the same fund. In addition to US equity mutual funds, which

variables for ten portfolios constructed based on fund ESG scores. Each month funds are sorted into deciles based on their ESG scores in an increasing order such that portfolio 1 includes funds with the lowest ESG scores (Low) and portfolio 10 consists of funds with the highest ESG scores (High). Additionally, a high-minus-low (High-Low) portfolio is formed using the two extreme ESG groups. According to the summary statistics, the High ESG mutual fund portfolio exhibits smaller flow-performance sensitivity, larger TNA, lower expense ratio, and worse past 12-month return. In addition, mutual funds in the High ESG portfolio tend to be older.

2.3 Mutual fund ESG choice and manager compensation

Motivated by the fact that portfolio managers make final investment decisions, I investigate how manager compensation structure affects ESG investment of portfolio managers in this section. I first examine the relation between firm ESG scores and stock returns in order to provide some insight into managerial decisions on ESG investment from the perspective of financial performance. Then, I test my hypotheses regarding the relation between manager compensation and fund ESG choice. Finally, I check whether the observed relation can be explained by fund investment horizon.

2.3.1 Firm ESG score and stock performance

The existing literature offers inconclusive evidence on the relation between firm ESG ratings and stock performance. Many studies find the relation to be negative, for example, Hong and Kacperczyk (2009) observe that “sin" stocks generate higher returns because they have limited risk sharing and greater litigation risk due to social norms. Di Giuli and Kostovetsky (2014) show that firms yield negative future returns after improvements in firm ESG performance. Krüger (2015) finds that stock prices respond negatively to some positive ESG news using event study analysis. In contrast, several papers document a positive relation between stock returns and firm ESG ratings in certain ESG categories. For example, Edmans (2011) finds a positive relation between employee satisfaction and long-term stock returns, and Eccles, Ioannou, and Serafeim

is the focal point of this paper, their sample includes other types of funds such as bond funds, global funds, sector funds etc.

(2014) document outperformance of high sustainability firms in the long run. In this paper, I consider all seven ESG categories in the MSCI database and focus on short-term implications of stock ESG ratings on its performance as short-term returns can be a major consideration for fund managers.

As a starting point, I first examine whether firm's ESG score is correlated with its characteristics and accounting performance. To do so, at the beginning of each year I rank stocks into deciles based on their industry-adjusted net ESG scores in an increasing order and check the average values of firm size, past 12-month return, book-to-market ratio, analyst coverage, and several accounting measures for stocks within each ESG group. As a result, group 1 includes firms with the lowest ESG scores (Low), while group 10 consists of firms with the highest ESG scores (High). A high-minus-low portfolio is also constructed using the top and bottom ESG groups. The summary statistics are reported in Table A.2, which shows that firms in the High ESG group are associated with larger market capitalizations, lower book-to-market ratios, higher profitability measures, fewer stock issues, and more analyst coverage.

Next, I conduct time-series regressions of a high-minus-low portfolio on different sets of risk factors. Each month stocks are sorted into quintiles based on their net ESG scores, and the high-minus-low portfolio is constructed by longing a value-weighted portfolio of stocks in the top ESG group and shorting a value-weighted portfolio of stocks in the bottom ESG group. Similar to Hong and Kacperczyk (2009) who examine returns of "sin" stocks relative to their industry comparables, I use stock's industry-adjusted return as its performance measure.[9] The generated time-series of the high-minus-low portfolio returns is then risk-adjusted using different models, including the CAPM model, Fama-French 3-factor model, Fama-French-Carhart 4-factor model, and Fama-French 5-factor model. Columns (2) to (5) of Table A.3 report the regression results, and column (1) presents the average return of the high-minus-low portfolio. Under all specifications, the risk-adjusted returns (i.e., alpha) of the high-minus-low portfolio are negative and statistically significant at the 5% level, which suggests that low ESG stocks perform better than high ESG stocks. In addition,

[9] I use Fama-French 48 industry classification in my analyses, but my inferences remain unchanged if I consider alternative industry classifications, such as 2-digit SIC code.

the economic magnitude of the outperformance of low ESG stocks appears to be substantial. For example, low ESG stocks outperform high ESG stocks by approximately 25 basis points per month when using Fama-French 5-factor model.

In sum, from portfolio sorting analysis, I find evidence that firms with low ESG scores tend to deliver higher returns, indicating a negative relation between firm ESG profile and short-term stock performance. This result is consistent with the equilibrium in the theoretical model of Pástor, Stambaugh, and Taylor (2020) in which “green” stocks have lower expected returns than “brown” stocks because investors derive utility and can hedge against climate risk by holding “green” stocks. It is also consistent with some empirical findings in the literature, such as Hong and Kacperczyk (2009), Di Giuli and Kostovetsky (2014), and Krüger (2015). Additionally, it suggests a trade-off between mutual fund portfolio returns and fund ESG investment, which helps to develop my hypotheses in the following analyses.

2.3.2 Mutual fund flow sensitivity and ESG investment

Using fund flows as an implicit incentive factor, I examine how fund managers adjust portfolio ESG investment based on fund flow sensitivity to either return performance or fund ESG scores in this subsection. To begin with, I first estimate each mutual fund’s profile of ESG investment, as well as its measures of flow-performance sensitivity and flow-ESG score sensitivity. Built upon firm ESG ratings, ESG choice of a mutual fund is measured as the value-weighted ESG scores of all stocks in its portfolio holdings. Specifically, the ESG score of fund i in quarter q, $MF\_ESG_{i,q}$, is calculated using the following equation:

$$MF\_ESG_{i,q} = \sum_{k \in i} \omega_{k,q-1} ESG_k \tag{2.1}$$

where $\omega_{k,q-1}$ is the relative weight of stock k in mutual fund i’s portfolio at the end of quarter $q-1$, and ESG_k is stock k’s most recent ESG score.

Similar to Sirri and Tufano (1998) and Ma, Tang, and Gómez (2019), I estimate fund flow-performance sensitivity and flow-ESG score sensitivity with the following regression:

$$Flow_{i,t+1} = \beta_0 + \beta_1 Perf\_rank_{i,t} + \beta_2 ESG\_rank_{i,t} + \beta_3 Flow_{i,t} + \beta' X_{i,t} + \varepsilon_{i,t+1} \tag{2.2}$$

where $Flow_{i,t+1}$ is fund i's investor flow in month $t+1$, $Perf\_rank_{i,t}$ is the percentile rank of fund i's performance in month t, $ESG\_rank_{i,t}$ is the percentile rank of fund i's portfolio ESG score in month t, and $X_{i,t}$ is a set of fund characteristics (i.e., fund TNA, expense ratio, fund age, past 12-month return, and a dummy variable that equals one if fund charges load fees and zero otherwise). The lagged fund flow, $Flow_{i,t}$, is included as well to control for potential autocorrelation in fund flow. I perform rolling regressions with a 36-month window to estimate the coefficients β_1 and β_2, which are measures of flow-performance sensitivity and flow-ESG score sensitivity, respectively.

If a mutual fund is characterized by high flow-performance sensitivity, it implies that investors of the fund respond more actively and aggressively to return performance through fund flows. Given that firms with high ESG scores yield lower short-term returns, it is expected that funds associated with large values of flow-performance sensitivity should avoid stocks with high ESG ratings in an attempt to deliver good return performance. On the contrary, if investors of a mutual fund value ESG investment and are willing to allocate more capital to the fund when there is an improvement in its ESG profile (captured by a large value of fund's flow-ESG score sensitivity), then it is expected that the aforementioned mutual fund will tilt its portfolio holdings toward firms with high ESG scores. Based on the discussion above, I propose the following hypothesis:

Hyppthesis 1. *If investor flow of a mutual fund is highly sensitive to return (ESG) performance, then the fund would invest less (more) in stocks with high ESG ratings. As a result, the fund should have low (high) ESG scores.*

To test Hypothesis 1, I first perform a portfolio sorting analysis. Based on either the estimated flow-performance sensitivity or flow-ESG score sensitivity metric, I rank mutual funds into quintiles each month in an increasing order such that group 5 includes funds with the largest sensitivity measures (High), and then check the average equal-weighted ESG scores, as well as other fund characteristics, of the five groups in the subsequent month. Figure A.4 plots the average ESG scores of the five mutual fund groups ranked on values of fund flow-performance sensitivity, and it shows a generally negative relation between flow-performance sensitivity and subsequent fund ESG scores. The two extreme quintiles, i.e., groups 1 (Low) and 5 (High), have average ESG scores of 1.13 and 0.92, respectively. The difference in average ESG scores between the two groups is 0.22 with a t-value of 3.33, which is statistically significant at the 1% level. Moreover, Panel A of Table A.4 reports the average values of ESG score, fund TNA, age, expense ratio, load fund dummy, and past 12-month return for the five groups that are constructed based on the flow-performance sensitivity measure. As indicated by the last row of Panel A, the High flow-performance sensitivity group exhibits smaller TNA, larger expense ratio, fewer funds that charge load fees, and higher past 12-month returns, in addition to having lower ESG scores. Similarly, Figure A.5 plots the average ESG scores of the five mutual fund groups that are ranked based on values of the flow-ESG score sensitivity measure, and it shows an overall positive relation between flow-ESG score sensitivity and fund ESG scores. The difference in average ESG scores between the High and Low groups is 0.09 with a t-value of 2.08. In addition, Panel A of Table A.5 reports the average values of ESG score and other fund-related variables for the five flow-ESG score sensitivity groups. As reported in the last row of Panel A, mutual funds in the High flow-ESG score sensitivity group tend to be younger and have lower past 12-month return, in addition to exhibiting higher ESG scores. Overall, the portfolio sorting results are consistent with Hypothesis 1.

Next, I conduct the following panel regression to examine whether a fund's flow-performance sensitivity or flow-ESG score sensitivity affects its future ESG investment:

$$MF\_ESG_{i,t+1} = \lambda_0 + \lambda_1 Flow\_perf_{i,t} + \lambda_2 Flow\_ESG_{i,t} + \lambda' X_{i,t} + \alpha_j + \alpha_t + \epsilon_{i,t+1} \quad (2.3)$$

where the dependent variable is the ESG score of fund i in month $t+1$, $Flow\_perf_{i,t}$ is fund i's flow-performance sensitivity measure, $Flow\_ESG_{i,t}$ is fund i's flow-ESG score sensitivity measure, and $X_{i,t}$ is the same set of fund characteristics defined in Eq.(2.2). Additionally, α_j and

α_t represent Morningstar style and month fixed effects, respectively. They are included to address the concern that mutual fund ESG investing may differ across various investment styles and change over time.[10] Both flow-performance sensitivity and flow-ESG score sensitivity are standardized for ease of interpretation.

Panel B of Table A.4 reports coefficient estimates from panel regressions of fund ESG scores on flow-performance sensitivity. Consistent with Hypothesis 1, the coefficients of flow-performance sensitivity are significantly negative in all model specifications, irrespective of whether I control for Morningstar style fixed effects and/or other fund characteristics. This finding suggests that on average mutual funds yield lower ESG scores if their investor flows are more sensitive to financial performance. With the identical setting, the results of regressing fund ESG scores on flow-ESG score sensitivity are reported in Panel B of Table A.5, where flow-ESG score sensitivity has significantly positive loadings. This finding, consistent with Hypothesis 1, indicates that fund managers are incentivized to focus more on ESG investment if they have historically attracted investor flow due to their strong portfolio ESG profiles. It is worth noting that for both flow sensitivity measures, the magnitude of their coefficients is much larger in the first two columns of Panel B in Table A.4 and Table A.5 that do not include Morningstar style fixed effects. For example, when I exclude and include Morningstar style fixed effects, the coefficients of flow-performance sensitivity in the last two columns of Panel B in Table A.4 equal -0.065 and -0.024, respectively. This finding provides evidence of varying ESG choice across funds with different investment styles. In terms of economic significance, since the unconditional average mutual fund ESG score is 1.01 during the sample period, a one standard deviation increase in flow-performance sensitivity is associated with 6.4% (0.065/1.01) decrease in fund ESG scores when I include fund controls but exclude Morningstar style fixed effects. The result becomes a 5.9% (0.060/1.01) increase in fund ESG scores when there is a one standard deviation increase in flow-ESG score sensitivity.

The relations between mutual fund ESG choice and flow sensitivity measures remain little

[10] Morningstar classifies US equity mutual funds into nine categories based on fund investment style. Each fund is assigned to one category based on the combination of its size (Small, Mid, or Large) and value (Value, Blend, or Growth) investments.

changed if I include both flow sensitivity measures in the panel regression. For example, as reported in column (1) of Table A.13, the coefficient of flow-performance sensitivity changes from -0.065 in Table A.4 to -0.068, and the coefficient of flow-ESG score sensitivity changes from 0.060 in Table A.5 to 0.059, when I include month fixed effects and fund controls. The result remains the same when Morningstar style fixed effects are also added to the regression, as reported in column (2) of Table A.13.

As previously stated, the flow sensitivity measures are estimated using rolling regressions with a 36-month window. In addition, the observed relations between fund ESG choice and flow sensitivity measures are robust to alternative window lengths such as 24-month. Table A.14 report regression results when the flow sensitivity measures are estimated using a 24-month rolling window. The first and last three columns report the results of flow-performance sensitivity and flow-ESG score sensitivity, respectively. It shows that all the coefficients of both flow sensitivity measures remain the same respective sign and are statistically significant at the 5% level, which provides further evidence supporting Hypothesis 1.

To summarize, both portfolio sorting and panel regression results provide support to Hypothesis 1 of a negative (positive) relation between mutual fund's flow-performance sensitivity (flow-ESG score sensitivity) and its ESG investment.

2.3.3 Performance-based pay and ESG investment

In mutual fund industry, the majority of funds compensate their investment advisors with advisory fees that are *not* based on fund performance due to the prohibition of asymmetric incentive fees in advisory contracts. With the restriction, advisory fees are generally specified as a *fixed* percentage of fund assets. Portfolio managers, selected by investment advisors, are responsible for general trading strategies and day-to-day portfolio allocation, and they negotiate their compensation contracts directly with investment advisors. Unlike investment advisors, the restriction of symmetric incentive fees does not apply to compensation contracts of portfolio managers. In fact, the majority of portfolio managers in my sample *do* receive variable compensations. As shown in Panel B of Table A.1, more than 85% of funds explicitly link manager compensation to fund performance, which is in sharp contrast to the general compensation structure of investment advisors. Portfolio managers who receive performance-based compensation are anticipated to care more about fund returns, which leads to my following hypothesis:

Hyppthesis 2. *If a mutual fund manager's compensation is explicitly linked to fund performance, then he/she will invest less in stocks with high ESG ratings. Consequently, the fund will have lower ESG scores.*

To test Hypothesis 2, I first conduct a portfolio sorting analysis by assigning mutual funds into two groups based on the manager compensation variable *Performance-based pay*, which is an indicator variable that equals one if a manager's compensation is explicitly linked to fund financial performance and zero otherwise, and then check if there is a significant difference in average fund ESG score between the two groups. The portfolio sorting result, reported in Panel A of Table A.6, supports Hypothesis 2 that funds with performance-based manager compensation have lower ESG scores.

Next, I replace flow sensitivity measures in Eq.(2.3) with *Performance-based pay* and then apply the same panel regression setting to examine the relation between funds with performance-based manager compensation and ESG scores. The corresponding results are reported in Panel B of Table A.6. Both models include month fixed effects, and the second model additionally includes Morningstar style fixed effects. Significant at the 1% level, the negative coefficients of *Performance-based pay* indicate that funds, whose managers' compensations are explicitly linked to investment performance, are associated with lower ESG scores. In terms of economic significance, the average ESG score of funds that link manager compensation to investment performance is 0.31 smaller than that of funds without *Performance-based pay* when Morningstar style fixed effects are not included. The difference represents 30.9% (0.312/1.01) of the average mutual fund ESG score. When Morningstar style fixed effects are included, the difference becomes smaller in magnitude with a value of -0.089. Nevertheless, it is significant at the 5% level and represents 8.8% (0.089/1.01) of the average mutual fund ESG score.

In sum, the finding of smaller ESG scores for mutual funds that apply *Performance-based pay* in manager compensation contracts is consistent with Hypothesis 2.

2.3.4 Mutual fund investment horizon and ESG investment

Starks, Venkat, and Zhu (2018) document a significant positive relation between investment horizon and ESG profile of institutional investors. Motivated by their finding, I investigate whether the observed relation between manager compensation and fund ESG choice can be explained by investment horizon in this subsection. To start with, I first examine whether mutual funds with short investment horizon are indeed correlated with low ESG scores. To this end, I use mutual fund portfolio turnover ratio as proxy for fund short-termism (i.e., a larger value of turnover ratio, equivalently more frequent trading, indicates greater extent of fund short-termism), based on which I sort mutual funds into quintiles in an increasing order such that portfolio 1 includes funds with least short-termism (Low) and portfolio 5 consists of funds with most short-termism (High). Then I calculate average fund ESG scores, together with other fund characteristics, for the five groups and report the sorting result in Panel A of Table A.7. The result shows that the average fund ESG score decreases monotonically from Low to High short-termism group. In addition, the difference in average ESG score between the two groups is equal to -0.57, which is statistically significant at the 1% level. Therefore, the portfolio sorting result confirms the previous finding of a positive relation between investment horizon and fund ESG choice.

To further explore the relation between investment horizon and ESG profile of mutual funds, I regress mutual fund ESG scores on fund short-termism after controlling for Morningstar style fixed effects, month fixed effects, and fund characteristics. For ease of interpretation I standardize fund short-termism, and report the regression results in Panel B of Table A.7. The coefficients of fund short-termism are negative and statistically significant at the 1% level in both models. In the first column that excludes Morningstar style fixed effects, the coefficient of fund short-termism equals -0.129, which indicates that on average a one standard deviation increase in fund short-termism is associated with a decrease of 0.129 in fund ESG score. The coefficient decreases to -0.067 in magnitude, but is still statistically significant when Morningstar style fixed effects are included. The significant negative relation between fund short-termism and ESG score is again consistent with the finding of previous studies that long-term investors prefer stocks with high ESG scores.

Now I have documented a significant relation between mutual fund ESG choice and investment horizon using both portfolio sorting and panel regression analyses, I next investigate whether the observed connection between mutual fund ESG choice and manager compensation can be explained by fund investment horizon. To this end, I add to Eq.(2.3) fund short-termism and its interaction with manager compensation variables, and perform panel regressions under the same setting. The corresponding results are reported in Table A.8, which show that both implicit and explicit manager compensation variables retain the direction and statistical significance when fund short-termism is added to the regression. This finding indicates that the relation between manager compensation and fund ESG choice cannot be explained by investment horizon.

To summarize, I observe that funds with greater extent of short-termism (i.e., larger turnover ratio) have lower ESG scores, which is consistent with the finding of existing studies. More importantly, investor horizon cannot explain the relation between manager compensation and fund ESG choice, as the relation remains to be significant even after I control for fund short-termism.

