NBER WORKING PAPER SERIES

ESG SPILLOVERS

Shangchen Li
Hongxun Ruan
Sheridan Titman
Haotian Xiang

Working Paper 31248
http://www.nber.org/papers/w31248

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
May 2023

We thank Greg Weitzner, David Xu, Jedrzej Bialkowski, audiences at Peking University, Renmin University, National University of Singapore, and China Five-Star Finance Workshop for helpful comments. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

ESG Spillovers
Shangchen Li, Hongxun Ruan, Sheridan Titman, and Haotian Xiang
NBER Working Paper No. 31248
May 2023
JEL No. G14,G2

ABSTRACT

We study ESG and non-ESG mutual funds managed by overlapping teams. We find that non-ESG mutual funds include more high ESG stocks after the creation of an ESG sibling, and the high ESG stocks they select exhibit superior performance. The low ESG stocks selected by ESG funds also exhibit superior performance and despite being more constrained, the ESG funds outperform their non-ESG siblings. The latter result is consistent with fund families making choices that favor ESG funds. Specifically, ESG funds tend to trade illiquid stocks prior to their non-ESG siblings and get preferential IPO allocations.

Shangchen Li
Peking University
Guanghua School of Mangement
No.5 Yiheyuan Road
Haidian District
Beijing
China
lishangchen@pku.edu.cn

Hongxun Ruan
Peking University
Guanghua School of Management
Finance Department
Beijing
China
hongxunruan@gsm.pku.edu.cn

Sheridan Titman
Finance Department
McCombs School of Business
University of Texas at Austin
Austin, TX 78712-1179
and NBER
titman@mail.utexas.edu

Haotian Xiang
Peking University
No.5 Yiheyuan Road
Haidian District
Beijing 100871
China
xiang@gsm.pku.edu.cn

1 Introduction

As a first approximation, the prime objective of mutual funds is to attract investors who are willing to pay their fees. While investment performance continues to be important for attracting new investors, investor interest in environmental, social, and governance (ESG) issues have been growing, and with this increase in their interest, we have seen a remarkable boom in the number of mutual funds that cater to this demand. Our analysis of SEC filings reveals that at least 10% of the U.S. active diversified equity funds formally incorporated ESG considerations into their investment decision making in 2020, representing a total AUM of $366 billion.

To learn more about how an increase in ESG investing affects the mutual fund industry we study a sample of U.S. mutual fund families that created new active diversified ESG equity funds between 2013 and 2020. We are particularly interested in the 60% of these ESG funds that are managed by individuals who also manage active non-ESG equity funds. Specifically, we test the idea that adding an ESG fund to a management team's responsibility affects how the managers allocate their attention, and how that, in turn, influences their portfolio choices as well as their investment performance.

We identify and test a number of hypotheses that follow from this premise. The first is that the added attention to high ESG stocks will increase the average ESG score of non-ESG sibling funds. Our evidence is consistent with this hypothesis. We find that the portfolios of non-ESG sibling funds have significantly higher ESG scores than standalone non-ESG funds, and this difference becomes stronger as the duration of co-management increases. Moreover, with attention shifted towards high ESG stocks, we expect the managers to perform better in their selection of high ESG stocks, but worse in their selection of low ESG stocks. We compare the stock selection performance of sibling and standalone non-ESG funds by examining their large non-flow-induced trades, and provide evidence that is consistent with this hypothesis.

Our second hypothesis is that ESG funds should underperform their non-ESG sibling funds. Both funds are managed with the same information, but the ESG fund has the disadvantage that it is maximizing performance subject to an additional constraint. We examine this hypothesis directly by comparing the alphas of the different funds and we also measure the performance of the individual stocks picked by the funds, conditioned on their ESG scores. We expect the non-ESG funds to do especially well selecting high ESG stocks since they are unconstrained, and thus have the discretion to "cherry-pick" the best of these stocks. Similarly, the ESG funds are expected to select better performing low ESG stocks, because they have less incentive to pick these stocks, and will thus only do so when the stocks have especially high expected returns.

Consistent with our hypotheses, the high ESG stocks selected by non-ESG sibling funds outperform the high ESG stocks selected by ESG funds, whereas the low ESG stocks selected by ESG funds tend to outperform those chosen by non-ESG sibling funds. However, the overall performance of ESG funds beats their non-ESG siblings, which is inconsistent with our hypothesis. The average difference in alpha between co-managed ESG and non-ESG funds is close to 1% per annum. We do not find a significant performance difference between ESG and standalone non-ESG funds, and in the appendix, we provide evidence that returns of individual stocks are not reliably related to ESG scores during our sample period.[1]

The second part of the paper examines whether the underperformance of the non-ESG sibling funds arises because mutual fund families make choices that favor the ESG funds. We conjecture that by doing this, the mutual fund families benefit by increasing total mutual fund flows. To show why this may be the case, we first show that the flows of ESG funds tend to respond more favorably to good performance than the flows of non-ESG funds.[2] Given this

[1]There is a large literature that compares the performance difference between ESG and non-ESG funds and that between high- and low-ESG stocks. The evidence is mixed. For example, Hartzmark and Sussman (2019) and Geczy, Stambaugh, and Levin (2021) find no significant difference between what they characterize as responsible and non-responsible funds, and Avramov, Cheng, Lioui, and Tarelli (2021) find no significant difference between high- and low-ESG stocks. There is, however, evidence that stock returns are positively related to firms' environmental performance as measured by the Pastor, Stambaugh, and Taylor (2022) E score, but measured carbon emissions are not negatively related to returns (Bolton and Kacperczyk, 2021; Pedersen, Fitzgibbons, and Pomorski, 2021). Hong and Kacperczyk (2009) find higher returns for sin stocks. In Appendix B.5 we show that the underperformance of sibling non-ESG funds relative to ESG funds cannot be explained by their difference in fund-level ESG scores and that ESG scores do not explain stock returns in our time period.

[2]Our results are consistent with Bollen (2007) and Bialkowski and Starks (2016), who show that inflows to

observation, mutual fund families can potentially attract greater aggregate flows by making choices that benefit ESG-fund performance at the expense of their non-ESG siblings.

To better understand how a mutual fund family can favor their ESG funds, we build on Gaspar, Massa, and Matos (2006) and explore two specific ways in which mutual fund families can effectively transfer performance between individual funds.[3] First, we examine whether the families tend to execute the trades of their ESG mutual funds prior to the trades of their non-ESG siblings. This possibility is explored by looking at large non-flow-induced trades of ESG funds and their non-ESG siblings. We find that for illiquid stocks, both buy and sell orders tend to be executed first for the ESG funds. Consistent with the literature studying asymmetric price impacts, we find that this tendency is stronger when the funds are selling than buying. It is noteworthy that we do not find evidence of the ESG funds executing the trades of liquid stocks prior to their non-ESG siblings.