2.4 Mutual fund ESG choice and return performance

The negative relation between firm ESG profile and short-term stock performance suggests a potential trade-off between mutual fund ESG investment and financial performance. In this section, I examine whether mutual fund ESG choice comes at the cost of fund returns using both portfolio sorting and Fama-MacBeth regression analyses.

At the beginning of each month t, I sort mutual funds into deciles based on values of their ESG scores in month $t-1$ in an increasing order, such that mutual funds in group 1 (10) have the lowest (highest) ESG scores, and then construct ten equal-weighted portfolios using mutual fund returns in month t. I form an additional high-minus-low ESG portfolio using the top and bottom groups, and perform a time-series regression for each ESG portfolio using Fama-French 5-factor model. The first row of Table A.9 reports portfolio returns, and the remaining rows report risk-adjusted return (i.e., alpha) and risk factor loadings for each group. The portfolio sorting result reveals a somewhat negative relation between fund ESG scores and financial performance, with group

1 yielding the largest alpha among the ten ESG groups. However, the high-minus-low portfolio delivers an average return of -11 basis points per month. In addition, its risk-adjusted return is equal to -7 basis points per month. The two measures are insignificant from both economic and statistical perspectives. To sum up, the portfolio sorting result provides limited evidence that funds with low ESG scores yield better financial performance.

Next, I examine the relation between mutual fund ESG choice and financial performance using the following regression:

$$MF\_ret_{i,t+1} = \theta_0 + \theta_1 MF\_ESG_{i,t} + \theta_2 Perf\_pay_{i,t} + \theta' X_{i,t} + e_{i,t+1} \tag{2.4}$$

where the dependent variable is the return performance of fund i in month $t+1$, $MF\_ESG_{i,t}$ is fund i's ESG score in month t, $Perf\_pay$ is the manager compensation variable *Performance-based pay*, and $X_{i,t}$ is the set of fund characteristics defined in Eq.(2.2). I use either return or alpha estimated from Fama-French 5-factor model (FF5 alpha) as the fund's return performance measure, and report Fama-MacBeth regression coefficients in Table A.10.[11] Under all specifications, the coefficients of fund ESG score are not significantly different from zero regardless of the choice of fund's return performance measure. Funds that apply *Performance-based pay* in manager compensation contracts seem to yield higher returns, as indicated by the positive coefficients in columns (2) and (3). However, the magnitude of the coefficients is small, in addition, the fund's FF5 alpha is not significantly affected by *Performance-based pay*. Overall, the Fama-MacBeth regression results do not reveal a significant relation between fund ESG scores and financial performance.[12]

The finding of an insignificant relation between fund ESG score and return performance is similar to the findings of some existing studies, such as Hartzmark and Sussman (2019) in which they document an insignificant return difference between low- and high-sustainability funds. However, this finding seems to be inconsistent with the stock-level finding that low ESG stocks deliver

[11]For each mutual fund, the FF5 alpha is estimate using 36-month rolling regressions.

[12]I also conduct a panel regression to investigate the relation between mutual fund ESG choice and fund returns, and I report the regression results in Table A.15. All the coefficients of fund ESG score are close to zero, and my inference that mutual fund ESG choice has no significant impact on fund performance remains unchanged.

greater short-term returns than high ESG stocks. One possible explanation for this inconsistency could be the argument of Berk and Green (2004) that outperformance of low ESG funds would be eliminated by new investor flow due to decreasing returns to scale.

In sum, I do not find convincing evidence that mutual fund ESG score is significantly related to fund return. This insignificant relation can be consistent with the equilibrium of Berk and Green (2004) who argue that performance-induced investor flow would eliminate any fund outperformance due to decreasing returns to scale. Additionally, some evidence exists that *Performance-based pay* has a small positive impact on fund return, but has no significant impact on fund's risk-adjusted performance.

2.5 Robustness and additional analyses

2.5.1 Manager compensation structure and fund ESG choice

In this subsection, I study the impact of manager compensation structure on fund ESG investment using the constructed manager compensation variables. To this purpose, I apply the same panel regression setting in Eq.(2.3) but replace flow sensitivity measures with manager compensation variables. All model specifications include Morningstar style and month fixed effects, and the regression results are reported in Table A.11. The first four columns present results of *Performance-based pay*, *Advisor-profit pay*, *AUM-based pay*, and *Deferred compensation* respectively, while the last column reports the regression result when all manager compensation variables are included.

Table A.11 shows that only *Performance-based pay* and *Advisor-profit pay* significantly affect mutual funds' choice on ESG investment. The impact of *Performance-based pay* has been discussed in Section 2.3.3. As reported in column (2) of Table A.11, the coefficient of *Advisor-profit pay* equals 0.098 and is statistically significant at the 1% level. This suggests that funds that tie manager compensation to overall profits of investment advisors invest more in firms with good ESG ratings. One possible interpretation for the positive relation is that managers with *Advisor-profit pay* care less about fund performance as they are able to receive a fraction of investment advisor profits, which is generally a percentage of fund assets and is not directly linked to fund performance. As a result, the managers are less motivated to deliver good return performance. Instead, they pay more attention to ESG investment since funds with better ESG profile receive more investor flow and are able to charge higher fees, as documented in Hartzmark and Sussman (2019) and Cao, Titman, Zhan, and Zhang (2020). The coefficients of *Performance-based pay* and *Advisor-profit pay* remain their significance when I include all variables of manager compensation structure in the regression.

In summary, *Performance-based pay* (*Advisor-profit pay*) makes portfolio managers more (less) incentivized to focus on fund performance. From opposite directions, my findings regarding *Performance-based pay* and *Advisor-profit pay* are both consistent with Hypothesis 2.

2.5.2 flow-ESG score sensitivity funds: skills vs. clientele effect

In Section 2.3.2, I have shown that mutual fund whose investor flow is more sensitive to its ESG profile exhibits higher ESG scores in the future. Given this finding, I now explore why some investors allocate more capital to funds with high flow-ESG score sensitivity in this subsection. One potential explanation is that funds with high flow-ESG score sensitivity have skills in picking ESG stocks with better performance, while an alternative explanation is that such funds could attract capital from certain clients (e.g., investors with strong social preferences).

To test these two stories, I examine whether funds with high flow-ESG score sensitivity hold outperforming high ESG stocks. To this purpose, I perform Fama-MacBeth regressions of holdings-based returns of high ESG stocks on fund flow-ESG score sensitivity. Specifically, I focus on fund holdings of high ESG stocks only, and calculate fund i's holdings-based return in quarter t as the value-weighted return of high ESG stocks held by fund i in this quarter, using stock returns in quarter t and fund i's stock holdings at the end of quarter $t-1$. Under this setting, the fund skills explanation suggests a significantly positive relation between the holdings-based returns and flow-ESG score sensitivity. However, the insignificant negative coefficients of flow-ESG score sensitivity (reported in the first two columns of Table A.12) do not support this story. As an additional test, each month I rank mutual funds into quintiles based on values of flow-ESG score sensitivity, and construct a dummy variable *I(high flow-ESG score sensitivity)* that equals one if a fund belongs to the highest quintile group and zero otherwise. Then I replace flow-ESG score sensitivity with the dummy variable *I(high flow-ESG score sensitivity)* in the regression to check whether there exists a nonlinear relation between the holdings-based returns and flow-ESG score sensitivity. The corresponding results are reported in the last two columns of Table A.12, and they again do not support the fund skills explanation. Overall, the findings suggest that a clientele effect is more likely to account for the existence of high flow-ESG score sensitivity funds.

2.6 Conclusion

In this paper, I examine whether mutual fund manager compensation has any impact on fund's choice of ESG investing. Using investor flow as an implicit incentive of manager compensation, I document that mutual funds with lower flow-performance sensitivity or higher flow-ESG score sensitivity are associated with greater ESG investment. Moreover, funds that explicitly link manager compensation to investment performance exhibit lower portfolio ESG scores. The connection between manager compensation and ESG investment cannot be explained by fund investment horizon. Overall, the findings provide evidence that managers consider pecuniary benefits when they make decisions on ESG investment. Furthermore, I investigate whether mutual funds' financial performance is related to ESG choice. I find limited evidence of return difference across funds with varying ESG levels, which can be consistent with the theoretical model of Berk and Green (2004).

My novel analysis of mutual fund ESG choice, from the perspective of manager compensation, is important and provides evidence that managers' pecuniary benefits can have a significant impact on their decisions on ESG investment. This finding has important implications on the design of manager compensation contracts. For future research, it would be interesting to investigate whether the documented relation between manager compensation and fund ESG choice is present in a global setting.

3. DO INVESTORS CARE ABOUT TAIL RISK? EVIDENCE FROM MUTUAL FUND FLOWS

3.1 Introduction

Understanding investors' risk preference is essential to finance research. Since it is not directly observable, one common approach is to examine revealed preference through investor behavior. For this purpose, the mutual fund industry is an attractive setting to detect investor attitude. As of 2019, US mutual funds manage nearly $18 trillion with about 45% of households owning fund shares (ICI Fact Book). More importantly, substantial fluctuations in investor flows exist across individual funds, providing ample opportunities to examine investor behavior. Indeed, a large literature has linked investor flows to fund performance.[1] As Berk and van Binsbergen (2016) point out, however, while flows strongly correlate with risk-adjusted alphas, what drives the fraction of flows unrelated to traditional beta risks is still an open question and the answer can be “highly informative about how risk in incorporated into asset prices" (p. 19). In this paper, we investigate the relation between fund flows and tail risk as one potential driving factor of investor decisions.

Tail events with extreme negative realizations occur more often than prescribed by normality in stock markets.[2] The uncertainties associated with such events generate tail risk. There has been growing interest in examining the economic impacts of tail risk that differs from traditional risk metrics, such as the CAPM beta. Several papers present pioneering evidence that tail risk significantly predicts stock returns in both cross-section and time-series (Kelly and Jiang, 2014; Bali, Cakici, and Whitelaw, 2014). These findings suggest that investors may well be averse to tail risk and require a compensation for bearing the risk. However, there has been no *direct* evidence

[1] A partial list of the papers on the flow-performance relation in mutual funds includes Ippolito (1992), Chevalier and Ellison (1997), Sirri and Tufano (1998), Zheng (1999), Del Guercio and Tkac (2002, 2008), Wermers (2003), Huang, Wei, and Yan (2007), Lou (2012), Berk and van Binsbergen (2016), Barber, Huang, and Odean (2016), Chen and Qin (2017), and Goldstein, Jiang, and Ng (2017).

[2] For example, the stock market crash on the Black Monday of 1987 (October 19) had a single-day negative realization over 20 sigma away from the historical mean, which would occur once over a time period at cosmological scales if stock market returns followed a normal distribution. See Kindleberger and Aliber (2011) for narratives of many market crashes in history.

on investor attitude toward tail risk. Our study fills this gap by studying whether mutual fund investors care about tail risk in their decision-making.

In our setting, tail risk is defined as fund return's comovement with the stock market during the market's tail events relative to normal times. Empirically, we measure the risk by tail beta for each fund in each month using a rolling-window regression coefficient that captures the fund's market exposure in tail events in excess of its average market exposure. Our inference is robust to using alternative measures. Following the mutual fund literature, we compute monthly investor flows as the net money inflows to the fund, i.e., change of fund size after accounting for fund return over the month. Our main analysis is to test whether and how fund flows are responsive to tail risk in the cross-section of mutual funds.

From a sample of 3,850 equity mutual funds with around 445,000 fund-month observations during the period January 1991–June 2020, we obtain a rich set of empirical results. First, we document a large heterogeneity in tail risk across individual funds. For example, the tail beta at the top 10% cutoff is 0.221, versus -0.145 at the bottom 10% level. Relative to the average market beta being around one among the mutual funds, such a difference in tail risks is economically substantial. To address the effect of nonnormality in the cross sectional distribution of tail risk among individual funds, we follow Kosowski, Timmermann, Wermers, and White (2006) to use a bootstrap approach to analyze fund-level tail risk. The result suggests that a sizeable fraction of mutual funds possesses tail beta, positive or negative, that cannot be attributed to pure luck. Thus, the wide variation in tail risk provides an ideal setting to investigate the flow-tail risk relation in the mutual fund industry.

Second, we find strong evidence that mutual fund investors do care about tail risk. The result from Fama and MacBeth (1973) regressions reveals a negative sensitivity of fund flows to tail beta consistent with investors' aversion to tail risk. On average, a one standard deviation increase in tail beta in the cross section is associated with a decrease of fund flow by about 12 basis points (t-statistic = 3.11) per month, or about 1.44% per year. Thus, the flow-tail risk relation is both economically and statistically significant. The effect remains significant after we control for lagged fund flow, fund performance (raw return and risk-adjusted return), as well as fund characteristics (such as fund size and expense ratio). This inference is robust to the choice of asset pricing models based on which tail beta is estimated, including the CAPM, the Fama-French-Carhart four-factor model, and the Fama-French five-factor model. We also perform panel regressions of fund flows on tail risk with controls of not only fund-specific variables but also aggregate market conditions. The panel regressions provide consistent evidence that fund flows are negatively sensitive to tail risk.

Finally, we investigate the economic mechanism underlying the flow-tail risk relation. Motivated by Guiso, Sapienza, and Zingales (2018) who find that fear accounts for the time variation of investors' risk aversion, we perform analysis using terrorist attacks and COVID-19 as shocks to investors' fear level. Consistent with the idea that terrorism infuses fear to investors, Wang and Young (2020) find large money withdrawals from equity mutual funds after major terrorist attacks. Different from their analysis of aggregate fund flows, we examine investor flow sensitivity to tail risk in the cross section of mutual funds after terrorist events. Furthermore, we examine the change of the flow-tail risk sensitivity surrounding COVID-19. In such tests, we define February and March 2020 as the onset of the pandemic in the United States. Our hypothesis is that due to elevated risk aversion, investor flows will respond to tail risk in a more sensitive way following terrorist activity and the start of COVID-19. Consistent with the hypothesis, we find that mutual funds with high tail-risk experience significantly larger fund outflows than those with low tail-risk, following the months with salient terrorist attacks and during the onset of COVID-19. In particular, the flow-tail risk sensitivity during the onset of COVID-19 is about 4.5–10 times as large as the average flow-tail risk sensitivity in other periods. Therefore, these findings suggest that investor behavior in response to tail risk can be explained by fear-induced risk aversion.

Our paper contributes to three distinct strands of literature. First, our paper advances the understanding of how investor flows are determined in mutual funds. Prior research (e.g. Chevalier and Ellison, 1997; Sirri and Tufano, 1998) shows that fund investors chase past performance. Zheng (1999) finds that mutual fund flows can predict future fund performance in the cross section, suggesting information-based investment decisions. Berk and van Binsbergen (2016) and Barber, Huang, and Odean (2016) examine the sensitivity of mutual fund flows to alternative performance metrics such as the CAPM alpha and multi-factor alphas. While these performance metrics use various risk adjustments in explaining fund flows, the focus of our paper on tail risk is new in the literature.

Second, we present direct evidence that investors care about tail risk in capital allocation. Starting from Kahneman and Tversky (1979), there has been mounting evidence that investors are loss averse. Relatedly, we show that mutual fund investors direct money flows in response to left-tail risk in the cross section, even after controlling for fund returns. This finding also provide micro-evidence based on investor behavior to the notion that tail risk enters the stochastic discount factor and serves as a priced risk (Kelly and Jiang, 2014; Bali, Cakici, and Whitelaw, 2014; Chabi-Yo, Ruenzi, and Weigert, 2018).[3] Hence, our paper complements these studies to show that nonnormality of stock returns together with investor aversion to tail losses gives rises to the priced tail risk.

Finally, our study relates to how investor's emotional attitude affects their risk aversion. Time-varying risk aversion has long been recognized in asset pricing models (e.g., Constantinides, 1990; Campbell and Cochrane, 1999). Recently, Guiso, Sapienza, and Zingales (2018) argue that the variation in investor risk aversion surrounding the 2008-2009 crisis is more likely caused by changes in fear level rather than wealth.[4] Based on aggregate flows of the mutual fund industry, Wang and Young (2020) provide further evidence that fear increases aggregate risk aversion. Extending the analysis to the cross section of mutual funds, we show that mutual funds with higher tail risk experience more severe money outflows following terrorist attacks. Thus, our result points to fear-induced risk aversion, instead of wealth changes, as the underlying mechanism of the rela-

[3]It is worth noting that tail risk, emphasizing large negative realizations, differs from downside beta (e.g., Bawa and Lindenberg, 1977; Ang, Chen, and Xing, 2006) both conceptually and empirically. Conceptually, tail risk focuses on return comovement when left-tail events occur rather than when market returns are below the mean/median or zero. Empirically, Bali, Cakici, and Whitelaw (2014) and Chabi-Yo, Ruenzi, and Weigert (2018) show that the effects of tail risk on stock returns are significantly different from those of downside beta.

[4]In an earlier study, Brunnermeier and Nagel (2008) show that wealth changes do not affect US households' portfolio allocation to risky assets.

tion between tail risk and investor flows.

The rest of the paper is organized as follows. Section 3.2 introduces the measures of tail risk and the sensitivity of fund flows to tail risk. Section 3.3 describes the data. In Section 3.4, we present main results. Section 3.5 discusses the test using terrorist attacks and the COVID-19 as exogenous shocks to the investor fear level. Section 3.6 provides robustness checks and additional analysis. Finally, Section 3.7 concludes.

3.2 Measuring the sensitivity of fund flows to tail risk

In this section, we first describe the measure of tail risk based on monthly mutual fund returns. Then, we discuss how to capture the sensitivity of subsequent fund flows to tail risk in the cross section of mutual funds.

3.2.1 The tail risk measure

For each fund, its time-varying tail risk is defined as the difference between the fund's market exposure in months when the stock market experiences left-tail realizations and the fund's average market exposure in the other months over a rolling-window period. Specifically, we can express the tail risk using the following time-varying market beta:

$$\beta_t = \beta_0 + \beta^{Tail} I\left(r_{m,t} < h\right), \tag{3.1}$$

where r_m is excess market return over the risk-free rate. h is the left-tail return threshold, such as the 5th percentile in the monthly return distribution of the market portfolio. $I(\cdot)$ is an indicator function that equals one if the excess market return falls below the threshold and zero otherwise. β_0 denotes market exposure in normal non-tail months. The tail beta β^{Tail} captures tail risk as abnormal exposure to the market when the market is in the left-tail state.

To empirically measure tail beta for mutual funds, we use a regression analysis by substituting the dynamic beta in Eq.(3.1) into an asset pricing model such as the CAPM as follows.

$$\begin{aligned} r_{i,t} &= \alpha + \beta_t r_{m,t} + \varepsilon_{i,t} \\ &= \alpha + \beta_0 r_{m,t} + \beta^{Tail} r_{m,t} I\left(r_{m,t} < h\right) + \varepsilon_{i,t}. \end{aligned} \tag{3.2}$$

From the regression, we obtain the measure of time-varying tail risk for individual mutual funds over each rolling window.[5] For our empirical tests, we set the length of the rolling window to 60 months up to the current month and require at least 50 non-missing monthly observations during the window period. Our inference is robust to other window lengths such as 48 months.

Performing the above regression to each mutual fund in rolling windows produces a large cross section of tail betas for the funds over the sample period. Compared with existing tail risk measures based on daily stock returns, our tail beta measure from monthly fund returns is well suited for analyzing mutual fund flows. First, since monthly mutual fund return data are more readily available than daily data, the measure can be obtained for a longer period and a more representative mutual fund sample. Second and more importantly, existing research on mutual funds has focused on fund flows at monthly (or even lower) frequency due to the fact that investors may not monitor their fund investment on a daily basis. Therefore, following the literature, our evidence on the flow-tail risk relation can be compared directly with the prior findings on the flow-performance relation.

3.2.2 Fund flow sensitivity to tail risk

The next measure required for testing fund flow sensitivity to tail risk is mutual fund flows. Following the literature (e.g., Chevalier and Ellison, 1997; Sirri and Tufano, 1998), we calculate monthly net fund flows (i.e., the amount of inflows in excess of outflows) for each fund as follows:

$$Flow_{i,t+1} = \frac{TNA_{i,t+1} - TNA_{i,t} \cdot (1 + R_{i,t+1})}{TNA_{i,t}}. \tag{3.3}$$

[5]A similar regression has been used in Chen (2011) and Chen, Dai, and Sorescu (2020) for other purposes in different settings than mutual funds.

where $TNA_{i,t+1}$ is the total net assets (i.e., fund size) of fund i at the end of month $t+1$, and $R_{i,t+1}$ is the fund return over month $t+1$. Thus, the fund flow measure captures the net change of fund size from one month end to the next month end, after accounting for fund return over the month. In our analysis, we winsorize investor flows at the top and bottom 1% levels to remove the effect of outliers. This treatment also mitigates the impact of fund mergers and splits that mechanically result in drastic fund flows (see Huang, Wei, and Yan, 2007).

$$Flow_{i,t+1} = \lambda_0 + \lambda_1 \hat{\beta}^{Tail}_{i,t} + \lambda_2 Flow_{i,t} + \lambda_3 Perf_{i,t} + \kappa' \mathbf{x_{i,t}} + e_{i,t}, \tag{3.4}$$

$\hat{\beta}^{Tail}$ is the estimated fund tail beta, $Flow_{i,t}$ is the lagged investor flows, $Perf_{i,t}$ is either fund i's raw return or risk-adjusted return (i.e., alpha) in month t, and $\mathbf{x}$ is a set of fund characteristics (i.e., fund TNA, expense ratio, and a load fund dummy). The coefficient λ_1 captures how sensitive investors respond to fund tail risk. A negative λ_1 indicates that investors are averse to tail risk, since they allocate more capital to those funds with less tail risk. In Section 3.4, we analyze the flow-tail risk relation using both Fama-MacBeth regression and panel regression.

3.3 Data

In this section, we discuss the mutual fund dataset used in the paper, and provide summary statistics for our sample of US domestic equity mutual funds.

3.3.1 Mutual funds

Our mutual fund sample is from the CRSP Survivor-Bias-Free US Mutual Fund Database that provides data of open-ended mutual funds. The CRSP database provides mutual fund data at the share-class-level. While different share classes of a mutual fund could be offered to clients with differential needs, they tend to hold the same investment portfolio with the only difference being the fee structure. Therefore, for each mutual fund with multiple share classes, we aggregate all share classes (e.g., retail and institutional share classes) to the fund level and compute value-weighted fund returns and fund characteristics. We restrict our sample to actively managed equity mutual funds, since tail risk, by construction, captures time-varying return comovement between mutual funds and the stock market. As a result, we exclude balanced funds, bond funds, sector funds, index funds, and ETFs. To mitigate data biases associated with incubation period (Evans, 2010), we restrict our sample to funds with total net assets (TNA) of at least \$10 million and age of more than one year.

The final sample contains 3,850 individual mutual fund and approximately 445,000 fund-month observations over the period from January 1991 to June 2020. Table B.1 provides summary statistics of fund-month observations in our sample. The mutual funds offer an average monthly net-of-fee return of 0.71% and a slightly negative average monthly risk-adjusted return (i.e., alpha) estimated from conventional asset pricing models. Specifically, the monthly CAPM alpha, the Fama-French-Carhart four-factor alpha, and the Fama-French five-factor alpha are -0.02%, -0.07%, and -0.04%, respectively. While the average fund manages approximately \$1,365 million, the median fund is significantly smaller and manages around \$276 million, indicating a right skewness in fund size. Moreover, the average fund has an age of 172 months (14.3 years), and the median fund age is 142 months (11.8 years). Finally, the average fund in our sample charges an annual expense ratio of 1.19%, and approximately 51% of the funds receive either a front-end load or a rear-end load.

3.3.2 Investor flows

Fund flows are calculated using Eq.(3.3) each month for each mutual fund included in our final sample. Since the CRSP mutual fund database started to cover monthly total net assets (which is required to calculate fund flows) from 1991 onward, our sample starts from January 1991. As shown in Table B.1, the average fund experiences a monthly investor flow of -0.19% with a standard deviation of 6.91%. In addition, the interquartile range of investor flows is 2.20%, which indicates substantial variation in the cross section of fund flows. In general, these values are consistent with the literature on mutual fund flows.

3.4 Main results

In this section, we first show that there exists substantial variation in the cross section of mutual fund tail risk. We then present evidence of a negative association between fund flows and tail risk, under both Fama-MacBeth and panel regression settings.

3.4.1 Tail risk in the cross section

Tail risk for individual mutual funds is estimated using Eq.(3.2), where we choose 5% as the left-tail return threshold. The coefficient β^{Tail} captures fund-specific tail risk. A positive (negative) β^{Tail} indicates that the fund has higher (lower) market exposure during market left-tail events than during normal times. Table B.2 reports the cross-sectional distribution of fund tail beta based on the CAPM model.[6] The median tail beta is fairly close to zero at 0.03, but there is a wide difference across individual funds. The tail beta is -0.203 at the 5th percentile and 0.308 at the 95th percentile. Given that the average fund in our sample has a stock market beta of 0.97, this range of tail beta indicates substantial heterogeneity across individual mutual funds in terms of their risk exposure during market tail events. More than 40% of mutual funds in our sample have negative tail betas, suggesting that a sizeable fraction of actively managed funds could lower their market exposure ahead of market left-tail events.

To address the issue that the cross section of tail beta among mutual funds are not normally distributed, we follow Kosowski, Timmermann, Wermers, and White (2006) and perform bootstrap analysis to infer the statistical significance of tail risk. In Table B.2, the empirical p-values indicate the chances that the estimated tail beta, or its t-statistic, can be attributed to sampling variability, i.e., pure luck. As shown in the table, regardless of whether we examine tail beta or its t-statistic, about 20% of mutual funds have significantly negative tail risk, i.e., exhibiting lower market exposure when the stock market falls within its left-tail, which cannot be explained by pure luck as evidenced by close to zero empirical p-values. On the other hand, about 30% mutual funds show significantly positive tail betas. The existence of low tail risk is akin to the existing

[6] As a robustness check, we also estimate mutual fund tail beta with the Fama-French-Carhart four-factor model and the Fama-French five-factor model. Our inference remains unchanged.

findings that mutual funds have reduced market beta during market downturns (Kosowski, 2011; Polkovnichenko, Wei, and Zhao, 2019). Nonetheless, unlike these studies that examine the aggregate mutual fund risk-taking and flows, we focus on the cross sectional relation between fund flows and tail risk at the individual fund level.

To summarize, we show evidence that tail risk varies substantially across individual mutual funds, and a sizeable fraction of funds exhibit statistically and economically significant (positive or negative) tail beta. This large heterogeneity of tail risk in mutual funds provides an ideal setting to understand how investors respond to differential levels of tail risk.

3.4.2 Sensitivity of investor flows to tail risk

Next, we examine the sensitivity of investor flows to tail risk based on the cross-sectional regression outlined in Eq.(3.4), in which the key explanatory variable is mutual funds' tail beta. To estimate tail beta, we consider three different models, namely the CAPM, the Fama-French-Carhart (FFC) four-factor model, and the Fama-French five-factor (FF5) model. For each model, we perform rolling regressions for each individual fund with a 60-month window, and retrieve the estimated tail beta.

Table B.3 reports the results of Fama-MacBeth regressions. Specifically, we perform the cross-sectional regression of fund flows on tail beta (along with control variables) once for each month, and then the average value of the coefficient λ_1 over time reveals the flow-tail risk relation. We adjust the standard errors using the Newey and West (1987) approach. As shown in the table, the negative λ_1 shows an aversion to tail risk, that is, investors allocate more (less) capital to those mutual funds that are less (more) subject to tail risks. The negative relation between tail risk and investor flows is statistically significant at the 1% level. In term of economic significance, a one standard deviation increase in tail beta in the cross section would be associated with a decrease of fund flow by about 12 basis points (0.215×0.557) per month, or about 1.44% per year, based on the tail beta estimated from the CAPM. Similarly, moving from the 10th percentile (-0.145) to the 90th percentile (0.221) of tail risk (see Table B.2), the investor flows would reduce by an average of 20 bps (0.366×0.557) per month or about 2.4% per year. Given the average monthly fund flow of -0.19% over the sample period, this level of fund flow is economically significant. The negative flow-tail beta relation is robust to the choice of asset pricing model. Consistent with existing research, funds with better performance tend to attract more investor flows.

We present the results of panel regressions in Table B.4. The panel regressions lead to a similar finding to that from the Fama-MacBeth regressions that investor flows are negatively sensitive to tail beta in the cross section of mutual funds. The sensitivity appears both economically and statistically significant under this alternative regression method. In addition, considering that investor flows may respond to macroeconomic conditions, we follow Chen and Qin (2017) to include in the panel regression the following macroeconomic variables: industrial production growth, inflation rate, term spread (return spread between long-term and short-term government bond indexes), and default spread (return spread between high-yield bond index and the intermediate government bond index). Some macroeconomic variables exhibit modest explanatory power for investor flows even after we control for fund performance and tail risk. For example, industrial production and inflation are positively associated with subsequent fund flows.

Thus far, the results have shown a strong and robust inverse relation between fund tail beta and subsequent investor flows. This relation is distinct from the well-known flow-performance sensitivity in mutual funds, as we have explicitly controlled for the effect of fund performance on flows. Overall, our evidence suggests that investors are averse to tail risk, and this finding also complements the recent result that tail risk is priced in the stock market.

3.5 Time-Varying Tail Risk Aversion: Evidence from Terrorist Attacks and COVID-19

In this section, we explore the root behind the flow-tail risk relation. Fund investors rebalance portfolios and allocate money into and out of mutual funds for many reasons. Both theoretical and empirical studies show that fund investors chase past fund performance (e.g., Chevalier and Ellison, 1997; Sirri and Tufano, 1998; Berk and Green, 2004). As discussed above, however, chasing performance is unlikely to account for the systematic relation between fund flows and tail risk, since our tests have controlled for fund performance. Instead, our evidence is more consistent with an aversion to tail risk. Moreover, the tail risk aversion varies over time, as suggested by the changing coefficient in the Fama-MacBeth regression (see Figure B.1). What explains the time variation? The answer to this question can help understand the source of the aversion to tail risk. Guiso, Sapienza, and Zingales (2018) suggest that the increase in investor's risk aversion, inferred from their portfolio decisions, following the 2008-2009 crisis are more likely caused by emotional shock (e.g., fear) rather than wealth changes. In this section, we investigate two shocks that plausibly impact the investor fear level: terrorist attacks and the recent COVID-19 crisis.

3.5.1 Terrorist attacks and the flow-tail risk sensitivity

We first examine how terrorist activity affects the flow response to tail risk in the cross-section of mutual funds. Wang and Young (2020) find significant capital outflows from equity mutual funds after serious terrorist activity. Here, using terrorist attacks as exogenous shocks to fear among investors, we examine whether fear can explain the time-varying sensitivity of investor flows to tail risk in the cross section of mutual funds. Our hypothesis is that following a salient terrorist attack, investors will become more averse to tail risk and consequently investor flows will show greater sensitivity to tail beta (i.e., a more negative association with tail beta in the cross section).

To test the effect of terrorist attacks on the fund flow-tail risk relation, we check how investor flows respond to the interaction term of tail risk and the number of monthly terrorist attacks in the panel regression setting. We follow Wang and Young (2020) to obtain monthly data of terrorist attacks that occurred in the US and extend their sample through 2018 based on the Global Terrorism Database (GTD) and the International Terrorism: Attributes of Terrorist Events (ITERATE) database.[7] Figure B.2 plots the number of terrorist attacks that happened in the US in each month over our sample period. Although there is no clear time trend in the number of terrorist attacks, the figure shows substantial variation in terrorist activity over time which would induce different levels of fear among investors according to existing research. As we have included year fixed effects in this panel regression, the test focuses on how within-year variation in terrorist attacks impacts the flow-tail risk relation.

[7] See Wang and Young (2020) for details about the two databases.

Table B.5 reports the regression results. First, the coefficient of fund flows on terrorist attacks are significantly negative across the four alternative regression specifications (due to different asset pricing models used to estimate tail beta and fund performance). This shows that on aggregate money flows out of equity mutual funds following serious terrorist attacks, consistent with the finding of Wang and Young (2020). More importantly, the coefficient of the interaction term between tail beta and terrorist attacks is negative and statistically significantly at the 5% level. This result suggests that mutual funds with higher tail betas (i.e., larger market exposure in market tail events) experience greater fund outflows following terrorist attacks relative to those with lower tail betas, which provides support to our hypothesis.

In addition, We explore whether the overall market condition has any effect on the fund flow-tail risk relation. To this end, we examine the response of fund flows to the interaction term of tail risk and three candidate variables of market condition, namely the stock market return (Mkt), the CBOE volatility index (VIX), and a dummy variable that equals one if the previous month falls into the NBER recession period. The coefficient of the interaction term captures potential time variation in the flow-tail risk relation attributable to the market condition. For example, since the main effect of flow-tail beta is negative, a significant negative coefficient of the interaction term between tail beta and NBER recession would indicate greater sensitivity of investor flows to tail beta following a period of recession. Similarly, for the overall stock market return, we use an interaction term between tail beta and a dummy variable that equals one if the excess market return is below zero such that a negative coefficient of the interaction term indicates increased sensitivity of investor flows to tail beta. We report the panel regression results in Table B.14. In general, none of these coefficients of the interaction term are significantly different from zero. This finding suggests that the variation in investor's aversion to tail risk is less likely to stem from a wealth effect but more likely to be affected by fear.

3.5.2 COVID-19 and the flow-tail risk sensitivity

The outbreak of COVID-19 in the US in early 2020 (though it started earlier outside the US) caused a nation-wide health-related concern. We conjecture that the elevation of fear at the onset of the pandemic can also affect investor's attitude toward tail risk. In the setting of mutual funds, the onset of COVID may prompt investors to become more sensitive to tail risk, if negative sentiment is indeed behind risk aversion, as argued by Guiso, Sapienza, and Zingales (2018).

Employing the COVID-19 as another exogenous shock to investor fear, we perform additional analysis on whether the time-variation in flow-tail risk relation can be explained by investor fear. Using the same panel regression setting as in Table B.5, we perform regressions of fund flow on tail beta and a COVID-19 dummy variable. Similar to concurrent studies, we set the value of the COVID-19 dummy variable to one if the month is either February or March of 2020.[8]

Table B.6 reports the corresponding results. Across all the four regression specifications, the coefficients on tail beta remain significantly negative, indicating that mutual fund flows are inversely related to tail risk in the cross-section. Furthermore, the coefficients on the COVID-19 dummy variable are significantly negative. This suggests that equity mutual funds experienced large capital outflows at the onset of COVID-19, consistent with the finding of Pástor and Vorsatz (2020). More importantly, the interaction term between tail beta and the COVID-19 dummy variable displays negative regression coefficients that are statistically significantly at the 1% level. In other words, mutual funds with greater tail risk suffer larger fund outflows at the onset of COVID-19 than those with smaller tail risk. The economic magnitude appears to be substantial. For example, in the test using the CAPM alpha as the performance measure, the coefficient on tail beta is -0.208 (t-value = 2.74) while the coefficient on the interaction term is -1.928 (t-value = 3.77), suggesting a sharp increase of the flow-tail risk sensitivity during the onset of COVID-19. Depending on the performance measure used in the tests, the flow-tail risk sensitivity during the onset of COVID-19 is about 4.5–10 times as large as the sensitivity in other periods. In addition, the R-squared of the panel regression, using the CAPM alpha measure, has increased from 0.034 in Table B.4 without including the COVID-related variables to 0.114 with the COVID-19 effect. Similar evidence obtains from the other fund performance measures. Taken together, these results

[8]For example, Albuquerque, Koskinen, Yang, and Zhang (2020) use February 24 as their COVID-19 event date; Pástor and Vorsatz (2020) define the COVID-19 crash period as February 20 to March 23, 2020; and Ramelli and Wagner (2020) set February 24 and March 20 as the start and end of their "fever" period, respectively.

provide strong support to our hypothesis that fear-induced risk aversion accounts for the flow-tail risk sensitivity.

To sum, based on tests using terrorist activity and COVID-19, we find that the time variation in the flow-tail risk relation is significantly related to shocks to the investor fear level. These findings suggest that fear, as a negative emotion, is one important root of investors' aversion to tail risk.

3.6 Robustness and additional analyses

In this section, we first check the robustness of our inference to alternative measures of tail risk and fund performance. Then, we present additional evidence about the persistence of fund tail risk, time trend in the flow-tail risk relation, and potential difference in the flow-tail risk relation between retail funds and institutional funds.

3.6.1 Alternative tail risk measure

In this subsection, we consider an alternative tail risk measure of equity mutual funds and check the robustness of our finding on the relation between tail risk and fund flows. To this end, we adopt the measure of Kelly and Jiang (2014) and estimate fund tail risk (denoted KJ metric) with the following procedures. We first retrieve a common component of return tails from the cross section of daily returns of all common stocks traded on NYSE/AMEX/NASDAQ for each month.[9] Then we regress individual fund returns on the common tail component along with other risk factors, and use the factor loading on the common tail component as the estimate of fund's exposure to aggregate tail risk. Thus, mutual funds that load more heavily on the tail component are more sensitive to market's tail events and thus possess greater tail risk.

Using the 60-month rolling window regression, we estimate the KJ metric as a measure of tail risk and subsequently examine the relation between tail risk and fund flows using the Fama-MacBeth regression. As before, we control for fund characteristics and fund performance measure by raw return as well as alphas from with the CAPM, FFC, and FF5 models. Table B.7 presents the regression results, where the KJ metric is standardized for ease of interpretation. In particular,

[9]Please refer to Kelly and Jiang (2014) for more details on the estimation of the common tail component.

the coefficients in the first row indicate that a one standard deviation increase in the KJ metric leads to an outflow ranging from 14.2 to 17.6 basis points per month (also statistically significant at the 1% level) or about 1.7-2.1% per year, which is consistent with the finding from tail beta. This is not surprising, since a larger KJ metric captures greater exposure to aggregate tail risk, which is equivalent to a larger tail beta in Eq.(3.4). Therefore, the results in Table B.7 confirms the sensitivity of investor flows to tail risk, based on an alternative tail risk measure.