The allocation of potentially underpriced IPOs provides a second potential channel for favoring ESG funds. Mutual fund families have discretion in how they allocate IPOs and our estimates suggest that they allocate more of the most underpriced IPOs to their ESG funds than to their non-ESG siblings. In particular, we find that ESG funds generate significantly larger returns than their non-ESG siblings on the days when substantially underpriced IPOs are issued.

The analysis in this paper contributes to four different literatures. The first literature explores ESG mutual funds and the extent to which socially responsible investing influences mutual fund performance. This is a growing literature, and in general researchers do not find significant differences in the performance of ESG and non-ESG funds.[4] By examining ESG and

SR funds respond more aggressively to good performance compared to non-SR funds. In contrast, Benson and Humphrey (2008) and El Ghoul and Karoui (2017) do not find such a difference. Note, however, that these studies investigate the pre-2011 period, when ESG investing is less prevalent.

[3] Gaspar, Massa, and Matos (2006) provide evidence that mutual fund families make choices that transfer performance from low fee to high fee funds, and from small to large funds. At the beginning of our sample period, ESG funds did have higher average fees than non-ESG funds, but the fee differences declined considerably over our sample period. Given this, we do not think fee differences provide an incentive to transfer performance in our sample period. Moreover, ESG funds are also relatively smaller.

[4] See e.g., Bollen (2007), Benson and Humphrey (2008), Bialkowski and Starks (2016), Hartzmark and Sussman

non-ESG sibling funds, we have a more focused comparison and uncover a dimension along which ESG funds do significantly outperform—that is, when compared to the non-ESG funds that are co-managed with them. We also provide possible explanations for why they outperform. The second literature we contribute to studies the co-management of mutual funds in general.[5] While this literature also considers possible spillovers between mutual funds, our paper contributes by providing a hypothesis about the direction of the spillovers and by identifying additional channels that can contribute to these spillovers. The third relevant literature examines mutual fund holdings and asks whether one can identify which stocks are associated with superior performance.[6] We find that abnormal stock returns can be predicted using information about mutual fund flows in combination with the ESG scores of the stocks acquired by the mutual funds. For example, we find that low-ESG stocks bought in a large quantity by ESG funds who face an outflow are more likely to perform well. The final literature explores the importance of investor attention on the portfolio choices of institutional investors.[7] We contribute to this literature by highlighting how investor objectives influences attention and by providing a clean experiment that illustrates how shocks to attention affects portfolio choices as well as performance in different sectors.

The paper is organized as follows. Section 2 develops our hypotheses with a two-stage

(2019), and Geczy, Stambaugh, and Levin (2021).

[5]Evans and Fahlenbrach (2012) study the co-management of retail and institutional mutual funds and find that the performance of the retail funds improves when they are co-managed with institutional twins. More recently, Agarwal, Ma, and Mullally (2018) find some evidence that when managers split their attention between funds, performance deteriorates. A related literature studies the co-management of mutual funds and hedge funds. For example, Nohel, Wang, and Zheng (2010) find that the co-management of mutual funds and hedge funds benefits mutual fund investors but Cici, Gibson, and Moussawi (2010) find the opposite. More recently, using hand-collected data from mandatory SEC filings, Del Guercio, Genc, and Tran (2018) find that mutual funds whose managers also manage hedge funds significantly underperform.

[6]Early papers evaluating the informativeness of mutual fund trades include Grinblatt and Titman (1989, 1993) and Chen, Jegadeesh, and Wermers (2000). More recently, Alexander, Cici, and Gibson (2007) show that one can uncover stronger evidence of information by conditioning fund trades on the direction and magnitude of investor flows.

[7]There is a large literature that examines investor attention (e.g. Barber and Odean, 2008; Da, Engelberg, and Gao, 2011). More recently, researchers have considered the possibility that limited attention also influences the choices of institutions. Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016) propose a theory that fund managers with limited attention choose to process information about aggregate shocks in recessions and idiosyncratic shocks in booms, and provide consistent empirical evidence.

descriptive framework. Section 3 describes our data and summary statistics. Section 4 tests our hypotheses about the implications of co-management on funds' investment process. Section 5 documents the underperformance of sibling non-ESG funds and establishes the underlying rationale through flow-performance sensitivities. Section 6 presents evidence on cross-fund subsidization through the timing of trades and IPO allocations. Section 7 concludes.

2 Hypothesis Development

To develop the hypotheses that we will be testing, we start by first outlining a two-stage descriptive framework that approximates the investment process of many active mutual funds. In the first stage, a standalone non-ESG mutual fund selects an investment universe consisting of N stocks, based perhaps on a quantitative overview. The idea is that the managers have limited attention that is allocated among a fixed number of stocks. These stocks are then closely scrutinized in the second stage using fundamental analysis, generating a score or ranking for each stock that is monotonically related to its estimated expected rate of return. The fund will then include stocks into its portfolio, starting from the highest ranked stocks, moving down to lower ranked stocks, until the diversification benefit from adding an additional stock is more than offset by the negative effect that the addition of a marginal stock has on the portfolio's expected return.

When a non-ESG investment team with such a two-step process is asked to manage a new ESG fund, we assume that the investment process is altered as follows. First, we assume that since the same team is managing both ESG and non-ESG portfolios, they will select stocks for both funds from a single investment universe. Because an ESG fund is constrained by its investment mandate to tilt towards stocks that have high ESG scores, the team has an incentive to include more high ESG stocks in its investment universe in the first step when its responsibility includes an ESG as well as a non-ESG fund. Second, while we assume that the selection criterion for the non-ESG fund is based only on expected financial performance, to tilt the choices of the ESG fund towards high ESG stocks the team employs a selection criterion under which it effectively adds an ESG premium or discount to the financial scores when selecting stocks for the ESG fund. One can interpret this ESG premium as a convenience yield that provides utility to the mutual fund holders that is in addition to the fund's financial benefits (e.g., Pastor, Stambaugh, and Taylor, 2021; Goldstein, Kopytov, Shen, and Xiang, 2021).[8] For example, it may add a 1% ESG convenience yield to the expected excess returns of electrical utilities with solar generation or subtract 1% from the expected excess returns of those with coal-fired power plants.

This simple setting generates a number of testable hypotheses. The first hypothesis is a direct implication of our assumption that the addition of an ESG fund to a manager's responsibilities changes the makeup of the stocks included in the first step of the investment process. If managers who manage an ESG and a non-ESG fund at the same time include more high ESG stocks in the first step, more high ESG stocks will ultimately be included in the non-ESG fund's portfolio, even if their stock selection criteria in the second step for the non-ESG fund do not involve an explicit preference for high ESG stocks. This point is of interest because it directly implies that the initiation of an ESG fund creates a spillover effect on their non-ESG siblings.