3.6.2 Additional fund performance measures

Now we check whether the negative flow-tail risk relation is robust to additional measures of fund performance. In earlier sections, we have used alphas estimated from conventional asset pricing models. Here, we consider three "model-free" performance measures, including the manipulation-proof performance measure (MPPM) proposed by Goetzmann, Ingersoll, Spiegel, and Welch (2007)), the Morningstar risk-adjusted return (MRAR), and Morningstar ratings.[10]

Each month, we calculate MPPM and MRAR for each mutual fund using its past returns with risk aversion parameter of three. Morningstar ratings are discrete variables offered at share-class-level, therefore, we calculate TNA-weighted ratings for mutual funds with multiple share classes, and generate a dummy variable that equals one if a fund has Morningstar ratings that is above the median across funds in each month. We apply the Fama-MacBeth regression setting in the analysis.

Table B.8 reports the regression results. We find that these alternative performance measures, including Morningstar ratings, are significantly related to fund flows, consistent with the results in Evans and Sun (2020) and Ben-David, Li, Rossi, and Song (2019). Similar to the results in Table B.3, however, the effect of fund performance on investor flows cannot subsume the sensitivity of flows to tail risk, suggesting that investors' aversion to tail risk goes over and above their care for fund performance judging by various performance measures.

[10]MRAR and Morningstar ratings are related as Morningstar ratings are assigned based on weighted MRAR calculated over different time horizons. For details, please refer to the Morningstar manual, which is available at `https://www.morningstar.com/content/dam/marketing/shared/research/methodology/771945_Morningstar_Rating_for_Funds_Methodology.pdf`.

3.6.3 Persistence of tail risk

In this subsection, we apply different time frames to examine persistence of the tail beta measure. To do so, each month we sort mutual funds into five groups based on values of their estimated tail betas, and then report the 1-year, 2-year, and 3-year transition matrix to check the persistence of fund tail beta. We report the results in Table B.9, where the numbers in the diagonal line show the percentage of funds that stay in the same group after the indicated time period. For example, the first number of the diagonal line in Panel A shows that 52.63% of the funds in group one remain in the same group after 12 months. That number decreases to approximately 32.43% as the time period extends to 36 months. In general, the numbers in the diagonal line are greater than the unconditional probability of 20%, especially for the two extreme tail beta groups. Taken together, the results in Table B.9 show evidence of strong persistence in fund tail beta.

3.6.4 Time trend in the flow-tail risk relation

In a recent paper, Dannhauser and Pontiff (2019) attribute recent changes to the flow-performance relation for active mutual finds to the trending emergence of passive investment vehicles such as exchange-traded funds. In this subsection, we check whether the flow-tail risk performance would exhibit any time trend. Specifically, we perform the cross-sectional regression of Eq.(3.4) each month, and store the coefficient of tail beta λ_1. The coefficient λ_1 captures the relation between fund tail risk and its subsequent investor flows for that month. As a result, we obtain the time series of the flow-tail risk relation in mutual funds. Next, we run a simple linear trend regression for the time-series of λ_1. As reported in Table B.13, the coefficient on the time variable is not significantly different from zero. Therefore, although the flow-tail risk relation is time varying, there is no evidence of a secular trend in the sensitivity of investor flows to tail risk.

3.6.5 Retail investors vs. institutional investors

So far, we have presented evidence suggesting that fear-induced risk aversion explains the observed negative relation between investor flows and tail risk in the cross section of mutual funds. An interesting question arises: could the sensitivity to tail risk differ between retail investors and institutional investors in mutual funds? It seems plausible, since retail investors are generally deemed less sophisticated than institutional investors. For example, Frazzini and Lamont (2008) show that retail investors tend to allocate capital to the funds that hold stocks with poor future performance. In our paper, we are interested in whether retail investors would be unsophisticated so as to not care about tail risk, in which case their flows would not be sensitive to the funds' tail risk. On the other hand, fear is basic human emotion that should be experienced by all types of investors, and hence the flow-tail risk relation is expected to hold for both retail and institutional investors. To empirically test for a possible difference, we repeat out analysis for retail funds and institutional funds separately. The classification of retail versus institutional funds is based on the indicator of share class type from the CRSP mutual fund data. In particular, we use the same Fama-MacBeth regression as in Section 3.4.

We report the regression results in Table B.10. The first four columns (Panel A) correspond to retail funds, with the coefficient on tail beta ranging from -0.51 to -0.60. The last four columns (Panel B) are for institutional funds, with the same coefficient ranging from -0.68 to -0.75. All of the coefficients on tail beta are statistically significantly at the 5% level. Thus, both retail and institutional investors show significant aversion to tail risk in mutual funds. Meanwhile, consistent with the earlier tables, the R-squared is generally small, similar to the observation of Berk and van Binsbergen (2016).

3.6.6 The determinant of tail beta

In this subsection, we examine the determinant of mutual funds' tail beta by checking whether the cross-sectional variation of tail beta comes from intentional or unintentional choices. In particular, we test whether tail beta is related to the activeness of mutual funds. We consider the two alternative measures of fund activeness: the active share measure of Cremers and Petajisto (2009) and the R-squared measure of Amihud and Goyenko (2013). For each mutual fund, active share measures the absolute difference in portfolio weights between a fund's holdings and its benchmark index. As a result, a larger value of active share indicates more active management of the fund. R-squared, as an alternative measure, is the R-squared of the fund's monthly returns with respect to risk factors. A smaller R-squared reveals that fund returns are less explained by systematic factors and suggests that the fund is actively managed instead of closely tracking a benchmark. Following Amihud and Goyenko (2013), we use $1 - R^2$ as the measure such that a larger value of $1 - R^2$ associates with greater fund activeness. In a similar fashion to the estimation of tail beta, we consider the CAPM, FFC model, and FF5 model to retrieve fund R-squared. For each model, we perform rolling regressions with a 60-month window. We obtain active share data from Antti Petajisto's website, which cover the period from 1980 to 2009.

Table B.11 reports the Fama-MacBeth regression results of both active share (in Panel A) and $1-R^2$ (in Panel B). The three columns in each panel correspond to regression results of the CAPM, the FFC model, and the FF5 model, respectively. We find that tail beta is significantly positively associated with fund activeness in the cross section. This finding holds with both activeness measures and across all the three asset pricing models.[11] Therefore, the relation between tail beta and fund activeness provides support to the notion that tail beta comes, at least partially, from the fund's intentional choice.

3.7 Conclusion

In this paper, we investigate investors' attitude toward tail risk through examining mutual funds. In particular, we observe how fund flows respond to the variation in tail risk across individual funds, with tail risk measured as tail comovement between fund return and the stock market return. From a sample of more than 3,800 mutual funds over the period from January 1991 to June 2020, we find strong evidence that investor flows are sensitive to tail risk, in that a high tail risk is associated with significantly lower subsequent fund flows in the cross section. This result is robust to controlling for fund performance and fund characteristics. Our evidence suggests that investors care about tail risk as a separate factor in the decision-making, over and above the impacts of fund performance.

Furthermore, we investigate the economic mechanism underlying the flow-tail risk relation. Since the relation survives controls of fund performance, it indicates that other factors than a wealth

[11] The magnitude appears particularly large for the tail beta estimated using the CAPM in comparison to those estimated from the other two asset pricing models. This suggests that tail beta estimated from the CAPM (with fewer risk factors) contains information that can be explained by fund activeness.

effect may play a role in explaining investors' aversion to tail risk. Using terrorist attacks as proxy for shocks to investors' fear level, we show that fund flows become increasingly sensitive to tail risk following terrorist events, suggesting that fear is one important source of the risk aversion to tail risk.

Taken together, our analysis of mutual fund investor behavior provides micro-evidence to the finding that tail risk is priced in equilibrium. For future research, it would be interesting to extend our investigation of US mutual fund investors' decision-making to other countries and explore country-level variation in investor attitude toward tail risk.

4. SUMMARY AND CONCLUSIONS

In this dissertation, I study the investment of institutional investors using mutual funds as a laboratory. In the first essay, “Why Do Good? ESG Investment in Mutual Funds", I examine the impact of manager compensation on managers’ choice of ESG investment. Using investor flow as an implicit incentive factor of manager compensation, I find that mutual funds with lower flow-performance sensitivity or higher flow-ESG score sensitivity tend to invest more in stocks with better ESG practices. Moreover, I observe that fund managers whose compensations are explicitly linked to fund financial performance invest less in high ESG stocks. These findings provide strong evidence to the argument that managers take pecuniary benefits into consideration when they make ESG investment decisions. This essay contributes to the literature by studying institutions’ ESG choice from a novel perspective, i.e., manager compensation, and my finding that pecuniary benefits can play a significant role in managerial decisions on ESG investmen is new in the literature.

In the second essay, “Do Investors Care About Tail Risk? Evidence from Mutual Fund Flows", coauthored with Yong Chen, we investigate whether investors care about tail risk among equity mutual funds. We measure tail risk as return comovement between mutual fund and the stock market during market distress, and find that mutual funds with higher tail risk are associated with lower subsequent investor flows even after controlling for fund performance and characteristics, which suggests that investors consider fund tail risk when they make decisions on capital allocation. Furthermore, using terrorist attacks and the COVID-19 as shocks to investors’ fear level, we document significantly more sensitive flow-tail risk relations following these shocks, and thus identify fear as one important source of tail risk aversion. This essay provides micro-evidence to the finding of priced tail risk in equilibrium. Extending our investigation of investors’ decision-making to other countries and exploring potential country-level heterogeneity in investors’ attitude toward tail risk would be interesting venues for future research.

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APPENDIX A

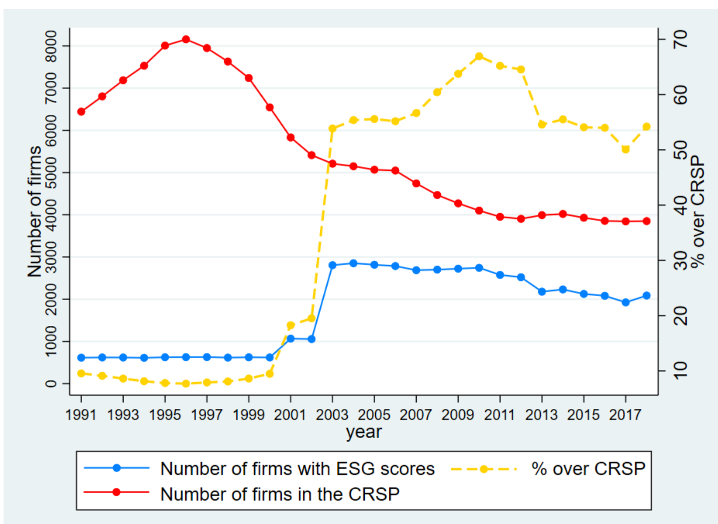
FIGURES, TABLES, AND APPENDIX FOR SECTION 2

A.1 Figures and Tables

Figure A.1. Coverage of firms with ESG scores

The blue and red solid lines in Panel A plot the number of stocks with ESG scores and the total number of common stocks in the CRSP universe. The dashed line plots the ratio (in percentage points) of number of stocks with ESG scores to number of stocks in the CRSP. The blue and red solid lines in Panel B plot the market value ($trillions) of covered firms and the total market value of CRSP. The dashed line plots the percentage of market value of covered firms relative to all firms in the CRSP. The stock-level ESG scores are from the MSCI ESG KLD STATS database which covers the period from 1991 to 2018.

Panel A: Number of covered firms in the CRSP universe



Panel B: Market value of covered firms relative to the CRSP universe

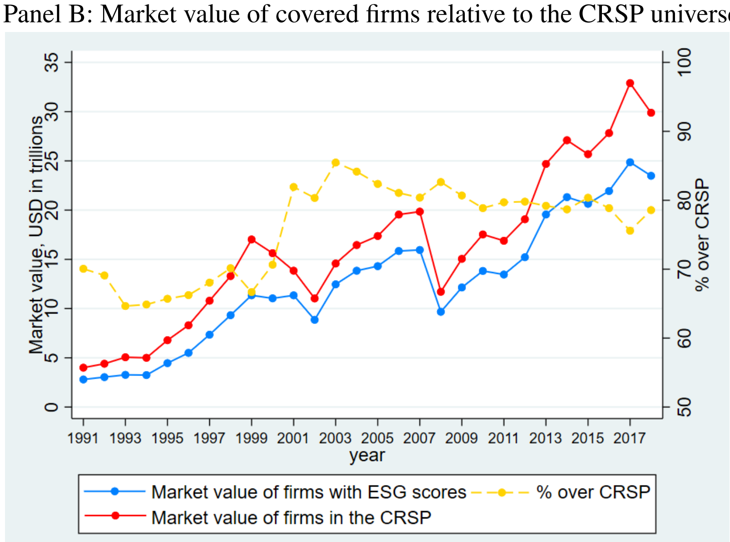
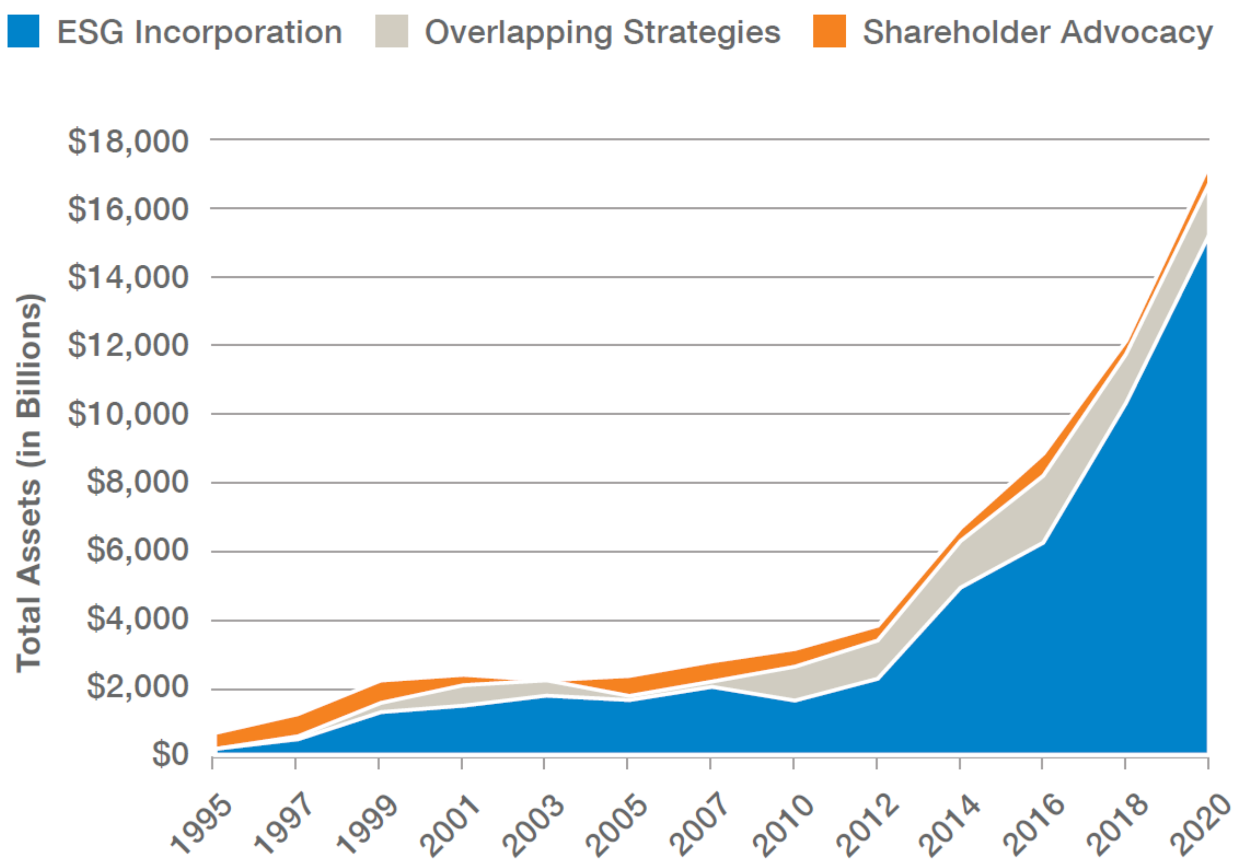


Figure A.2. ESG Investing in the United States 1995-2020

This figure plots the total assets ($billions) of the US ESG investment universe from 1995 to 2020. The blue or orange area represents the assets associated with ESG incorporation or shareholder advocacy, respectively. The gray area represents the assets associated with both strategies.



SOURCE: US SIF Foundation.

Figure A.3. Organizational structure of a mutual fund

This figure plots organizational structure of a mutual fund. Shareholders of a mutual fund elect the board of directors to monitor the fund's management and operations. The investment advisor, selected by the board of directors, handles day-to-day management of the fund and consequently receives advisory fees. As employees of the investment advisor, portfolio managers are responsible for portfolio allocation decisions and are compensated by the investment advisor.

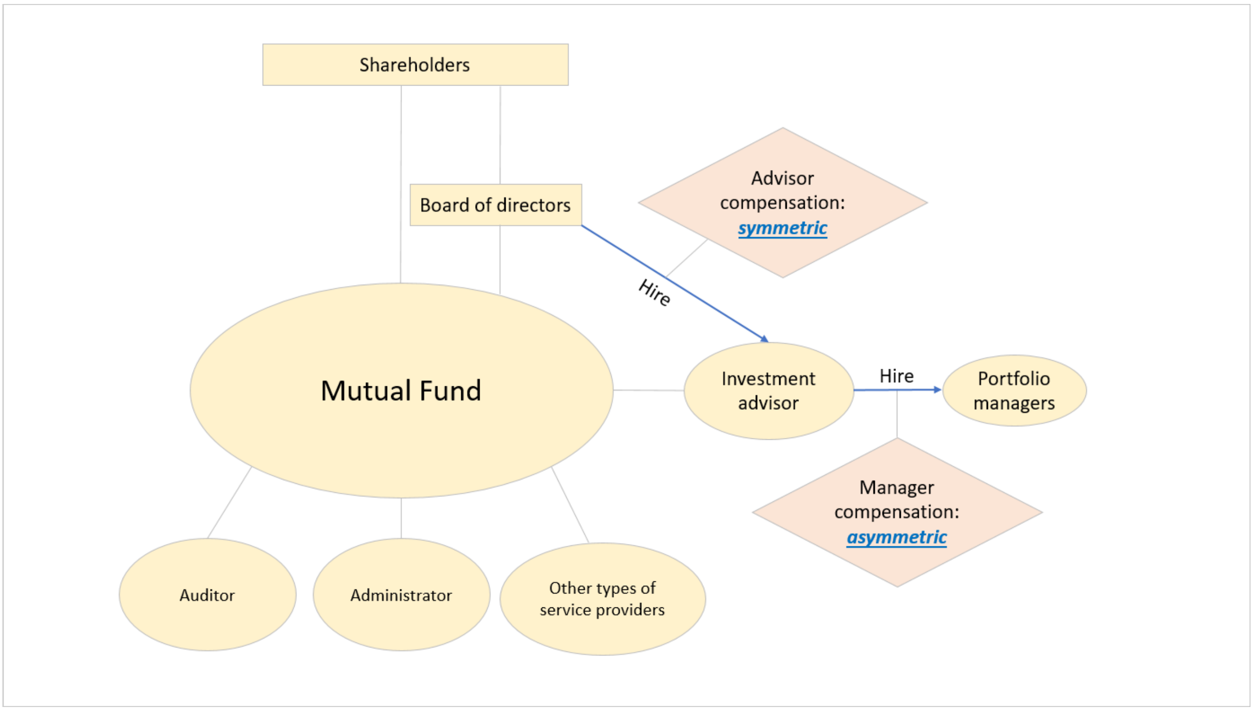


Figure A.4. Mutual fund ESG score and rankings of flow-performance sensitivity

Each month, mutual funds are sorted into quintiles based on the estimated flow-performance sensitivity measure in an increasing order such that group 1 (5) consists of funds with the smallest (largest) flow-performance sensitivity. This figure plots the average next-month ESG scores of funds included in each group.