Formally, our first hypothesis states:

H1: *A non-ESG fund will increase its holdings of high ESG stocks when its investment team initiates an ESG fund.*

Since the investment universe of the sibling non-ESG funds contains more high ESG stocks than the investment universe of standalone non-ESG funds, sibling non-ESG funds are likely to find better performing high ESG stocks than standalone non-ESG funds. This implies that the high ESG stocks selected by sibling non-ESG funds will tend to outperform the high ESG stocks selected by standalone non-ESG funds. Similarly, the investment universe of standalone non-ESG funds contains relatively more low ESG stocks, which suggests that the low ESG stocks

[8] That investors sacrifice financial returns for non-pecuniary benefits has been documented for individual investors by Riedl and Smeets (2017) and for venture capitalists by Barber, Morse, and Yasuda (2021).

selected by standalone non-ESG funds are expected to outperform the low ESG stocks selected by sibling non-ESG funds.

Formally, our second hypothesis states:

H2: *The high ESG stocks picked by sibling non-ESG funds outperform the high ESG stocks picked by standalone non-ESG funds, whereas the low ESG stocks picked by sibling non-ESG funds underperform the low ESG stocks picked by standalone non-ESG funds.*

The third hypothesis relates to differences in the performance of sibling non-ESG funds and ESG funds. Because ESG funds attach an ESG convenience yield to high ESG stocks, they are willing to include in their portfolios high ESG stocks with a relatively low expected excess return. This implies that the high ESG stocks selected by non-ESG funds outperform the high ESG stocks selected by ESG funds. In contrast, we expect the low ESG stocks selected by non-ESG funds to underperform those selected by ESG funds, since only the low ESG stocks with especially high expected excess returns will be included in the portfolio of ESG funds. For example, the ESG fund will include an electric utility with coal-fired plants only if its expected rate of return exceeds the expected returns of electrical utilities with solar generation plus their associated ESG convenience yields.

Formally, our third hypothesis states:

H3: *The high ESG stocks picked by sibling non-ESG funds outperform the high ESG stocks picked by ESG funds, whereas the low ESG stocks picked by sibling non-ESG funds underperform the low ESG stocks picked by ESG funds.*

The last hypothesis is related to fund performance. We expect the financial performance of non-ESG sibling funds to be better than that of their co-managed ESG funds. This is because the managers are constrained to hold higher ESG stocks in their ESG fund even if the expected returns are lower. Clearly, ceteris paribus, an unconstrained portfolio should have superior expected performance than a constrained portfolio managed with the same information.

Formally, our fourth hypothesis states:

H4: *Sibling non-ESG funds will tend to exhibit better investment performance than their ESG siblings.*

3 Data

3.1 Data Sources

Our data comes from multiple sources. We use the Center for Research in Security Prices (CRSP) mutual fund database to construct a sample of actively-managed diversified open-ended U.S. domestic equity funds following the methodology of Kacperczyk, Sialm, and Zheng (2008), which is described in detail in Appendix A.1. We then identify ESG funds based on funds' prospectuses. The CRSP mutual fund database provides fund characteristics such as TNA, returns, expense ratios, and turnover ratios. We obtain the names and tenure of fund managers, fund portfolio holdings, and three-by-three fund size/value style categories from Morningstar Direct. Compared to Thomson Reuters CDA/Spectrum, which reports fund holdings mostly at a quarterly frequency, Morningstar offers monthly holdings for over 50% of the funds in our sample, which enables us to identify the trades made by mutual funds at a higher frequency.[9] Another advantage of using the Morningstar holdings data is that it has better coverage of newly established funds in the past decade (Zhu, 2020).

For the ESG scores of individual stocks, we collect data from MSCI ESG Research (formerly KLD). Stock characteristics including monthly returns, prices, and trading volumes are gathered from CRSP. We obtain risk-free rates, returns of Fama-French risk factors, and ME breakpoints for NYSE stocks from Ken French's website.

[9] Appendix A.2 provides a brief summary of how we use holdings reported under different frequencies for our analyses.

3.2 Variable Constructions

We primarily use fund summary prospectuses (filing type 497K) filed between 2010 and 2021 to determine each fund's ESG attribute.[10] In particular, we utilize the information from the mandatory section "Principal Investment Strategies", where funds typically disclose their incorporation of ESG principles.[11] Specifically, in Appendix A.1 we first expand the ESG dictionary in Baghai, Becker, and Pitschner (2020) by adding keywords related to negative screening and sustainable investments. For funds that have mentioned at least one of our ESG keywords in the "Principal Investment Strategies" section of one of their 497Ks, we manually read their 497Ks and supplementary 497Ks to identify ESG funds and the date of their ESG adoption. For funds whose 497K filings cannot be found in EDGAR, we use their grouped prospectuses (form 485BPOS) and identify their ESG attributes manually. We construct a dummy variable *ESG* equal to 1 if a fund is an ESG fund in a given month.

Next, we identify non-ESG sibling funds through the portfolio managers of these ESG funds. We classify a fund as a non-ESG sibling fund in a given month if it is a non-ESG fund and has at least one manager sitting in the management team of an ESG fund in that month.[12] We identify 198 distinct non-ESG sibling funds, about 80% of which started as standalone non-ESG funds but later evolved into siblings as members of their management teams began to manage ESG funds. If a fund is a sibling (standalone) non-ESG fund in a given month, the dummy variable *SNE* (*ANE*) equals 1.

Other key variables for our empirical analyses include stock- and fund-level ESG scores. MSCI KLD provides binary indicators of a firm's ESG strengths and concerns along 7 dimensions: community, corporate governance, diversity, employee relations, environment, human rights, and product. To construct the ESG score for a firm, we first average non-missing indica-

[10] Baghai, Becker, and Pitschner (2020) show the advantages of using summary prospectuses over the standard prospectuses for textual analysis, as they are typically short, standardized, and specifically designed for retail investors.

[11] Morningstar also identifies ESG funds based on the information from the "Principal Investment Strategies" section without disclosing the exact criteria (Hale, 2021).

[12] In Appendix B.3, we exclude funds managed by a team of more than 3 managers. Our main results become stronger.

tors separately for its strengths and concerns, and then take the difference between these two. Since KLD ratings may not be updated annually, we use the closest observation within the past 3 years as a firm's ESG score. We compute fund-level ESG scores (*score*) by value-weighting ESG scores of firms in their portfolios. A higher score indicates better ESG performance. For funds reporting quarterly, we extrapolate their ESG performance using the disclosed values at the end of the last quarter.