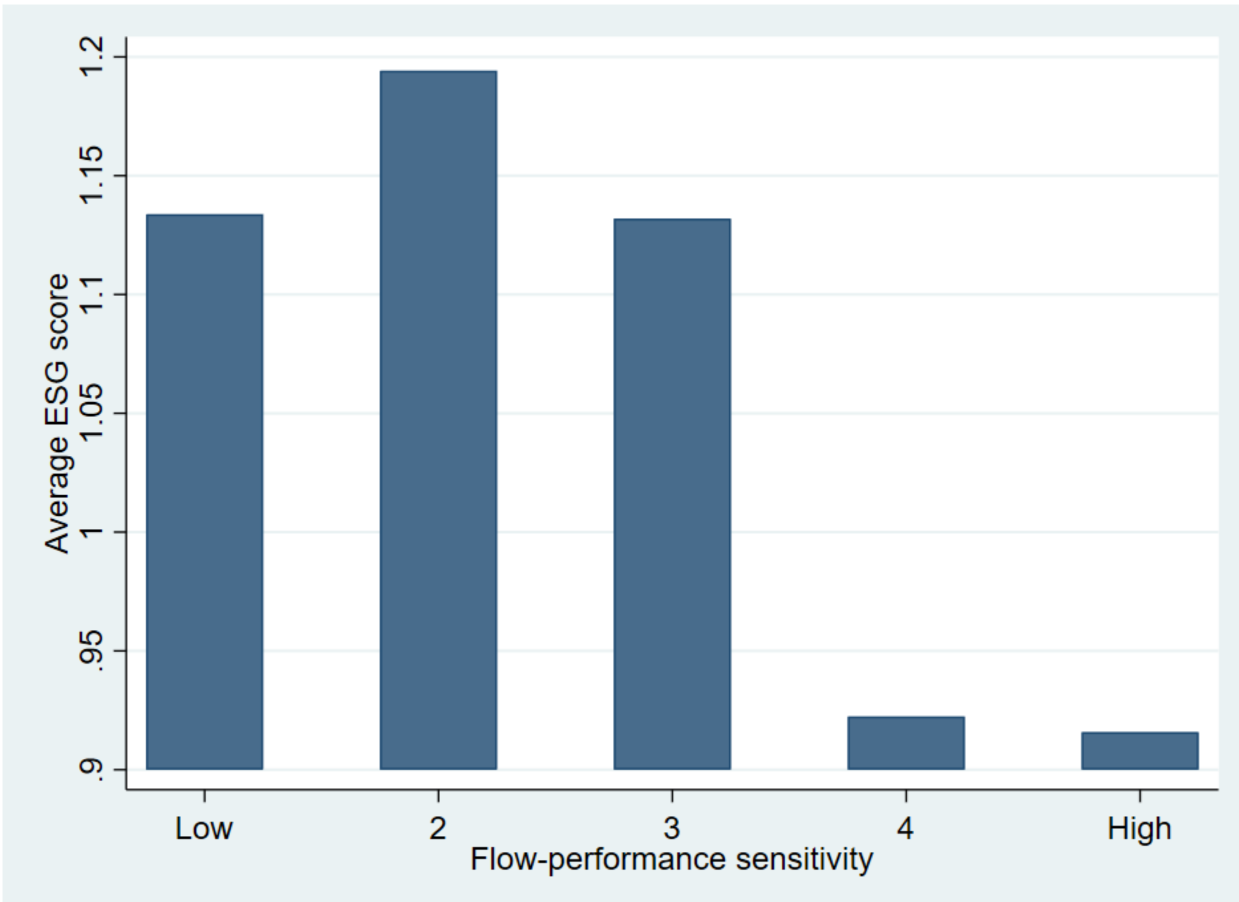


Figure A.5. Mutual fund ESG score and rankings of flow-ESG score sensitivity

Based on the estimated flow-ESG score sensitivity measure, each month mutual funds are sorted into quintiles in an increasing order such that group 1 (5) consists of funds with the smallest (largest) flow-ESG score sensitivity. This figure plots the average next-month ESG scores of funds within each group.

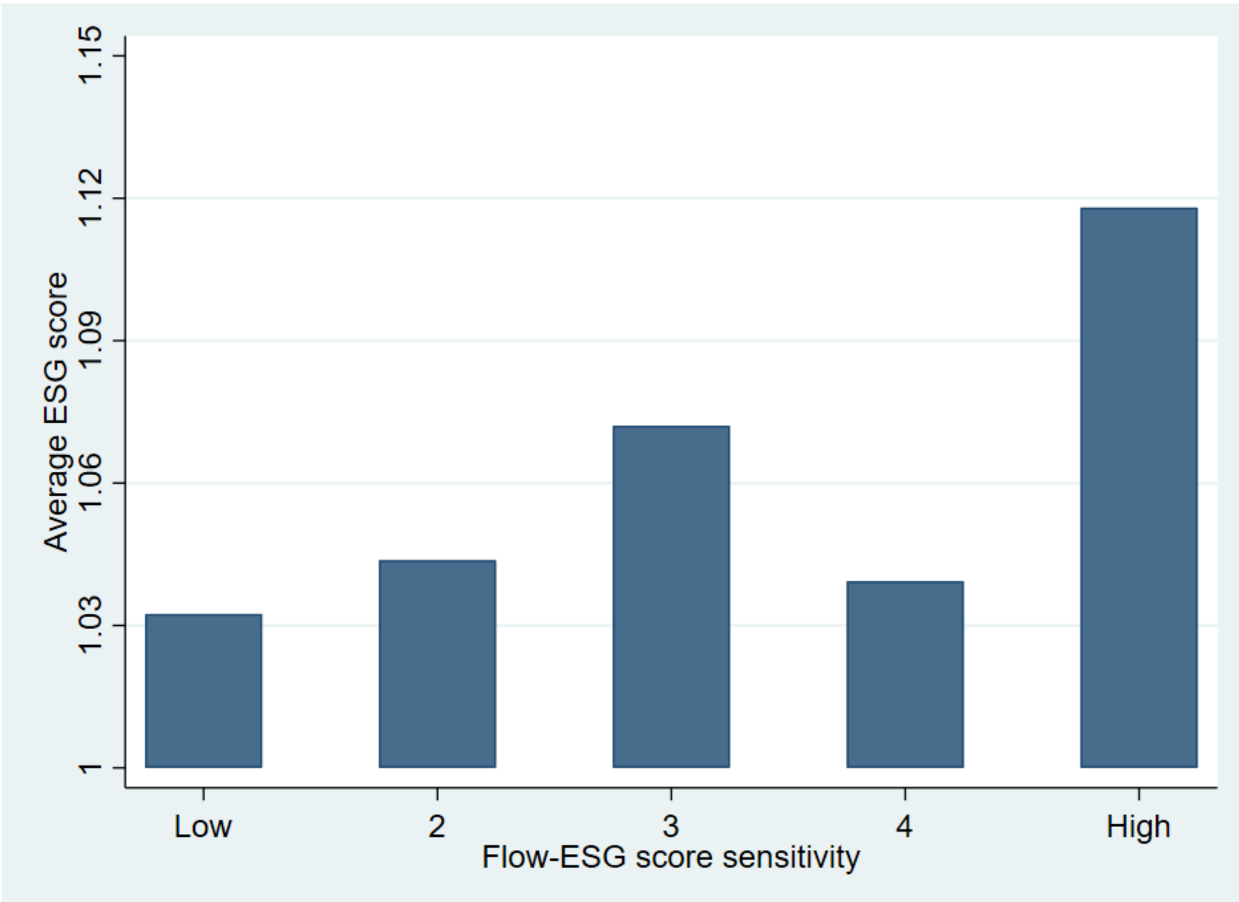


Table A.1. Summary statistics

Panel A of this table provides summary statistics of mutual fund ESG scores and other fund characteristics (fund TNA, expense ratio, a load dummy, fund age, and past 12-month return) for 217,288 fund-month observations in the final sample. Panel B reports summary statistics of variables of manager compensation structure for 19,505 fund-year observations from 2006 to 2018. *Fixed salary* is a dummy variable that equals one if portfolio manager receives only a fixed payment as compensation, and zero otherwise. *Variable salary* is dummy variable that equals one if portfolio manager's compensation consists of a variable component, and zero otherwise. Among variables of *Variable salary*, *Performance-based pay* is a dummy variable that equals one if manager's compensation is specifically linked to fund investment performance, and zero otherwise. *Advisor-profit pay* is a dummy variable that equals one if portfolio manager receives part of the investment advisor's profits as compensation, and zero otherwise. *AUM-based pay* is a dummy variable that equals one if manager's compensation is tied to fund AUM, and zero otherwise. *Deferred compensation* is a dummy variable that equals one if portfolio manager is provided with a deferred compensation plan, and zero otherwise. Panel C presents summary statistics of variables of mutual fund portfolios ranked based on fund ESG scores. Each month funds are sorted into deciles based on their ESG scores in an increasing order such that portfolio 1 includes funds with the lowest ESG scores (Low) and portfolio 10 consists of funds with the highest ESG scores (High). A high-minus-low (High-Low) portfolio is constructed using the Low and High ESG groups. The average values of ESG score, flow-performance sensitivity, flow-ESG score sensitivity, TNA, age, expense ratio, load fund dummy, and past 12-month return are reported for funds included in each portfolio. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is from 2004 to 2018.

Panel A: ESG choice and fund characteristics

	Mean	Median	Std	10%	90%
ESG score	1.01	0.60	1.79	-0.96	3.76
TNA ($millions)	2013.52	386.50	7275.48	36.30	4033.10
Age (years)	18.04	14.33	14.05	5.92	33.08
Expense ratio (%)	1.16	1.13	0.42	0.75	1.59
Load fund dummy	0.52	1.00	0.50	0.00	1.00
Past 12-month return (%)	9.19	10.45	18.58	-9.97	27.58

Panel B: Manager compensation structure

	Observations	Percentage of total sample
Total	19,505	100%
Fixed salary	851	4.36%
Variable salary	18,654	95.64%
Performance-based pay	16,629	85.26%
Advisor-profit pay	6,184	31.70%
AUM-based pay	1,912	9.80%
Deferred compensation	6,178	31.67%

Table A.1. Continued

Panel C: Summary statistics of mutual fund ESG portfolios								
ESG ranking	ESG score	Flow-performance sensitivity	Flow-ESG sensitivity	TNA ($millions)	Age (years)	Expense ratio (%)	Load fund dummy	Past 12-month return (%)
1 (Low)	-0.79	0.06	0.01	744.59	14.53	1.27	0.49	10.22
2	-0.45	0.02	-0.05	997.17	14.62	1.20	0.50	9.80
3	-0.18	0.01	-0.03	989.79	14.68	1.25	0.51	9.19
4	0.28	0.04	-0.03	1203.08	15.67	1.22	0.51	9.14
5	0.79	0.06	-0.02	1780.38	16.37	1.20	0.51	9.34
6	1.26	-0.01	-0.02	2374.38	17.51	1.14	0.51	9.37
7	1.67	-0.05	0.03	2372.08	18.45	1.09	0.51	8.89
8	2.06	-0.05	-0.01	2583.38	18.52	1.05	0.50	8.41
9	2.47	-0.05	0.01	2812.29	19.94	1.05	0.50	8.01
10 (High)	3.18	-0.08	0.04	2605.16	20.23	1.09	0.48	7.78
High-Low	3.96***	-0.14***	0.03	1860.58***	5.70***	-0.17***	-0.02	-2.45**

Table A.2. ESG scores and stock characteristics

This table reports average stock characteristics for portfolios constructed based on firm ESG scores. At the beginning of each year, stocks are sorted into deciles based on their industry-adjusted net ESG scores in an increasing order such that portfolio 1 includes firms with the lowest ESG scores (Low) and portfolio 10 consists of firms with the highest ESG scores (High). In addition, a high-minus-low (High-Low) portfolio is constructed using the Low and High ESG groups. The average values of firm size, stock past 12-month return, book-to-market ratio, number of analyst coverage, and several accounting measures are reported for stocks included in each portfolio. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

ESG ranking	Net ESG score	Aggregate strengths	Aggregate concerns	Market cap ($billions)	Past 12-month return (%)	Book-to-market
1 (Low)	-2.61	0.52	3.13	9.27	9.55	0.63
2	-1.39	0.38	1.77	3.48	9.13	0.60
3	-1.08	0.42	1.50	3.31	10.48	0.59
4	-0.64	0.51	1.16	3.15	8.33	0.57
5	-0.53	0.63	1.16	3.64	8.15	0.59
6	-0.07	0.83	0.89	3.76	8.45	0.56
7	0.34	1.19	0.85	5.35	9.94	0.60
8	0.84	1.64	0.80	5.96	8.74	0.59
9	1.76	2.65	0.89	10.73	8.33	0.58
10 (High)	4.77	6.20	1.43	29.73	9.62	0.55
High-Low	7.38***	5.68***	-1.71***	20.46***	0.07	-0.08***

ESG ranking	Gross profit	Operating profit	Asset growth	Investment growth	Net stock issues	Analyst coverage
1 (Low)	0.28	0.21	0.11	0.26	0.03	8.84
2	0.30	0.17	0.13	0.37	0.04	7.79
3	0.28	0.18	0.17	0.41	0.04	7.37
4	0.26	0.16	0.12	0.38	0.04	7.39
5	0.31	0.21	0.14	0.33	0.03	7.63
6	0.26	0.10	0.15	0.44	0.05	8.01
7	0.28	0.22	0.11	0.30	0.02	8.24
8	0.29	0.19	0.14	0.35	0.03	8.93
9	0.30	0.24	0.11	0.25	0.02	10.69
10 (High)	0.30	0.29	0.09	0.18	0.01	15.58
High-Low	0.02**	0.08***	-0.02	-0.08	-0.02**	6.75***

Table A.3. ESG score and stock returns

This table reports results of time-series regressions of a high-minus-low portfolio on different sets of risk factors. The sample period is from 2004 to 2019, and each month stocks are sorted into quintiles based on their net ESG scores, then a high-minus-low portfolio is constructed by longing High (the monthly industry-adjusted return of a value-weighted portfolio that includes stocks in the top ESG group) and shorting Low (the monthly industry-adjusted return of a value-weighted portfolio that includes stocks in the bottom ESG group). The first column reports the average return of the high-minus-low portfolio, and columns (2)–(5) present the risk-adjusted return (i.e., alpha) and factor loadings estimated from conventional asset pricing models, namely the CAPM model, Fama-French 3-factor model, Fama-French-Carhart 4-factor model, and Fama-French 5-factor model. The standard errors, adjusted using Newey and West (1987) method, are displayed in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable = High-Low portfolio return				
	(1)	(2)	(3)	(4)	(5)
Constant	-0.211**	-0.237**	-0.197**	-0.191**	-0.252***
	(0.101)	(0.116)	(0.092)	(0.093)	(0.076)
Mktrf		0.036	0.031	0.016	0.046
		(0.054)	(0.039)	(0.031)	(0.029)
SMB			-0.115**	-0.115**	-0.086
			(0.054)	(0.055)	(0.054)
HML			0.192***	0.157***	0.213***
			(0.044)	(0.047)	(0.067)
MOM				-0.053	
				(0.038)	
CMA					-0.054
					(0.138)
RMW					0.176**
					(0.080)

Table A.4. Flow-performance sensitivity and ESG choice

Based on the values of flow-performance sensitivity, each month mutual funds are sorted into quintiles in an increasing order such that portfolio 1 includes funds with the lowest flow-performance sensitivity (Low) and portfolio 5 consists of funds with the highest flow-performance sensitivity (High). A high-minus-low (High-Low) portfolio is constructed using the Low and High groups. Panel A presents the average values of ESG score, TNA, age, expense ratio, load fund dummy, and past 12-month return for funds included in each portfolio. Panel B reports regression coefficient estimates from panel regressions of mutual fund ESG scores on fund flow-performance sensitivity. Fund flow-performance sensitivity measure is estimated using Eq.(3.2) with 36-month rolling regressions. Fund TNA, age, expense ratio, past 12-month return, and a dummy variable that equals one if fund charges load fees and zero otherwise, are included as controls. All model specifications include month fixed effects, and the last column includes Morningstar investment style fixed effects as well. The standard errors, double clustered by fund and month, are displayed in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Portfolio sorting based on flow-performance sensitivity

Portfolio	ESG score	TNA ($millions)	Age (years)	Expense ratio	Load fund dummy	Past 12m return
1 (Low)	1.13	1011.59	14.96	1.12	0.50	8.83
2	1.19	2904.17	20.98	1.15	0.54	9.06
3	1.13	3292.89	21.75	1.16	0.54	9.17
4	0.92	1805.72	18.02	1.18	0.51	9.37
5 (High)	0.92	868.86	14.70	1.17	0.48	9.88
High-Low	-0.22***	-142.73**	-0.26	0.04***	-0.02**	1.06***

Panel B: Panel regression

	Dependent variable = mutual fund ESG score		
	(1)	(2)	(3)
Flow-performance sensitivity	-0.081***	-0.065***	-0.024**
	(0.020)	(0.019)	(0.012)
Ln(TNA)		-0.016	-0.004
		(0.017)	(0.009)
Ln(age)		0.207***	0.011
		(0.041)	(0.022)
Expense ratio		-0.585***	-0.017
		(0.113)	(0.052)
Load fund dummy		0.044	-0.051**
		(0.051)	(0.023)
Past 12-month return		-0.009***	0.002
		(0.003)	(0.002)
Fund style FE	No	No	Yes
Month FE	Yes	Yes	Yes
Observations	217288	217288	217288
Adj. R^2	0.383	0.406	0.708