To obtain the gross return before expenses (*grossret*), we add one-twelfth of the fund expense ratio to the monthly net return. We value-weight returns across share classes using the previous month's TNA of each share class. We use Carhart (1997)'s four-factor alpha (*alpha*) to measure the risk-adjusted performance of funds. To do so, we estimate rolling betas using data from the previous 60 months, requiring a minimum of 24 monthly observations.[13] The fund size (*size*) is the logarithm of the combined TNA across all share classes in the fund. The fund age (*age*) is the age of the oldest share class in the fund. The expense ratio (*expratio*) and the turnover ratio (*turnratio*) are value-weighted across share classes by the previous month's TNA. The net fund flow in percentage (*perflow*) is computed by taking the difference between the growth rate of the fund size and the gross return of the fund. The net fund flow in dollar (*dollarflow*) is the product of the net fund flow in percentage and the fund size in the previous month. We winsorize all continuous variables at 1% and 99% levels.

3.3 Sample Overview

Our sample spans from January 2013 to December 2020. While our data starts from 2010, we follow the literature, e.g., Pastor, Stambaugh, and Taylor (2022), and study data after 2013, coinciding with a discontinuous increase in the coverage of MSCI KLD ESG ratings. Figure 1 plots the time series of the number and the combined TNA of ESG, sibling non-ESG, and standalone non-ESG funds. During our sample period, the U.S. active diversified equity funds

[13]We use out-of-sample alphas to avoid the look-ahead bias. For robustness, we have replicated our analyses related to fund alphas using in-sample alphas. Our main results are robust.

that incorporate ESG principles experienced a remarkable growth. In June 2013, there were 33 ESG funds, accounting for only 2.7% of all funds and 0.8% of the combined TNA. At the end of 2020, 138 funds (11.6% of all funds) in our sample adopted ESG investment strategies with a combined TNA of $366 billion. The co-management of ESG funds and non-ESG funds is prevalent in our sample. For all funds that started adopting ESG principles after 2013, about 60% of them have at least one non-ESG sibling. At the end of 2020, our sample includes 106 non-ESG siblings with a combined TNA of $413 billion, 13% larger than the combined TNA of ESG funds.

—Insert Figure 1 about here—

Table 1 reports some key statistics for ESG funds, non-ESG sibling funds, and standalone non-ESG funds, respectively. The average ESG score of ESG funds is 25.26, which is significantly higher than the score of standalone non-ESG funds. The average ESG score of the non-ESG sibling funds lies between these two, which is consistent with our hypothesis *H1*. In our sample, ESG funds are smaller but attract more investor flows relative to non-ESG funds, reflecting their increasing popularity. Interestingly, even though the demand for ESG funds was strong over the past decade, we do not find a significant difference in the fees of ESG and non-ESG funds.[14] Finally, we do not observe significant differences in the typical factor exposures of the ESG and non-ESG funds.

—Insert Table 1 about here—

It is worth noting that ESG funds in our sample include two types; sibling ESG and standalone ESG funds. We do not observe significant differences in their portfolio ESG scores or

[14] In the early part of our sample, fees of ESG funds were higher—for instance, there was a 20-bp difference in 2013. However, these differences decline quickly and have been below 2 basis points since 2016.

performance, with formal testing results reported in Appendix B.6. We will not directly analyze differences between these categories of ESG funds, but our focus on cross-fund spillovers can potentially create differences.

4 Investment Process under Co-management

4.1 ESG Spillovers

Our hypothesis *H1* states that managers of ESG funds tend to include more stocks with high ESG scores in their non-ESG funds than those who manage standalone non-ESG funds. Consistent with *H1*, Table 1 reports that the average portfolio ESG score of non-ESG sibling funds is indeed higher than that of standalone non-ESG funds. To formally test for such a difference, we run the following regression:

$$score_{i,t+1} = \alpha + \beta_1 ESG_{i,t} + \beta_2 SNE_{i,t} + \sum_k \gamma_k Controls^k_{i,t} + u_i + \epsilon_{i,t}. \quad (1)$$

where $score_{i,t+1}$ is the value-weighted ESG score for fund i in month $t+1$, and $ESG_{i,t}$ and $SNE_{i,t}$ are two dummies indicating whether fund i is an ESG fund or a sibling non-ESG fund in month t. Control variables include fund size, fund age, expense ratio, and turnover ratio as well as fund-fixed effects, u_i. Given that we include fund fixed effects, our estimates essentially compare the average ESG scores before and after a fund changes its status (i.e., converting from a standalone non-ESG fund into an ESG fund or a sibling non-ESG fund). Effectively, this means that funds that maintain the same sibling versus standalone status throughout the sample period don't contribute to the estimates of interest.[15]

Our estimates of the above expression, reported in column (1) of Table 2, reveal statistically significant coefficient estimates of 3.4 and 1.0 for the ESG and SNE dummies, respectively. For ESG funds, a point estimate of 3.4 represents a close to 17% increase in the ESG score, and

[15] Therefore, our results are similar if we drop observations where non-ESG sibling funds were born after their ESG counterparts.

for sibling funds, a point estimate of 1.0 represents close to a 5% increase in the ESG score. The latter result is consistent with a spillover effect, i.e., when non-ESG managers start to manage ESG funds, the average ESG scores of their non-ESG funds increase.

—Insert Table 2 about here—

Given the presence of trading costs such as transaction costs or execution shortfalls (e.g., Gârleanu and Pedersen, 2013), we expect the portfolio ESG score of non-ESG sibling funds to increase gradually after the introduction of a co-managed ESG mutual fund. To investigate this hypothesis, we include a series of dummies indicating the length of co-management into equation (1), where SNE_3y+, SNE_2y, SNE_1y, SNE_0y are dummies which equal 1 if the fund is a sibling non-ESG fund and has been co-managed with ESG funds for more than 3 years, 2-3 years, 1-2 years, 0-1 years, respectively. Dummy SNE_-1y is equal to 1 if the fund is a standalone non-ESG fund but will become a non-ESG sibling fund in one year.

Estimates of this regression are presented in column (2) of Table 2. We find that the coefficients of the dummies for $-1y$ to $1y$ are statistically insignificant, whereas the coefficients of the dummies greater than 2 years are positive and statistically significant. These results indicate: 1) The spillover effect unfolds gradually; 2) Before co-management, the predecessor of non-ESG sibling funds do not have higher ESG scores than other standalone non-ESG funds. One might expect that non-ESG sibling funds hold more high ESG stocks because managers who specialize in analyzing high ESG assets are more likely to be assigned by the fund family to manage newly initiated ESG funds. However, the above evidence is inconsistent with this hypothesis.

To alleviate the concern that the higher ESG score that we observe for non-ESG sibling funds after co-management might be driven by aggregate trends, we conduct difference-in-differences (DID) analyses in Appendix B.1. In particular, we first match a non-ESG sibling fund (and its standalone non-ESG predecessor) with a fund that remains a standalone non-ESG fund throughout our sample period and shares similar characteristics. We then show that the gap in funds' ESG scores within matched pairs widens significantly after co-management.