Table A.5. Flow-ESG score sensitivity and ESG choice

Based on the values of flow-ESG score sensitivity, each month mutual funds are sorted into quintiles in an increasing order such that portfolio 1 includes funds with the lowest flow-ESG score sensitivity (Low) and portfolio 5 consists of funds with the highest flow-ESG score sensitivity (High). A high-minus-low (High-Low) portfolio is formed using the Low and High groups. Panel A presents the average values of ESG score, TNA, age, expense ratio, load fund dummy, and past 12-month return for funds included in each portfolio. Panel B reports regression coefficient estimates from panel regressions of mutual fund ESG scores on fund flow-ESG score sensitivity. Fund flow-ESG score sensitivity measure is estimated using Eq.(3.2) with 36-month rolling regressions. Fund TNA, age, expense ratio, past 12-month return, and a dummy variable that equals one if fund charges load fees and zero otherwise, are included as controls. All model specifications include month fixed effects, and the last column additionally includes Morningstar investment style fixed effects. The standard errors, double clustered by fund and month, are displayed in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Portfolio sorting based on flow-ESG score sensitivity

Portfolio	ESG score	TNA ($millions)	Age (years)	Expense ratio	Load fund dummy	Past 12m return
1 (Low)	1.03	1177.42	15.66	1.13	0.50	9.54
2	1.04	2516.36	19.18	1.16	0.53	9.16
3	1.07	2835.66	21.41	1.17	0.53	9.19
4	1.04	2169.14	19.06	1.18	0.52	9.16
5 (High)	1.12	1220.69	15.21	1.13	0.50	9.24
High-Low	0.09**	43.27	-0.46**	0.00	-0.01	-0.30**

Panel B: Panel regression

	Dependent variable = mutual fund ESG score		
	(1)	(2)	(3)
Flow-ESG score sensitivity	0.063**	0.060**	0.036**
	(0.030)	(0.029)	(0.017)
Ln(TNA)		-0.019	-0.006
		(0.018)	(0.009)
Ln(age)		0.227***	0.021
		(0.044)	(0.023)
Expense ratio		-0.646***	-0.017
		(0.125)	(0.055)
Load fund dummy		0.046	-0.054**
		(0.054)	(0.024)
Past 12-month return		-0.008**	0.002
		(0.004)	(0.002)
Fund style FE	No	No	Yes
Month FE	Yes	Yes	Yes
Observations	217288	217288	217288
Adj. R^2	0.373	0.399	0.718

Table A.6. Performance-based pay and ESG choice

Each month mutual funds are sorted into two portfolios based on whether compensations of their managers are explicitly tied to fund investment performance. A third portfolio (Yes-No) is also formed. Panel A presents the average values of ESG score, TNA, age, expense ratio, load fund dummy, and past 12-month return for funds included in each portfolio. Panel B reports regression coefficient estimates from panel regressions of mutual fund ESG scores on *Performance-based pay*, which is a dummy variable that equals one if manager's compensation is explicitly linked to fund investment performance, and zero otherwise. Fund TNA, age, expense ratio, past 12-month return, and a dummy variable that equals one if fund charges load fees and zero otherwise, are included as controls. Both model specifications include month fixed effects, and the last column additionally includes Morningstar investment style fixed effects. The standard errors, double clustered by fund and month, are displayed in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Portfolio sorting based on Performance-based pay

Performance-based pay	ESG score	TNA ($millions)	Age (years)	Expense ratio	Load fund dummy	Past 12m return
No	1.18	476.78	13.13	1.34	0.25	8.67
Yes	1.11	2289.69	18.52	1.11	0.55	9.79
Yes-No	-0.07***	1812.91***	5.39***	-0.24***	0.30***	1.11***

Panel B: Panel regression

	Dependent variable = Mutual fund ESG score	
	(1)	(2)
Performance-based pay	-0.312***	-0.089**
	(0.097)	(0.045)
Ln(TNA)	-0.014	0.000
	(0.018)	(0.008)
Ln(age)	0.155***	0.008
	(0.034)	(0.017)
Expense ratio	-0.810***	-0.053
	(0.103)	(0.046)
Load fund dummy	0.090*	-0.046**
	(0.053)	(0.022)
Past 12-month return	-0.010**	0.003
	(0.005)	(0.003)
Fund style FE	No	Yes
Month FE	Yes	Yes
Observations	178245	178245
Adj. R^2	0.268	0.656

Table A.7. Investment horizon and ESG choice

Each month mutual funds are sorted into quintiles based on their turnover ratios in an increasing order such that portfolio 1 includes funds with the smallest turnover ratios (Low) and portfolio 5 consists of funds with the largest turnover ratios (High). A high-minus-low (High-Low) portfolio is formed using the Low and High groups. Panel A presents the average values of ESG score, TNA, age, expense ratio, load fund dummy, and past 12-month return for funds included in each portfolio. Panel B reports results from panel regressions of mutual fund ESG scores on investment horizon. Mutual fund investment horizon (short-termism) is proxied by portfolio turnover ratio such that a larger value of turnover ratio indicates greater extent of fund short-termism. Fund TNA, age, expense ratio, past 12-month return, and a dummy variable that equals one if fund charges load fees and zero otherwise, are included as controls. Both model specifications include month fixed effects, and the last column additionally includes Morningstar investment style fixed effects. The standard errors, double clustered by fund and month, are displayed in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Portfolio sorting based on short-termism

Portfolio	ESG score	TNA ($millions)	Age (years)	Expense ratio	Load fund dummy	Past 12m return
1 (Low)	1.38	3017.27	19.60	1.12	0.44	10.28
2	1.12	2966.83	17.55	1.13	0.49	10.09
3	1.06	1600.13	16.90	1.14	0.53	9.99
4	0.93	1076.17	16.38	1.15	0.56	9.73
5 (High)	0.81	703.94	15.27	1.24	0.51	9.42
High-Low	-0.57***	-2313.34***	-4.33***	0.12***	0.08***	-0.86**

Panel B: Panel regression

	Dependent variable = mutual fund ESG score	
	(1)	(2)
Short-termism	-0.129***	-0.067***
	(0.024)	(0.012)
Ln(TNA)	-0.029*	-0.009
	(0.017)	(0.009)
Ln(age)	0.210***	0.010
	(0.041)	(0.022)
Expense ratio	-0.571***	-0.016
	(0.114)	(0.052)
Load fund dummy	0.055	-0.045**
	(0.051)	(0.023)
Past 12-month return	-0.003	0.001
	(0.002)	(0.001)
Fund style FE	No	Yes
Month FE	Yes	Yes
Observations	216043	216043
Adj. R^2	0.409	0.712

Table A.8. Investment horizon, manager compensation, and ESG choice

This table reports results from panel regressions of mutual fund ESG scores on fund short-termism and its interaction with manager compensation variables. Mutual fund short-termism is proxied by portfolio turnover ratio such that a larger value of turnover ratio indicates greater extent of fund short-termism. *Performance-based pay* is a dummy variable that equals one if manager's compensation is explicitly linked to fund investment performance, and zero otherwise. Fund flow-performance and flow-ESG score sensitivity measures are estimated using Eq.(3.2). Fund TNA, age, expense ratio, past 12-month return, and a dummy variable that equals one if fund charges load fees and zero otherwise, are included as controls. All model specifications include Morningstar investment style and month fixed effects. The standard errors, double clustered by fund and month, are displayed in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable = Mutual fund ESG score		
	(1)	(2)	(3)
Short-termism	-0.117	-0.130***	-0.132***
	(0.099)	(0.024)	(0.023)
Performance-based pay	-0.284**		
	(0.105)		
Performance-based pay×Short-termism	0.022		
	(0.071)		
Flow-performance sensitivity		-0.065***	
		(0.019)	
Flow-performance sensitivity×Short-termism		0.021	
		(0.019)	
Flow-ESG score sensitivity			0.051**
			(0.025)
Flow-ESG score sensitivity×Short-termism			-0.031
			(0.029)
Ln(TNA)	-0.024*	-0.025	-0.025
	(0.013)	(0.017)	(0.017)
Ln(age)	0.166**	0.202***	0.205***
	(0.059)	(0.041)	(0.041)
Expense ratio	-0.829***	-0.578***	-0.582***
	(0.107)	(0.113)	(0.113)
Load fund dummy	0.093	0.051	0.054
	(0.072)	(0.050)	(0.050)
Past 12-month return	-0.012*	-0.015***	-0.016***
	(0.006)	(0.005)	(0.005)
Month FE	Yes	Yes	Yes
Observations	178150	216043	216043
Adj. R^2	0.408	0.413	0.413

Table A.9. ESG choice and fund performance

This table reports return performance of mutual fund portfolios that are built based on fund ESG scores. At the beginning of each month, mutual funds are sorted into deciles based on values of their ESG scores in the previous month, and ten equal-weighted return portfolios, as well as a high-minus-low portfolio, are subsequently formed. The first row reports portfolio returns, and the remaining rows report risk-adjusted returns (i.e., alpha) and risk factor loadings of Fama-French 5-factor model for each portfolio. The standard errors, adjusted using Newey and West (1987) method, are displayed in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Portfolio ranking	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	High-Low
Return	0.767**	0.764**	0.731**	0.742**	0.743**	0.746**	0.705**	0.682**	0.671**	0.654**	-0.113
	(0.365)	(0.371)	(0.363)	(0.353)	(0.336)	(0.324)	(0.312)	(0.307)	(0.306)	(0.300)	(0.138)
Alpha	-0.043	-0.087	-0.125**	-0.103**	-0.079*	-0.064*	-0.088***	-0.104***	-0.109***	-0.114**	-0.071
	(0.067)	(0.059)	(0.056)	(0.050)	(0.041)	(0.037)	(0.025)	(0.024)	(0.040)	(0.049)	(0.084)
Mktrf	0.967***	0.997***	1.004***	1.018***	1.013***	1.023***	1.010***	0.999***	0.998***	0.977***	0.010
	(0.027)	(0.022)	(0.020)	(0.014)	(0.013)	(0.010)	(0.007)	(0.008)	(0.011)	(0.012)	(0.028)
SMB	0.595***	0.616***	0.536***	0.405***	0.251***	0.074***	-0.004	-0.016	-0.019	-0.021	-0.616***
	(0.039)	(0.029)	(0.021)	(0.031)	(0.025)	(0.024)	(0.015)	(0.013)	(0.016)	(0.023)	(0.050)
HML	-0.048	-0.031	-0.020	-0.056***	-0.048**	-0.053**	-0.050***	-0.041**	-0.083***	-0.074***	-0.026
	(0.054)	(0.045)	(0.032)	(0.020)	(0.021)	(0.024)	(0.018)	(0.017)	(0.025)	(0.028)	(0.060)
CMA	-0.190***	-0.119***	-0.118***	-0.161***	-0.124***	-0.149***	-0.088***	-0.040**	0.011	0.054	0.244***
	(0.050)	(0.036)	(0.042)	(0.039)	(0.035)	(0.029)	(0.023)	(0.019)	(0.030)	(0.036)	(0.070)
RMW	-0.110***	-0.038	-0.009	-0.034	-0.040	-0.044	-0.032	-0.021	-0.030	-0.014	0.096
	(0.041)	(0.034)	(0.032)	(0.037)	(0.027)	(0.029)	(0.020)	(0.020)	(0.031)	(0.039)	(0.059)

Table A.10. ESG choice and fund performance: Fama-MacBeth regression

This table reports Fama-MacBeth regression results of mutual fund return performance on fund ESG score using the following specification: $MF\_ret_{i,t+1} = \theta_0 + \theta_1 MF\_ESG_{i,t} + \theta_2 Perf\_pay_{i,t} + \theta' X_{i,t} + e_{i,t+1}$. The dependent variable is the return performance of fund i in month $t+1$. $MF\_ESG_{i,t}$ is fund i's ESG score, *Performance-based pay* ($Perf\_pay_{i,t}$) is a dummy variable that equals one if manager's compensation is explicitly linked to fund investment performance and zero otherwise, and $X_{i,t}$ is a set of fund characteristics (i.e., fund TNA, age, expense ratio, past 12-month return, and a load fund dummy). Either fund return or Fama-French 5-factor alpha (FF5 alpha) is used as the return performance measure. The standard errors, adjusted using Newey and West (1987) method, are displayed in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable =					
		Return			FF5 alpha	
	(1)	(2)	(3)	(4)	(5)	(6)
Fund ESG score	-0.054		-0.053	-0.007		-0.007
	(0.039)		(0.039)	(0.019)		(0.020)
Performance-based pay		0.059**	0.054***		0.010	0.011
		(0.025)	(0.021)		(0.017)	(0.017)
Ln(TNA)	-0.005	-0.007	-0.006	0.001	0.001	0.001
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Ln(age)	0.009	0.004	0.008	-0.004	-0.004	-0.004
	(0.008)	(0.011)	(0.008)	(0.006)	(0.008)	(0.006)
Expense ratio	-0.104***	-0.094**	-0.094***	-0.076***	-0.076***	-0.075***
	(0.031)	(0.047)	(0.031)	(0.021)	(0.022)	(0.021)
Load fund dummy	-0.003	-0.010	-0.011	-0.012	-0.014	-0.013
	(0.011)	(0.011)	(0.011)	(0.009)	(0.009)	(0.009)
Past 12-month return	0.009*	0.006	0.009*	0.004	0.004	0.004
	(0.005)	(0.006)	(0.005)	(0.003)	(0.003)	(0.003)
Observations	205171	205171	205171	205171	205171	205171
Number of months	180	180	180	180	180	180
Avg. R^2	0.204	0.115	0.207	0.072	0.050	0.074

Table A.11. Manager compensation structure and ESG choice

This table reports regression coefficient estimates from panel regressions of mutual fund ESG scores on variables of manager compensation structure. *Performance-based pay* is a dummy variable that equals one if manager's compensation is specifically linked to fund investment performance, and zero otherwise. *Advisor-profit pay* is a dummy variable that equals one if portfolio manager receives part of the investment advisor's profits as compensation, and zero otherwise. *AUM-based pay* is a dummy variable that equals one if manager's compensation is tied to fund AUM, and zero otherwise. *Deferred compensation* is a dummy variable that equals one if portfolio manager is provided with a deferred compensation plan, and zero otherwise. Fund TNA, age, expense ratio, past 12-month return, and a dummy variable that equals one if fund charges load fees and zero otherwise, are included as controls. All model specifications include Morningstar investment style and month fixed effects. The standard errors, double clustered by fund and month, are displayed in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable = Mutual fund ESG score				
	(1)	(2)	(3)	(4)	(5)
Performance-based pay	-0.089**				-0.059**
	(0.045)				(0.022)
Advisor-profit pay		0.098***			0.093**
		(0.027)			(0.034)
AUM-based pay			-0.004		-0.031
			(0.040)		(0.046)
Deferred compensation				-0.003	0.006
				(0.024)	(0.021)
Ln(TNA)	0.001	0.001	-0.002	-0.002	0.002
	(0.008)	(0.008)	(0.008)	(0.009)	(0.014)
Ln(age)	0.008	0.003	0.007	0.007	0.004
	(0.017)	(0.017)	(0.016)	(0.017)	(0.017)
Expense ratio	-0.053	-0.052	-0.037	-0.038	-0.061
	(0.046)	(0.045)	(0.046)	(0.046)	(0.086)
Load fund dummy	-0.046**	-0.048**	-0.059***	-0.058***	-0.041**
	(0.022)	(0.022)	(0.022)	(0.022)	(0.017)
Past 12-month return	0.003	0.003	0.003	0.003	0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)
Fund style FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Observations	178245	178245	178245	178245	178245
Adj. R^2	0.656	0.656	0.655	0.655	0.656

Table A.12. Holdings-based return of high ESG stocks and flow-ESG score sensitivity

This table reports regression coefficient estimates from Fama-MacBeth regressions of mutual fund holdings-based returns on flow-ESG score sensitivity. The dependent variable is the value-weighted return of high ESG stocks held by each mutual fund. Fund flow-ESG score sensitivity measure is estimated using Eq.(3.2) with 36-month rolling regressions. *I(high flow-ESG score sensitivity)* is an indicator variable that equals one if the fund belongs to the highest quintile group sorted based on flow-ESG score sensitivity. Fund TNA, age, expense ratio, past 12-month return, and a dummy variable that equals one if fund charges load fees and zero otherwise, are included as controls. The standard errors, adjusted using Newey and West (1987) method, are displayed in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable = Holdings-based return of high-ESG stocks			
	(1)	(2)	(3)	(4)
Flow-ESG sensitivity	0.001	-0.001		
	(0.025)	(0.024)		
I(high flow-ESG sensitivity)			-0.009	-0.018
			(0.023)	(0.022)
Ln(TNA)		0.001		0.001
		(0.008)		(0.008)
Ln(age)		-0.037*		-0.039*
		(0.021)		(0.020)
Expense ratio		0.001		0.002
		(0.044)		(0.044)
Load fund dummy		-0.010		-0.009
		(0.022)		(0.022)
Past 12-month return		0.004		0.004
		(0.007)		(0.007)
Observations	218513	218513	218513	218513
Number of months	180	180	180	180
Avg. R^2	0.001	0.030	0.001	0.030

A.2 Appendix for Section 2

In this Appendix, I first define the variables of manager compensation structure used in Section 2, and then provide several examples on how I construct those variables based on disclosed information from mutual fund filings. Finally, I provide results of additional tests.

A.2.1 Definitions of manager compensation variables

Fixed salary is a dummy variable that equals one if portfolio manager receives only a fixed payment as compensation, and zero otherwise.

Variable salary is dummy variable that equals one if portfolio manager's compensation consists of a variable component, and zero otherwise.

Among variables of *Variable salary*, *Performance-based pay* is a dummy variable that equals one if manager's compensation is specifically linked to fund investment performance, and zero otherwise.

Advisor-profit pay is a dummy variable that equals one if portfolio manager receives part of the investment advisor's profits as compensation, and zero otherwise.

AUM-based pay is a dummy variable that equals one if manager's compensation is tied to fund AUM, and zero otherwise.

Deferred compensation is a dummy variable that equals one if portfolio manager is provided with a deferred compensation plan, and zero otherwise.

A.2.2 Examples of manager compensation structure

The following examples of manager compensation structure are extracted from each fund's Statement of Additional Information (SAI), respectively. The detailed information on SAI is available in Form N-1A filed by mutual fund companies.

Example 1: The Wall Street Fund, 2011

> *"The Portfolio Managers compensation is made up of a fixed salary which is paid by the Adviser. The Portfolio Managers receives no performance-based compensation in the form of bonuses or deferred compensation."*

Based on the disclosed information, the portfolio managers' compensation consists of a fixed component only, therefore, the dummy variable *Fixed salary* is equal to one, and all the remaining dummy variables related to *Variable salary* are equal to zero.

Example 2: Fidelity Large Cap Stock Fund, 2015

> *"Matthew Fruhan is the portfolio manager of Fidelity Large Cap Stock Fund and receives compensation for his services... portfolio manager compensation generally consists of a fixed base salary determined periodically (typically annually), a bonus, in certain cases, participation in several types of equity-based compensation plans, and, if applicable, relocation plan benefits... The primary components of each portfolio manager's bonus are based on the pre-tax investment performance of the portfolio manager's fund(s) and account(s) measured against a benchmark index and within a defined peer group assigned to each fund or account. The pre-tax investment performance of each portfolio manager's fund(s) and account(s) is weighted according to his tenure on those fund(s) and account(s) and the average asset size of those fund(s) and account(s) over his tenure. Each component is calculated separately over the portfolio manager's tenure on those fund(s) and account(s) over a measurement period that initially is contemporaneous with his tenure, but that eventually encompasses rolling periods of up to five years for the comparison to a benchmark index and rolling periods of up to three years for the comparison to a peer*

group..."