Recall our hypothesis that the average ESG scores of non-ESG funds increase when their managers start managing ESG funds because their exposures to high ESG stocks increase. Among ESG funds, there exists significant heterogeneity with regard to their portfolio ESG scores, i.e., some ESG funds are "more ESG" than other ESG funds. Our logic suggests that non-ESG siblings will have higher ESG scores when they are managed with ESG funds with higher ESG scores. We test this hypothesis in the regression reported in column (3) of Table 2, which is restricted to only sibling non-ESG funds. Specifically, we include the variable $score\_ESG$, which represents the ESG score of the ESG funds that the non-ESG fund is co-managed with. The estimated coefficient of $score\_ESG$ is positive and statistically significant, which supports our hypothesis.[16]

In Table 3, we further show that the high ESG stocks held by non-ESG funds do tend to be held by their ESG siblings. Specifically, in each month, we sort all stocks held by the non-ESG funds into 10 portfolios based on their ESG scores. For a stock held by fund i, we create a dummy that equals one if the stock appears in the latest disclosure of i's ESG siblings. We then average across i's to get the probability that a stock held by the non-ESG fund is simultaneously held by its ESG siblings. We find that the probability increases (almost) monotonically in the ESG score. For the stocks in the top decile, i.e. ones with the highest ESG score, the probability is close to 60%.

—Insert Table 3 about here—

4.2 Stock Return Performance

In this subsection we examine the stock-picking abilities of the mutual funds and test hypotheses *H2* and *H3*. To enhance the power of our tests, we focus only on significant changes in

[16]In Appendix B.8, we show that the portfolio ESG score of a non-ESG sibling fund also increases with the size of its ESG siblings, consistent with our theory of limited attention.

holdings that are likely to be based on a careful analysis of the stocks' fundamentals. To be more specific, we consider only those buy trades that satisfy the following two criteria.[17] First, they have a nontrivial size—in particular, the percentage holdings increase by at least 0.2%. Second, the acquisition is unlikely to be flow-induced. Specifically, we consider only those buy trades that are either observed when there is a fund-level net outflow (Alexander, Cici, and Gibson, 2007) or occur when there is a fund-level net inflow, but percentage-wise, the increase in the stock's position is ten times larger than the inflow. Following the literature, we exclude stocks that are either priced below \$5 or have a market capitalization in the bottom 10% using NYSE breakpoints.

We sort all buy trades into 5×3 groups according to the ESG score of the traded stock and the ESG attribute of the fund. We compute the alpha of each group by running the following regression:

$$\begin{aligned} hpa_{j,t} = &\alpha_0 + \sum_{q=1}^{5} \beta_q SNE\_quintile_{j,t}^{q} \\ &+ \sum_{q=1}^{5} \phi_q ANE\_quintile_{j,t}^{q} + \sum_{q=2}^{5} \delta_q ESG\_quintile_{j,t}^{q} + \sum_{k} \gamma_k Controls_{j,t}^{k} + v_t + \epsilon_{j,t}, \end{aligned} \tag{2}$$

where $hpa_{j,t}$ is the (cumulative) alpha of trade j placed at time t, assuming that the stock is held for 1 month, 1 quarter, or 1 year. For regressions where $hpa_{j,t}$ is the 1-month alpha, we restrict the sample to funds that disclose at a monthly frequency. For a buy trade j by a non-ESG sibling fund at time t, dummy variable $SNE\_quintile_{j,t}^{5}$ equals one if its underlying stock falls into the 5^{th} ESG quintile, i.e., top 20% in ESG scores. Similarly, for a buy trade j made by a standalone non-ESG fund (an ESG fund) at time t, the dummy variable $ANE\_quintile_{j,t}^{5}$ ($ESG\_quintile_{j,t}^{5}$) equals 1 if its underlying stock falls into the 5^{th} ESG quintile. The regression includes controls for standard stock characteristics such as size, book-to-market, momentum, and illiquidity (daily Amihud (2002)'s ratio averaged over the past 12 months). We have demeaned all control variables, and thus the intercept α_0 represents the average holding period

[17] Appendix B.4 varies these criteria and shows the robustness of our results.

alpha for the omitted group, i.e., $ESG\_quintile^1_{j,t} = 1$. The average holding period alphas for the other 14 groups are computed as $\{\beta_q + \alpha_0\}_{q=1}^5$, $\{\phi_q + \alpha_0\}_{q=1}^5$, and $\{\delta_q + \alpha_0\}_{q=2}^5$.

—Insert Table 4 about here—

Table 4 reports estimates of the above equation. To compare the performance of the stock picks of sibling and standalone non-ESG funds, we examine estimates of β and ϕ. For the 1-quarter alpha, we estimate $\beta_5 + \alpha_0 = 0.46\%$ and $\phi_5 + \alpha_0 = -0.25\%$; the difference between these estimates, 0.71%, is statistically significant. For 1-month and 1-year alphas, our results also exhibit significantly different β_5 and ϕ_5 estimates, indicating that the high ESG stocks selected by sibling non-ESG funds outperform those selected by standalone non-ESG funds. In contrast, the analysis of the selection of low-ESG stocks reveals the opposite result. For instance, for the 1-quarter alpha, we estimate $\beta_2 + \alpha_0 = -1.45\%$ and $\phi_2 + \alpha_0 = -0.86\%$, indicating that standalone non-ESG funds select low ESG stocks that outperform those selected by non-ESG sibling funds. These observations are all consistent with hypothesis *H2*.

We next consider hypothesis *H3*, and compare the stocks chosen by non-ESG sibling funds and ESG funds, i.e., we are interested in the difference between β and δ. Our results in the last column support this hypothesis. First, high ESG stocks purchased by non-ESG sibling funds perform better than the high ESG stocks purchased by ESG funds. Second, low ESG stocks purchased by non-ESG sibling funds perform worse than the low ESG stocks purchased by ESG funds. For the 1-quarter and 1-year alphas, we find differences that are economically and statistically significant. For the 1-month alpha, the estimated sign is consistent with our hypothesis, but the difference is not always statistically significant.

5 Fund Performance

Hypothesis *H4* indicates that non-ESG sibling funds, because they are unconstrained, will outperform their constrained ESG siblings. However, the empirical results reported in this section are inconsistent with this hypothesis. Our subsequent analysis suggests that mutual fund families may have an incentive to take actions that favor ESG funds over their non-ESG sibling funds and we conjecture that this may explain part of the underperformance of the non-ESG siblings. We present circumstantial evidence that is consistent with this conjecture in Section 6.