According to the above description, the portfolio manager of Fidelity Large Cap Stock Fund receives a bonus component that is specifically linked to the pre-tax investment performance of his fund(s) and account(s). Therefore, the dummy variable *Fixed salary* is equal to zero, and the dummy variable *Performance-based pay* is set to one. Based on the excerpt, the portfolio manager does not receive bonus compensation that is tied to fund AUM or advisor's profit, in addition, he is not provided with a deferred compensation plan. As a result, *Advisor-profit pay*, *AUM-based pay*, and *Deferred compensation* are set to zero.

Example 3: Matrix Advisors Value Fund, 2016

> *"Mr. Katz's compensation in connection with his management of the Fund and other accounts includes a fixed base salary and a performance bonus. He does not receive deferred compensation. Compensation is based on the overall profitability of the Advisor which is driven by the Advisor's aggregate equity performance on its overall assets under management. Compensation is not tied to the performance or assets under management for any specific fund or account."*

In this example, it is clearly stated that the portfolio manager's compensation is based on the advisor's overall profit, and is not linked to investment performance or AUM of the fund he manages. For that reason, *Advisor-profit pay* is set to one, and the remaining dummy variables are set to zero.

Example 4: Touchstone Large Cap Growth Fund, 2010

> *"Portfolio managers receive a fixed base salary and incentive compensation. Incentive compensation is based upon the asset growth of the portfolio(s) for which they are responsible. Incentive compensation is based upon reaching certain asset levels and is measured on a quarterly basis. Incentive compensation is paid as a percentage of the management fees received from those portfolios for which the portfolio manager is directly responsible."*

Based on the above information, I set *AUM-based pay* to one since portfolio managers receive incentive compensation that is tied to "the asset growth of the portfolio(s) for which they are responsible". Since the incentive compensation is not linked other factors, I set the remaining dummy variables to zero.

Example 5: Pioneer Mid Cap Value Fund, 2011

> *"The compensation program for all Pioneer portfolio managers includes a base salary (determined by the rank and tenure of the employee) and an annual bonus program, as well as customary benefits that are offered generally to all full-time employees. Base compensation is fixed and normally reevaluated on an annual basis... The annual bonus is based upon a combination of the following factors: QUANTITATIVE INVESTMENT PERFORMANCE. The quantitative investment performance calculation is based on pre-tax investment performance of all of the accounts managed by the portfolio manager (which includes the fund and any other accounts managed by the portfolio manager) over a one-year period (20% weighting) and four-year period (80% weighting), measured for periods ending on December 31... PIONEER RESULTS AND BUSINESS LINE RESULTS. Pioneer's financial performance, as well as the investment performance of its investment management group, affect a portfolio manager's actual bonus by a leverage factor of plus or minus (+/-) a predetermined percentage... A portion of the annual bonus is deferred for a specified period and may be invested in one or more Pioneer funds."*

According to the disclosed information, the bonus component of portfolio manager's compensation is linked to investment performance of his/her managed accounts, so the dummy variable *Performance-based pay* is set to one. Additionally, the bonus component is affected by financial performance of Pioneer (i.e., the fund's investment advisor), so *Advisor-profit pay* is set to one as well. Finally, *Deferred compensation* is equal to one since a portion of the annual bonus is deferred.

Example 6: BlackRock Mid Cap Value Opportunities Fund, 2009

> *"The principal components of compensation include a base salary, a performance-based discretionary bonus, participation in various benefits programs and one or more of the incentive compensation programs established by BlackRock such as its Long-Term Retention and Incentive Plan... Discretionary incentive compensation is based on a formulaic compensation program. BlackRock's formulaic portfolio manager compensation program includes: pre-tax investment performance relative to appropriate competitors or benchmarks over 1-, 3- and 5-year performance periods and a measure of operational efficiency... A portion of the compensation paid to eligible BlackRock employees may be voluntarily deferred into an account that tracks the performance of certain of the firm's investment products. Each participant in the deferred compensation program is permitted to allocate his deferred amounts among various options. Messrs. Coyle and Balaraman have each participated in the deferred compensation program."*

In this example, the portfolio managers of BlackRock Mid Cap Value Opportunities Fund are compensated with a variable component that is based on pre-tax investment performance, in addition, they are provided with a deferred compensation program. As a result, the dummy variables *Performance-based pay* and *Deferred compensation* are set to one.

A.2.3 Tables of additional tests

Table A.13. Flow sensitivity and ESG choice

This table reports regression coefficient estimates from panel regressions of mutual fund ESG scores on fund flow sensitivity measures. Fund flow-performance and flow-ESG score sensitivity measures are estimated using Eq.(3.2). Fund TNA, age, expense ratio, past 12-month return, and a dummy variable that equals one if fund charges load fees and zero otherwise, are included as controls. Both model specifications include month fixed effects, and the last column additionally includes Morningstar investment style fixed effects. The standard errors, double clustered by fund and month, are displayed in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable = Mutual fund ESG score	
	(1)	(2)
Flow-performance sensitivity	-0.068***	-0.025**
	(0.020)	(0.011)
Flow-ESG sensitivity	0.059**	0.036**
	(0.029)	(0.017)
Ln(TNA)	-0.019	-0.006
	(0.018)	(0.009)
Ln(age)	0.225***	0.020
	(0.044)	(0.023)
Expense ratio	-0.640***	-0.015
	(0.125)	(0.055)
Load fund dummy	0.043	-0.055**
	(0.053)	(0.024)
Past 12-month return	-0.008**	0.002
	(0.004)	(0.002)
Fund style FE	No	Yes
Month FE	Yes	Yes
Observations	217288	217288
Adj. R^2	0.400	0.718

Table A.14. Flow sensitivity measures and ESG choice: alternative rolling window

This table reports regression coefficient estimates from panel regressions of mutual fund ESG scores on fund flow sensitivity measures. With a 24-month rolling window, both flow-performance sensitivity and flow-ESG score sensitivity measures are estimated using Eq.(3.2). Fund TNA, age, expense ratio, past 12-month return, and a dummy variable that equals one if fund charges load fees and zero otherwise, are included as controls. The first and last three columns report the regression results of flow-performance sensitivity and flow-ESG score sensitivity, respectively. All model specifications include month fixed effects, and some of them additionally control for Morningstar investment style fixed effects. The standard errors, double clustered by fund and month, are displayed in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable = Mutual fund ESG score					
	(1)	(2)	(3)	(4)	(5)	(6)
Flow-performance sensitivity	-0.088***	-0.070***	-0.028**			
	(0.021)	(0.020)	(0.013)			
Flow-ESG score sensitivity				0.067**	0.064**	0.052***
				(0.028)	(0.028)	(0.017)
Ln(TNA)		-0.014	-0.006		-0.015	-0.003
		(0.016)	(0.010)		(0.016)	(0.009)
Ln(age)		0.191***	0.028		0.192***	0.010
		(0.038)	(0.022)		(0.038)	(0.020)
Expense ratio		-0.577***	-0.014		-0.582***	-0.010
		(0.109)	(0.059)		(0.110)	(0.050)
Load fund dummy		0.044	-0.061**		0.047	-0.052**
		(0.049)	(0.024)		(0.050)	(0.023)
Past 12-month return		-0.009***	0.003		-0.009***	0.002
		(0.003)	(0.002)		(0.003)	(0.002)
Fund style FE	No	No	Yes	No	No	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	224872	224872	224872	224872	224872	224872
Adj. R^2	0.386	0.409	0.708	0.385	0.408	0.708

Table A.15. ESG choice and fund performance: panel regression

This table reports panel regression results of mutual fund return performance on fund ESG score using the following specification: $MF\_ret_{i,t+1} = \theta_0 + \theta_1 MF\_ESG_{i,t} + \theta_2 Perf\_pay_{i,t} + \theta' X_{i,t} + \mu_j + \mu_t + e_{i,t+1}$. The dependent variable is the return performance of fund i in month $t + 1$. $MF\_ESG_{i,t}$ is fund i's ESG score, *Performance-based pay* ($Perf\_pay_{i,t}$) is a dummy variable that equals one if manager's compensation is directly linked to fund investment performance and zero otherwise, and $X_{i,t}$ is a set of fund characteristics (i.e., fund TNA, age, expense ratio, past 12-month return, and a load fund dummy). μ_j and μ_t are Morningstar investment style and month fixed effects, respectively. Either fund return or Fama-French 5-factor alpha (FF5 alpha) is used as the return performance measure. The standard errors, double clustered by fund and month, are displayed in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable =					
		Return			FF5 alpha	
	(1)	(2)	(3)	(4)	(5)	(6)
Fund ESG score	0.012		0.013	0.013		0.013
	(0.033)		(0.033)	(0.014)		(0.014)
Performance-based pay		0.051***	0.053***		0.007	0.009
		(0.019)	(0.019)		(0.019)	(0.019)
Ln(TNA)	-0.003	-0.004	-0.004	0.002	0.002	0.002
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Ln(age)	0.005	0.005	0.005	0.001	0.001	0.001
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Expense ratio	-0.117***	-0.109***	-0.108***	-0.075***	-0.075***	-0.074***
	(0.024)	(0.025)	(0.025)	(0.020)	(0.020)	(0.020)
Load fund dummy	0.007	-0.002	-0.001	-0.010	-0.012	-0.011
	(0.009)	(0.008)	(0.008)	(0.011)	(0.010)	(0.010)
Past 12-month return	0.003	0.003	0.003	0.004	0.004	0.004
	(0.006)	(0.006)	(0.006)	(0.003)	(0.003)	(0.003)
Fund style FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	205171	205171	205171	205171	205171	205171
Adj. R^2	0.870	0.870	0.870	0.058	0.058	0.058

APPENDIX B

FIGURES AND TABLES FOR SECTION 3

Figure B.1. Time variation of the flow-tail risk relation

This figure plots the time series of the coefficient of investor flows on tail risk (January 1991 to June 2020, with controls of fund performance and characteristics) in the Fama-MacBeth regression. Fund performance is measured using the Fama-French five-factor model in this figure.

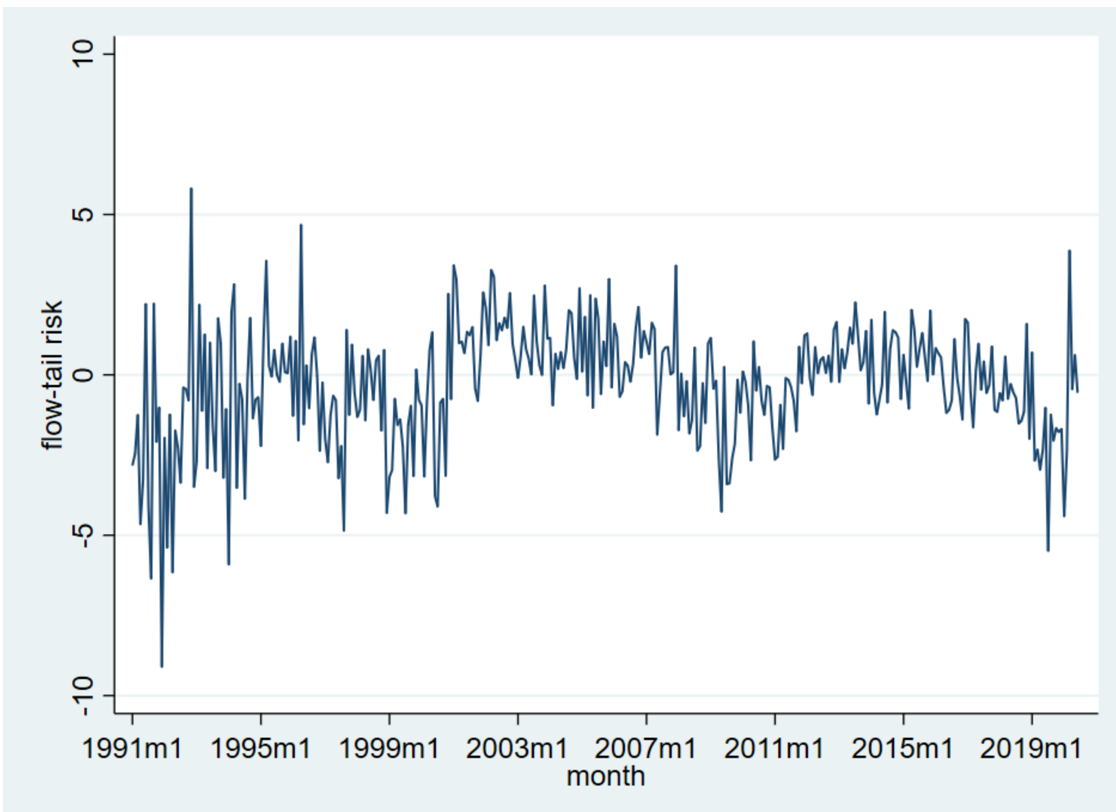


Figure B.2. Number of terrorist attacks

This figure plots the total number of terrorist attacks happened each month from January 1991 to December 2018. We follow Wang and Young (2020) and include only attacks that involve casualties or injuries or are covered in the news.

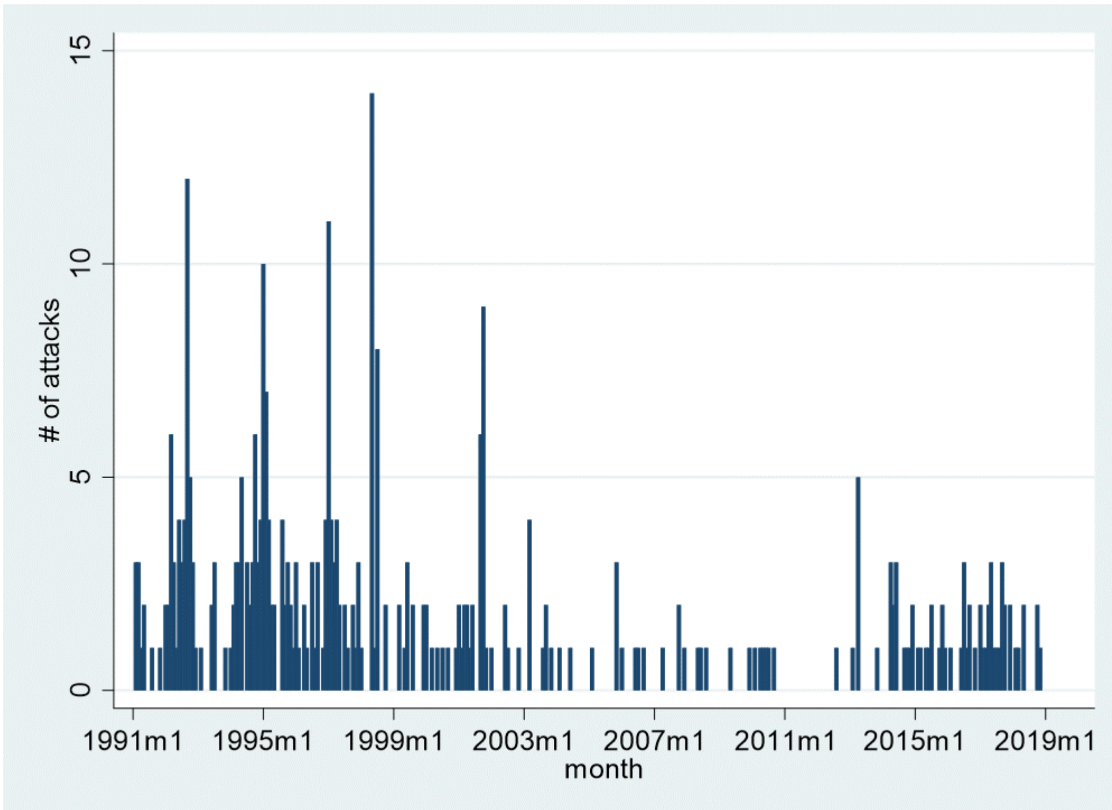


Table B.1. Summary Statistics

This table provides summary statistics of fund-month observations for US equity mutual funds. The sample period is from January 1991 to June 2020.

	observations	mean	std	p25	p50	p75
Return (%/mo.)	444857	0.71	4.90	-1.80	1.11	3.62
CAPM alpha (%/mo.)	444857	-0.02	0.38	-0.23	-0.05	0.15
FFC alpha (%/mo.)	444857	-0.07	0.30	-0.22	-0.07	0.08
FF5 alpha (%/mo.)	444857	-0.04	0.33	-0.22	-0.06	0.10
TNA ($mil)	444849	1365.50	5150.50	75.70	276.50	974.80
Age (months)	444857	172.57	110.55	90.00	142.00	222.00
Expense ratio (%)	416483	1.19	1.03	0.91	1.15	1.43
Load dummy	416483	0.51	0.50	0.00	1.00	1.00
Flow (%/mo.)	444808	-0.19	6.91	-1.66	-0.60	0.54

Table B.2. Cross-sectional distribution of tail beta

This table reports the cross-sectional distribution of tail beta for all US domestic equity funds in the final sample. For each fund, we estimate its tail beta using the following regression: $r_{i,t} = \alpha + \beta_0 r_{m,t} + \beta^{Tail} r_{m,t} I\left(r_{m,t} < h\right) + \varepsilon_{i,t}$. Funds are ranked based on the values of their tail betas, and the first and second rows report the estimate of tail beta and its bootstrapped p-values, respectively. Similarly, the third and fourth rows report result that is based on the ranking of the t-statistics of fund's tail beta.