5.1 Underperformance of Sibling Funds

To estimate how the performance of a mutual fund varies with its ESG attributes, we run both Fama and MacBeth (1973) regressions and pooled regressions with time fixed effects. Panel A of Table 5 reports estimate of these regressions in a subsample that includes only sibling pairs of ESG and non-ESG funds. We consider the following specification:

$$Perf_{i,t+1} = \alpha + \beta_1 SNE_{i,t} + \sum_k \gamma_k Controls_{i,t}^k + \epsilon_{i,t}. \tag{3}$$

We use two measures to gauge fund performance $Perf_{i,t+1}$—the Carhart four-factor alpha $alpha_{i,t+1}$ on the left panel and the gross return $grossret_{i,t+1}$ on the right panel. $SNE_{i,t}$ is equal to 1 if the fund i is a sibling non-ESG fund and is 0 if the fund i is a sibling ESG fund in month t. Control variables in all columns include fund size, fund age, expense ratio, and turnover ratio. When the gross return is the dependent variable, we also include loadings on the market, size, value, and momentum factors as controls. Lastly, we control for fund style fixed effects.

The estimates of these regressions are reported in Panel A of Table 5. These estimates reveal that sibling non-ESG funds underperform their ESG counterparts by close to 1% per annum. This significant difference is inconsistent with our hypothesis that states that the less constrained funds will tend to outperform their more constrained counterparts.

—Insert Table 5 about here—

Panel B reports estimates of similar regressions that also include standalone ESG and non-ESG funds. Specifically, we run the following regression:

$$Perf_{i,t+1} = \alpha + \beta_1 SNE_{i,t} + \beta_2 ESG_{i,t} + \sum_k \gamma_k Controls^k_{i,t} + \epsilon_{i,t}. \tag{4}$$

$SNE_{i,t}$ and $ESG_{i,t}$ indicate if fund i is a sibling non-ESG fund or an ESG fund in month t. We include the same set of controls as in (3). Notice that, Panel B compares the performance of ESG and sibling non-ESG funds relative to the performance of standalone non-ESG funds, whereas Panel A compares the performance of sibling non-ESG funds against sibling ESG funds.

Consistent with our previous estimates, these estimates indicate that non-ESG sibling funds underperform ESG funds. The coefficients of ESG are small and statistically insignificant under various specifications, indicating that the performances of ESG funds and standalone non-ESG funds are quite similar. Considering the fact that the majority of non-ESG funds in our sample are standalone, this evidence is consistent with Hartzmark and Sussman (2019) and Geczy, Stambaugh, and Levin (2021), who find no performance difference between ESG and non-ESG funds.[18]

5.2 Flow-performance Sensitivities for ESG and Non-ESG Funds

The previous section provided evidence that the non-ESG sibling funds underperformed their co-managed ESG siblings, which is inconsistent with hypothesis *H4*. In this section we try to better understand why this is the case. In Appendix B.5, we consider the possibility that ESG

[18] Appendix B.2 considers a portfolio approach. We estimate Carhart four factor alphas of long-short portfolios of non-ESG sibling funds and other funds and generate results that are consistent with those in Panel B of Table 5—that is, non-ESG sibling funds underperform both ESG and standalone non-ESG funds. In Appendix B.8, we follow the specifications in Table 2 and show that the (predecessors of) non-ESG sibling funds do not underperform prior to the co-management, which is complemented by a DID analysis in Appendix B.1. Consistent with Table 2, the evidence does not support the hypothesis that managers who are not good at picking non-ESG stocks are assigned to manage ESG funds.

funds outperform their sibling non-ESG funds because of return differences between high and low ESG stocks in our sample period. We find that this is not the case. Given this, we consider the possibility that mutual fund families make choices that effectively transfer performance from their non-ESG funds to their ESG siblings.

We first ask why a mutual fund family may choose to favor their ESG funds over their non-ESG funds. We argue that a fund family may choose to favor their ESG funds if flows into and out of these funds are more sensitive to performance than the flows of the non-ESG funds. To show that this is indeed the case, we estimate flow-performance sensitivities by running the following regression, which allows for a potential asymmetry between flow responses to good and bad performances:

$$\begin{aligned} flow_{i,t+1} =& \alpha_0 + \alpha_1 SNE_{i,t} + \alpha_2 ESG_{i,t} \\ &+ \sum_{h\in\{ANE,SNE,ESG\}} \sum_{s\in\{+,-\}} \beta_{h,s} I^{h,s}_{i,t} alpha_{i,t} + \sum_k \gamma_k Controls^k_{i,t} + v_t + \epsilon_{i,t}. \end{aligned} \tag{5}$$

The dependent variable $flow_{i,t+1}$ is either the percentage fund flow ($perflow$) or the dollar fund flow ($dollarflow$) for fund i in month $t+1$. ANE, SNE, and ESG are indicators for whether a fund is a standalone non-ESG fund, a sibling non-ESG fund or an ESG fund. Variable $s = +(-)$ indicates that $alpha_{i,t}$ is above (below) median in month t. $I^{h,s}_{i,t}$ are a series of dummies. For instance, $I^{SNE,+}_{i,t} = 1$ if fund i is a sibling non-ESG fund and gets an above median alpha in month t. We use the Carhart four-factor alpha with control variables being fund size, fund age, expense ratio, and turnover ratio. Time fixed effects are included.

—Insert Table 6 about here—

The coefficient $\beta_{h,+}$ ($\beta_{h,-}$) captures how flows of type-h funds respond to good (bad) performance. Our estimates reported in Table 6 reveal that for standalone non-ESG funds, the percentage flows are sensitive to both good and bad performance, i.e., there is an inflow when performance improves and an outflow when it worsens. Moreover, consistent with the previous literature, the relationship exhibits convexity—that is, the flows respond more aggressively as the performance improves (e.g., Sirri and Tufano, 1998).

The flow-performance relationship for non-ESG sibling funds exhibits a similar pattern as that for standalone non-ESG funds. However, the flows of ESG funds reveal a different pattern. While we find no difference in the sensitivities of their flows to bad performance, their flows are more sensitive to good performance than the flows of sibling and standalone non-ESG funds.[19] When we use the dollar flow as the dependent variable, the patterns are qualitatively similar. Specifically, the evidence in the third column of Table 6 indicates that when well-performing ESG funds generate an extra 1% alpha, they attract $7.98 million of net inflow on average. In contrast, it generates flows of only $0.53 million for well-performing non-ESG sibling funds, implying that the fund family can generate an additional flow of about $7.45 million if a 1% alpha is generated in its well-performing ESG fund rather than in its non-ESG sibling fund. It is worth noting here that since we have controlled for fund characteristics such as size and age, the distinct flow-performance pattern that ESG funds exhibit does not arise because they are relatively younger and smaller. Our results are consistent with the idea that as new money flows into a new investment theme, i.e., ESG, funds with superior past performance become extremely salient and attractive.

6 Evidence of Cross-fund Subsidization

The evidence described in the previous section suggests that the flows of ESG mutual funds tend to be more sensitive to good performance than the flows of their non-ESG siblings. In this section, we explore two possible channels that allow mutual fund families to transfer performance from one fund to another for the purpose of exploiting these flow-sensitivity differences.

[19] Previous literature studying the difference in flow-performance sensitivities between ESG and non-ESG funds examined the pre-2011 period when ESG investing was less prevalent and presented mixed evidence. See, e.g., Bollen (2007), Benson and Humphrey (2008), Bialkowski and Starks (2016), and El Ghoul and Karoui (2017).

The first has to do with the timing of their trades. Specifically, we examine the extent to which mutual funds buy and sell illiquid stocks for their ESG portfolio prior to when they buy and sell these stocks for their non-ESG portfolio. The second has to do with the allocation of IPOs. Specifically, we examine the allocation of IPOs, i.e., the extent to which ESG funds are allocated more and better IPOs.

6.1 Strategic Timing of Trades of Illiquid Stocks

To understand why the timing of the trades of individual mutual funds matters, suppose a portfolio manager identifies an underpriced stock that can potentially contribute to the alphas of both their ESG and non-ESG funds. If the stock is relatively illiquid, the fund that executes its trade first will trade at a better price than the fund that trades later. Hence, the fund family can favor the ESG fund by letting it trade first.[20]

To examine whether mutual fund families strategically time when different mutual funds trade, we examine the sample of mutual funds that disclose holdings at a monthly frequency. Our approach, which follows what we did in Section 4.2, examines non-flow-induced large sell trades as well as non-flow-induced large buy trades. Specifically, we identify what we classify as significant buy and sell trades that satisfy the following two criteria: First, the trade changes the position in the stock between months t and $t-1$ by more than 0.2% of the fund TNA in month t. Second, the buy (sell) trade is either observed in a month when the fund experiences a net outflow (inflow) or in a month when the fund experiences a net inflow (outflow) but the trade is percentage-wise ten times larger than the fund inflow (outflow). We again exclude trades with an underlying stock that is either priced below $5 or has a market capitalization within the bottom 10% using NYSE breakpoints. With this procedure, we identify 10,423 significant buy trades and 9,989 significant sell trades for 132 sibling pairs of ESG and non-ESG funds whose holdings are disclosed at a monthly frequency.

[20] Gaspar, Massa, and Matos (2006) show that the return gap between favored and unfavored funds increases in their tendency to trade in opposite directions. We find the significant trades by co-managed funds in opposite directions to be very rare in our sample.

To compute the extent to which ESG funds buy before their sibling funds, we first identify each significant buy trade of non-ESG sibling funds and calculate *ESG Lead*, which is the percentage of events in which their ESG siblings buy the same stock in the previous month. Similarly, we compute *SNE Lead* by first identifying the significant buys of ESG funds and then calculate the percentage of events in which their non-ESG sibling funds buy the same stock in the previous month. Under the null hypothesis that neither fund is favored, we expect *ESG Lead* and *SNE Lead* to be the same. Under the alternative that the ESG fund is favored, we expect *ESG Lead* to be larger. Similarly, we also examine whether ESG funds sell before their non-ESG sibling funds under a higher frequency, relative to how frequently non-ESG funds sell before their ESG siblings.

Because the incentive to time one's trades in this way depends on the liquidity of the stocks, we sort trades into two groups according to the liquidity of their underlying stocks based on the average daily Amihud ratio (*Amihud*) and the average daily dollar trading volume (*Volume*) over the past 12 months. The first group includes trades with top 20% illiquidity, and the second group includes the rest 80% of trades. We conduct the above tests separately for illiquid and liquid groups. Our examination of the liquid trades can be viewed as a placebo test, because the benefits of timing the liquid trades are likely to be minor.

—Insert Table 7 about here—

Table 7 presents our results. First, for illiquid stocks, we find strong evidence that ESG funds lead sibling funds in both buying and selling. For buys of illiquid stocks based on the Amihud ratio, the probability of ESG funds leading their non-ESG siblings is 13.69%, whereas that of non-ESG funds leading ESG funds is only 9.78%. This 3.91% difference is economically and statistically significant. For sells, the probability of ESG funds leading their non-ESG siblings is 12.02%, about 5.66% larger than that of sibling non-ESG funds leading ESG funds. These differences in probabilities are consistent with our conjecture that fund families have a tendency to have ESG funds trade before their non-ESG siblings as a way to subsidize the former. Moreover, that the difference on the sell side is larger is consistent with theory and evidence that suggests price impact is likely to be larger for sell orders.

Notably, for liquid stocks we don't find a significant lead-lag relationship. The difference between the probability of ESG funds leading sibling non-ESG funds and that of sibling non-ESG funds leading ESG funds is statistically insignificant. This evidence (or lack of evidence) makes sense, because fund families are not likely to benefit from the strategic management of trades that have only minor price impact.[21]

6.2 Allocation of IPOs

A second potential source of cross-fund subsidization comes from the allocation of IPOs. IPOs are on average underpriced and thus provide mutual fund families with opportunities to enhance the performance of favored funds. In this section, we test the hypothesis that mutual fund families provide more favorable IPO allocations to their ESG funds than to their non-ESG sibling funds.

Our tests examine 1,023 IPOs that are available on both the Securities Data Company's (SDC) database and CRSP between 2013 and 2020. For this sample of IPOs, the average and median first-day returns are 18.8% and 6.6%, respectively. Unfortunately, we do not directly observe whether a mutual fund is allocated an IPO. However, we use two approaches to indirectly estimate the extent to which the different mutual funds receive IPO allocations.

The first approach follows the literature and counts those IPOs as being allocated to a mutual fund if it is included in a mutual fund's first disclosed holdings following the IPO. Specifically, for an IPO offered in month t, we collect all of fund i's portfolio disclosures between months t and $t+1$ from Morningstar, and if the IPO appears in the disclosure, we classify fund i as having been allocated shares and define *Allocate Shares* as the number of shares reported.

[21] In Appendix B.7 we analyze the lead-lag relationship using Logit regressions that control for stock characteristics, and our results are robust.

We then construct *Offering* as the product of *Allocate Shares* and offering prices and *Underpricing dollar* as the product of *Allocate Shares* and first-day price changes. Although this is the standard approach for estimating IPO allocations, e.g., Gaspar, Massa, and Matos (2006), it provides a noisy and perhaps biased estimate of a mutual fund's allocation. It does not include those IPOs that are sold prior to the disclosure and may incorrectly include shares that are purchased in the after-market. This could be especially important for the ESG funds, which may choose to participate in the allocation of IPOs with high returns but unfavorable ESG scores, and then flip the shares prior to the reporting date. If this is the case, this approach may underestimate the favorable IPOs they receive.

The second approach, which we will describe in more detail later, indirectly infers allocations by measuring mutual fund returns on dates in which underpriced issues go public.