	Negative tail beta							Positive tail beta					
	1%	5%	10%	20%	30%	40%	Median	40%	30%	20%	10%	5%	1%
Tail beta	-0.407	-0.203	-0.145	-0.080	-0.034	-0.003	0.029	0.060	0.095	0.141	0.221	0.308	0.589
Emp p-value	0.008	0.002	0.000	0.000	0.999	1.000		0.227	0.042	0.000	0.000	0.000	0.000
t-value of tail beta	-3.354	-2.256	-1.613	-0.917	-0.414	-0.031	0.348	0.767	1.173	1.673	2.475	3.141	4.351
Emp p-value	0.000	0.000	0.000	0.043	1.000	1.000		0.005	0.000	0.000	0.000	0.000	0.000

Table B.3. Flow and tail beta: Fama-MacBeth regression

This table presents regression coefficient estimates from Fama-MacBeth regressions of fund flow on tail beta. Different fund performance measures are included as controls, namely fund raw returns, the CAPM alpha, Fama-French-Carhart four-factor alpha, and Fama-French five-factor alpha. Fund characteristics, such as the natural logarithm of fund size, expense ratio, and a load dummy that equals one if a fund charges front-end or back-end loads, are added as additional controls. The standard errors, adjusted using Newey and West (1987) method, are displayed in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable = monthly fund flow			
	(1)	(2)	(3)	(4)
Tail beta	-0.557***	-0.552***	-0.567***	-0.395**
	(0.179)	(0.175)	(0.190)	(0.199)
Lag flow	0.209***	0.209***	0.212***	0.157***
	(0.009)	(0.009)	(0.009)	(0.010)
Raw return	0.198***			
	(0.013)			
CAPM alpha		0.220***		
		(0.014)		
FFC alpha			0.222***	
			(0.014)	
FF5 alpha				0.230***
				(0.015)
Fund characs	Yes	Yes	Yes	Yes
Observations	416901	416901	416901	416901
Number of months	354	354	354	354
Avg. R^2	0.079	0.079	0.077	0.058

Table B.4. Flow and tail beta: panel regression

This table presents regression coefficient estimates from panel regressions of fund flow on tail beta. The independent variables include lagged fund flows, fund raw returns, the CAPM alpha, Fama-French-Carhart four-factor alpha, Fama-French five-factor alpha, industrial production growth, inflation rate, the return spread between long-term and short-term government bond indexes, and the return spread between high-yield bond index and the intermediate government bond index. The following fund characteristics are included as additional controls: the natural logarithm of fund size, expense ratio, and a load dummy that equals one if a fund charges front-end or back-end loads. The standard errors, double clustered at fund and month level, are displayed in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable = monthly fund flow			
	(1)	(2)	(3)	(4)
Tail beta	-0.399***	-0.246**	-0.534***	-0.360***
	(0.137)	(0.119)	(0.133)	(0.138)
Lag flow	0.173***	0.168***	0.216***	0.173***
	(0.013)	(0.014)	(0.013)	(0.013)
Raw return	0.063***			
	(0.007)			
CAPM alpha		0.176***		
		(0.014)		
FFC alpha			0.181***	
			(0.014)	
FF5 alpha				0.175***
				(0.013)
Industrial production	0.041*	0.041	0.029	0.028
	(0.024)	(0.033)	(0.028)	(0.029)
Inflation	0.227**	0.161*	0.132	0.160*
	(0.092)	(0.098)	(0.085)	(0.093)
Term spread	0.007	0.001	0.100	0.091
	(0.130)	(0.141)	(0.129)	(0.138)
Default spread	0.440*	-0.125	-0.052	-0.118
	(0.252)	(0.181)	(0.142)	(0.159)
Fund charcs	Yes	Yes	Yes	Yes
Observations	416901	416901	416901	416901
Adj. R^2	0.033	0.034	0.052	0.034

Table B.5. Flow and tail beta: terrorist attacks

This table presents regression coefficient estimates from panel regressions of fund flow on tail beta and terrorist attacks. The independent variables include number of terrorist attacks, an interaction term between tail beta and number of terrorist attacks, lagged fund flows, fund raw returns, the CAPM alpha, Fama-French-Carhart four-factor alpha, Fama-French five-factor alpha, industrial production growth, inflation rate, the return spread between long-term and short-term government bond indexes, and the return spread between high-yield bond index and the intermediate government bond index. The following fund characteristics are included as additional controls: the natural logarithm of fund size, expense ratio, and a load dummy that equals one if a fund charges front-end or back-end loads. The sample period is from January 1991 to December 2018 due to availability of terrorist attacks data. All models include year fixed effects. The standard errors, clustered at fund-year level, are displayed in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable = monthly fund flow			
	(1)	(2)	(3)	(4)
Tail beta	-0.329***	-0.315***	-0.339***	-0.343**
	(0.108)	(0.079)	(0.108)	(0.142)
Ln(1+attacks)	-0.060***	-0.040**	-0.059***	-0.057***
	(0.019)	(0.020)	(0.019)	(0.022)
Tail beta×ln(1+attacks)	-0.315**	-0.311**	-0.244**	-0.319**
	(0.122)	(0.153)	(0.122)	(0.149)
Lag flow	0.171***	0.153***	0.171***	0.096***
	(0.007)	(0.008)	(0.007)	(0.013)
Raw return	0.058***			
	(0.002)			
CAPM alpha		0.157***		
		(0.005)		
FFC alpha			0.167***	
			(0.006)	
FF5 alpha				0.169***
				(0.008)
Industrial production	0.046***	0.034**	0.032**	0.011
	(0.015)	(0.016)	(0.015)	(0.018)
Inflation	0.183***	0.142***	0.133***	0.137***
	(0.035)	(0.037)	(0.035)	(0.043)
Term spread	0.076*	0.053	0.113***	0.097*
	(0.043)	(0.045)	(0.043)	(0.057)
Default spread	0.280***	-0.268***	-0.253***	-0.320***
	(0.059)	(0.056)	(0.053)	(0.063)
Fund charcs	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	392758	392758	392758	392758
Adj. R^2	0.081	0.073	0.082	0.070

Table B.6. Flow and tail beta: COVID-19

This table presents regression coefficient estimates from panel regressions of fund flow on tail beta and COVID-19. The independent variables include a COVID-19 dummy variable that equals one if the month is either February or March of 2020, an interaction term between tail beta and the COVID-19 dummy, lagged fund flows, fund raw returns, the CAPM alpha, Fama-French-Carhart four-factor alpha, Fama-French five-factor alpha, industrial production growth, inflation rate, the return spread between long-term and short-term government bond indexes, and the return spread between high-yield bond index and the intermediate government bond index. The following fund characteristics are included as additional controls: the natural logarithm of fund size, expense ratio, and a load dummy that equals one if a fund charges front-end or back-end loads. All models include year fixed effects. The standard errors, clustered at fund-year level, are displayed in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable = monthly fund flow			
	(1)	(2)	(3)	(4)
Tail beta	-0.475***	-0.208***	-0.506***	-0.286***
	(0.090)	(0.076)	(0.089)	(0.090)
COVID-19	-0.385***	-0.467***	-0.539***	-0.527***
	(0.091)	(0.092)	(0.092)	(0.092)
Tail beta×COVID-19	-1.717***	-1.928***	-1.802***	-1.777***
	(0.558)	(0.512)	(0.561)	(0.581)
Lag flow	0.324***	0.322***	0.323***	0.324***
	(0.010)	(0.010)	(0.010)	(0.010)
Raw return	0.056***			
	(0.002)			
CAPM alpha		0.161***		
		(0.005)		
FFC alpha			0.171***	
			(0.006)	
FF5 alpha				0.160***
				(0.006)
Industrial production	0.042***	0.042***	0.031***	0.030***
	(0.009)	(0.009)	(0.009)	(0.009)
Inflation	0.149***	0.101***	0.088***	0.104***
	(0.026)	(0.026)	(0.026)	(0.026)
Term spread	0.046	0.016	0.106***	0.098***
	(0.033)	(0.033)	(0.033)	(0.033)
Default spread	0.522***	-0.032	0.019	-0.030
	(0.045)	(0.037)	(0.038)	(0.037)
Fund charcs	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	415198	415198	415198	415198
Adj. R^2	0.112	0.114	0.113	0.112

Table B.7. Alternative tail risk measure: Kelly and Jiang metric

This table presents regression coefficient estimates from Fama-MacBeth regressions of fund flow on the KJ metric, an alternative tail risk measure proposed by Kelly and Jiang (2014). The independent variables include lagged fund flows, fund raw returns, the CAPM alpha, Fama-French-Carhart four-factor alpha, and Fama-French five-factor alpha. The following fund characteristics are included as additional controls: the natural logarithm of fund size, expense ratio, and a load dummy that equals one if a fund charges front-end or back-end loads. The standard errors, adjusted using Newey and West (1987) method, are displayed in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable = monthly fund flow			
	(1)	(2)	(3)	(4)
KJ metric	-0.176***	-0.170***	-0.153***	-0.142***
	(0.055)	(0.054)	(0.044)	(0.047)
Lag flow	0.146***	0.146***	0.148***	0.148***
	(0.010)	(0.010)	(0.010)	(0.010)
Raw return	0.218***			
	(0.015)			
CAPM alpha		0.242***		
		(0.016)		
FFC alpha			0.242***	
			(0.015)	
FF5 alpha				0.234***
				(0.015)
Fund charcs	Yes	Yes	Yes	Yes
Observations	409839	407032	407032	407032
Number of months	348	348	348	348
Avg. R^2	0.059	0.060	0.057	0.057

Table B.8. Results from additional fund performance measures

This table reports regression coefficient estimates from Fama-MacBeth regressions of fund flow on tail beta, along with three additional fund performance measures: the manipulation-proof performance measure (MPPM), the Morningstar risk-adjusted return (MRAR), and a dummy variable that equals one if a fund has TNA-weighted Morningstar rating that is above median. Fund characteristics, such as the natural logarithm of fund size, expense ratio, and a load dummy that equals one if a fund charges front-end or back-end loads, are included as additional controls. The analysis with Morningstar ratings ends in December 2018 due to data availability. The standard errors, adjusted using Newey and West (1987) method, are displayed in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable = monthly fund flow		
	(1)	(2)	(3)
Tail beta	-0.296**	-0.323***	-0.343**
	(0.118)	(0.118)	(0.157)
Lag flow	0.193***	0.189***	0.191***
	(0.008)	(0.008)	(0.009)
MPPM	0.092***		
	(0.005)		
MRAR		0.101***	
		(0.004)	
$I(rating > median)$			1.850***
			(0.058)
Fund charcs	Yes	Yes	Yes
Observations	416901	416901	383540
Number of months	354	354	336
Avg. R^2	0.091	0.094	0.094

Table B.9. Persistence in tail beta

Each month, equity mutual funds are sorted into five groups based on the value of their tail beta, and this table reports the 1-year, 2-year, and 3-year transition matrix, respectively.

Tail beta group	1	2	3	4	5	Total
			Panel A: 1 year			
1	52.63	20.39	10.14	8.08	8.76	100
2	19.81	37.21	21.74	13.14	8.09	100
3	10.31	21.94	35.50	21.62	10.63	100
4	8.22	12.50	23.19	37.71	18.38	100
5	8.21	8.68	10.42	19.62	53.06	100
			Panel B: 2 years			
1	38.85	21.81	13.59	12.27	13.49	100
2	20.80	27.28	22.26	17.49	12.17	100
3	14.40	22.34	27.19	21.77	14.29	100
4	12.26	16.84	23.71	27.62	19.57	100
5	12.89	12.97	14.71	20.46	38.97	100
			Panel C: 3 years			
1	32.43	21.63	15.78	14.37	15.79	100
2	20.70	23.89	21.94	18.95	14.52	100
3	16.33	21.61	24.70	21.62	15.75	100
4	14.52	18.90	22.46	24.20	19.92	100
5	15.58	15.47	16.45	20.04	32.45	100

Table B.10. Flow-tail risk relation: retail vs. institutional funds

This table presents regression coefficient estimates from Fama-MacBeth regressions of fund flow on tail beta for retail and institutional funds, separately. Retail and institutional funds are differentiated based on indicators from the CRSP Mutual Fund Database. Fund characteristics, such as the natural logarithm of fund size, expense ratio, and a load dummy that equals one if a fund charges front-end or back-end loads, are included as additional controls. The standard errors, adjusted using Newey and West (1987) method, are displayed in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable = monthly fund flow							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Retail funds				Panel B: Institutional funds			
Tail beta	-0.553**	-0.565***	-0.600***	-0.511**	-0.676***	-0.705***	-0.750***	-0.685**
	(0.216)	(0.214)	(0.213)	(0.212)	(0.251)	(0.264)	(0.253)	(0.267)
Lag flow	0.197***	0.206***	0.203***	0.203***	0.180***	0.180***	0.178***	0.178***
	(0.017)	(0.015)	(0.015)	(0.015)	(0.008)	(0.008)	(0.008)	(0.008)
Raw return	0.252***				0.242***			
	(0.014)				(0.024)			
CAPM alpha		0.271***				0.241***		
		(0.015)				(0.025)		
FFC alpha			0.292***				0.294***	
			(0.017)				(0.029)	
FF5 alpha				0.287***				0.294***
				(0.015)				(0.026)
Fund charcs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	261865	261865	261865	261865	171301	171301	171301	171301
Num of months	210	210	210	210	210	210	210	210
Avg. R^2	0.084	0.080	0.086	0.087	0.057	0.057	0.063	0.065

Table B.11. Tail beta and fund activeness

This table presents regression coefficient estimates from Fama-MacBeth regressions of tail beta on fund activeness. Two measures of fund activeness are considered: active share of Cremers and Petajisto (2009), and $1 - R^2$ of Amihud and Goyenko (2013). Regression results of active share and $1 - R^2$ are reported in Panel A and Panel B, respectively. The active share data (up to the end of 2009) are from Antti Petajisto's website. Using three different models, namely the CAPM, the Fama-French-Carhart four-factor model (FFC), and the Fama-French five-factor model (FF5), tail beta or R^2 is estimated with 60-month rolling regressions. The three columns in Panel A (or Panel B) correspond to regression results of the CAPM, FFC model, and FF5 model. Fund characteristics, such as the natural logarithm of fund size, expense ratio, a load dummy that equals one if a fund charges front-end or back-end loads, and fund age, are included as controls. The standard errors, adjusted using Newey and West (1987) method, are displayed in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable = tail beta					
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Active share			Panel B: $1 - R^2$		
Activeness	0.272***	0.036**	0.034**	0.177***	0.086***	0.084***
	(0.054)	(0.014)	(0.014)	(0.042)	(0.027)	(0.021)
Log TNA	-0.001	-0.002**	-0.003***	0.001	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Expense ratio	0.007	-0.017***	-0.014***	-0.001	-0.003	-0.005**
	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Load fund dummy	-0.004*	-0.005	-0.003	0.000	-0.002	-0.001
	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Log age	-0.015***	-0.012***	-0.012***	-0.003	-0.005***	-0.008***
	(0.004)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
Observations	188333	188333	188333	417209	417209	417209
Number of months	228	228	228	354	354	354
Avg. R^2	0.110	0.028	0.026	0.084	0.036	0.028

Table B.12. Correlation matrix

This table reports pairwise correlations for fund flows, raw return, risk-adjusted alphas, and fund characteristics.

	Flow	Tail beta	Return	CAPM alpha	FFC alpha	FF5 alpha	TNA	Age	Expense ratio	Load
Flow (%/mo.)	1									
Tail beta	-0.01	1								
Return (%/mo.)	0.04	0.01	1							
CAPM alpha (%/mo.)	0.12	0.13	0.01	1						
FFC alpha (%/mo.)	0.12	0.21	0.01	0.75	1					
FF5 alpha (%/mo.)	0.11	0.16	0.01	0.66	0.82	1				
TNA ($mil)	0.01	0.01	0.01	0.06	0.08	0.08	1			
Age (months)	-0.05	0.02	0.01	-0.12	-0.07	-0.04	0.25	1		
Expense ratio (%)	0.01	0.03	-0.02	-0.05	-0.09	-0.06	-0.07	-0.06	1	
Load fund dummy	-0.01	-0.01	-0.01	-0.03	-0.05	-0.04	0.01	0.05	0.06	1

Table B.13. Time trend in the flow-tail risk relation

This table reports the result of linear trend analysis on the time-series of flow-tail risk relation. We use λ_1 from Eq.(3.4) as proxy for flow-tail risk relation, and we multiply the coefficient of month by 100 for ease of interpretation. We use different fund performance measures as controls in Eq.(3.4) (e.g., fund raw return, the CAPM alpha, Fama-French-Carhart four-factor alpha, and Fama-French five-factor alpha), and the results are reported in columns (1)–(4) respectively.

	Dependent variable = flow-tail risk			
	(1)	(2)	(3)	(4)
Month	0.206	0.232	0.226	0.235
	(0.182)	(0.177)	(0.195)	(0.175)
Constant	-1.634	-1.788*	-1.796	-1.636
	(1.087)	(1.064)	(1.134)	(1.007)
Number of months	354	354	354	354
Adj. R^2	0.010	0.013	0.009	0.012

Table B.14. Flow and tail beta

This table presents regression coefficient estimates from panel regressions of fund flow on tail beta and its interaction with variables of market condition. We consider three variables of market condition: stock market return (Mkt), the CBOE volatility index (VIX), and a dummy variable that equals one if the month falls into the NBER defined recession period. The independent variables include lagged fund flows, variables of market conditions and their interaction with tail beta, the CAPM alpha, Fama-French-Carhart four-factor alpha, Fama-French five-factor alpha, industrial production growth, inflation rate, the return spread between long-term and short-term government bond indexes, the return spread between high-yield bond index and the intermediate government bond index. The following fund characteristics are included as additional controls: the natural logarithm of fund size, expense ratio, and a load dummy that equals one if a fund charges front-end or back-end loads. The standard errors, double clustered at fund and month levels, are displayed in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable = monthly fund flow								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Tail beta	-0.437***	-0.548***	-0.389***	-0.505***	-0.571***	-0.411**	-0.345***	-0.453***	-0.334***
	(0.069)	(0.098)	(0.113)	(0.161)	(0.182)	(0.205)	(0.081)	(0.093)	(0.106)
Lag flow	0.138***	0.186***	0.142***	0.138***	0.184***	0.142***	0.138***	0.186***	0.142***
	(0.002)	(0.007)	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)	(0.007)	(0.008)
Mkt	0.025***	0.020***	0.022***						
	(0.003)	(0.003)	(0.003)						
Tail beta× $I(Mktrf < 0)$	0.189	0.095	0.238						
	(0.132)	(0.131)	(0.151)						
VIX				-0.001	0.001	-0.000			
				(0.002)	(0.002)	(0.002)			
Tail beta×VIX				0.013	-0.008	0.004			
				(0.009)	(0.008)	(0.010)			
NBER recession							-0.022	0.068	0.051
							(0.051)	(0.045)	(0.052)
Tail beta×NBER							-0.250	-0.187	-0.051
							(0.223)	(0.265)	(0.294)
CAPM alpha	0.166***			0.167***			0.166***		
	(0.005)			(0.006)			(0.006)		
FFC alpha		0.163***			0.165***			0.164***	
		(0.006)			(0.006)			(0.006)	
FF5 alpha			0.163***			0.163***			0.163***
			(0.007)			(0.007)			(0.007)
Industrial production	0.046***	0.036***	0.035***	0.104***	0.092***	0.077***	0.103***	0.092***	0.090***
	(0.011)	(0.010)	(0.011)	(0.018)	(0.015)	(0.017)	(0.019)	(0.016)	(0.019)
Inflation	0.252***	0.216***	0.248***	0.233***	0.198***	0.237***	0.240***	0.209***	0.241***
	(0.039)	(0.034)	(0.040)	(0.043)	(0.036)	(0.043)	(0.041)	(0.034)	(0.041)
Term spread	0.047	0.136***	0.133***	0.022	0.105**	0.111**	0.023	0.116***	0.106**
	(0.048)	(0.041)	(0.048)	(0.049)	(0.042)	(0.049)	(0.049)	(0.042)	(0.049)
Default spread	0.114*	0.116**	0.106*	-0.160***	-0.143***	-0.149**	-0.161***	-0.075	-0.157***
	(0.060)	(0.055)	(0.061)	(0.062)	(0.052)	(0.061)	(0.060)	(0.050)	(0.059)
Fund charcs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	414040	414040	414040	410343	410343	410343	411521	411521	411521
Adj. R^2	0.059	0.075	0.059	0.059	0.077	0.060	0.059	0.075	0.060