—Insert Table 8 about here—

Table 8 summarizes estimates of the extent that ESG and non-ESG sibling funds are allocated IPOs using the first approach. These estimates suggest that the ESG funds participate in 138 IPOs while the non-ESG sibling funds participate in 476 IPOs. At first glance, the larger number of IPOs for the non-ESG funds seems inconsistent with our conjecture that the ESG funds are favored.[22] We find, however, that even though ESG funds do not participate in as many IPOs as their sibling funds, they are allocated substantially more as a fraction of their assets in those deals in which they do have allocations. This is partly because the average size of ESG funds is about 53% of the size of non-ESG sibling funds, however, the average allocations are somewhat larger as well, and the average (median) *Offering to TNA* ratio per deal for the ESG funds is about 4.1 (4.6) times as large as that for the sibling non-ESG funds.

More importantly, the ESG funds seem to be allocated shares in better quality IPOs. We find that the average and median first-day returns of IPO deals offered to both types of mutual

[22]Indeed, previous research documents that favored funds, such as funds of a larger size or with a higher fee, are allocated more IPO deals (e.g. Gaspar, Massa, and Matos, 2006).

funds are quite high relative to the overall sample, which is consistent with prior literature that indicates that mutual funds receive favorable IPO allocations.[23] Moreover, our analysis of these first-day returns reveals that the IPOs allocated to ESG funds tend to be more underpriced than those allocated to sibling non-ESG funds. Given that non-ESG sibling funds are not constrained by their investment mandates from participating in these IPOs, this observation suggests that fund families allocate the more highly underpriced IPOs to their ESG funds. Combining a higher *Offering to TNA* along with greater underpricing, the ratio of *Underpricing dollar to TNA* per deal is significantly higher for ESG funds.

Overall, we compute *Monthly total underpricing to TNA* for different funds by first summing up *Underpricing dollar* across all deals that the fund participates in month t and then dividing it by the fund TNA at $t-1$. As we report in Panel B of Table 8, about $3.1 \times 12 \approx 37$ bps of the yearly excess performance of ESG funds come from IPOs, which is approximately double the contribution of IPOs to the performance of non-ESG sibling funds.

As noted earlier, the above analysis is based on a noisy and potentially biased estimate of IPO allocations. To address this issue, we consider an alternative approach, which is less direct but has no bias. Specifically, we look at the returns of mutual funds on the days in which underpriced IPOs are allocated. We hypothesize that mutual funds that are allocated the greatest number of the most underpriced IPO shares should generate the greatest excess returns on these days. We test this hypothesis by estimating the following regression:

$$alpha_{i,t} = \alpha + \beta_1 ESG_{i,t} + \sum_k \gamma_k Controls^k_{i,t} + v_t + \epsilon_{i,t}, \tag{6}$$

where $alpha_{i,t}$ is the daily Carhart 4-factor alpha for fund i in day t estimated using one-year rolling-window regressions. $ESG_{i,t}$ is a dummy indicating whether fund i is an ESG fund on day t. Control variables include fund size, fund age, expense ratio, turnover ratio, as well as

[23]Again, given that we do not observe the IPOs that are sold prior to the reporting date, this result should be viewed with some caution. For example, it might be the case that mutual funds tend to sell those IPOs that perform poorly prior to the reporting date, which would result in very favorable performance for those IPOs that were not sold.

style fixed effects. Day fixed effects v_t are also controlled. We restrict the sample to only include sibling pairs of ESG and non-ESG funds on those days when underpriced IPOs are allocated.

—Insert Table 9 about here—

To identify the days when the most underpriced IPOs are allocated we first compute the *IPO Dollar Underpricing* for each IPO as the product of the first-day price changes and the total number of shares offered. We then compute the total *IPO Dollar Underpricing* for each day by summing these amounts across deals for each day. We include only those days with a positive total *IPO Dollar Underpricing*.

Our results are provided in Table 9. In columns (1) and (2), we focus on the ESG sibling funds' excess performance over the non-ESG sibling funds on the days when the total *IPO Dollar Underpricing* is above the median. The estimated coefficients of *ESG* are 0.82 and 0.83, both of which are statistically significant. In columns (3) and (4), we focus on the days when the total *IPO Dollar Underpricing* is in the top 20%. The excess performance of ESG funds on these days is about 1.77 bps. To put these estimates in perspective, notice that, in total, ESG sibling funds outperform their non-ESG siblings by about 6 bps per month according to our Fama-MacBeth estimate in Table 5. There is about one such top-20% day per month in our sample. This means that the excess return of 1.77 bps coming from highly underpriced IPOs contributes about 1/3 of the overall excess performance of ESG sibling funds.

7 Conclusions

Many investors have broadened their investment objectives—considering social performance as well as financial performance when they select their investments. This broadening of objectives has a number of implications that have been examined in a growing literature on ESG and socially responsible investing. We contribute to this literature by examining what we refer to as

ESG and non-ESG sibling funds, which are mutual funds that have a common set of managers, but have different objectives.

One of our primary objectives in this research is to use these co-managed funds as an experiment that allows us to gauge the importance of investor attention. The idea is that an investment team's attention will naturally focus more on high ESG stocks when it is expected to overweight these stocks in one of the portfolios that they manage. If a management team's attention is diverted because of the objectives of one of its funds, this will have a spillover effect on its management of the other fund. As our simple two-stage descriptive framework illustrates, an active investor that endogenously considers more ESG stocks in the first stage will tend to hold more of these stocks in their non-ESG as well as their ESG portfolios.

We provide evidence that is consistent with this hypothesis. This evidence of spillover suggests that a mutual fund family that adds an ESG fund will cause the demand for ESG stocks to increase beyond what one would expect given the AUM of the ESG fund. We also provide evidence that supports our hypothesis that the increased attention on high ESG stocks combined with the ability to "cherry-pick" the best ones allow the non-ESG siblings to select better performing high ESG stocks. Finally, we initially expected the non-ESG sibling funds to outperform their ESG siblings, because the former are optimizing their risk-return tradeoff without the additional ESG constraint. However, we find that ESG mutual funds outperform their non-ESG siblings.

A secondary objective of this research is to use the investment choices of the sibling funds to study the incentives of mutual fund families to strategically "allocate" performance across the funds in their families. We first provide evidence that because inflows to ESG funds are more responsive to good performance, mutual fund families may be able to increase revenues from management fees by shifting performance from the non-ESG funds to their ESG funds. Such a shift would provide one explanation for the relatively poor performance of the non-ESG siblings. We explore two channels that can potentially allow mutual fund families to transfer performance from their non-ESG funds to their ESG siblings. The first is that they may choose to execute trades of less liquid stocks in their ESG funds prior to when they are executed in their non-ESG funds. The second is that they may allocate the more highly underpriced IPOs to their ESG funds. We find evidence that is consistent with both channels.

Mutual funds are required to act in the best interest of their clients by the fiduciary duties of care and loyalty under Section 206(1) and (2) of the Investment Advisers Act of 1940. From the perspective of the clients of sibling non-ESG funds, the transfer of performance is a violation of these rules. It should be stressed, however, that our evidence is indirect and thus circumstantial. We currently do not have alternative explanations but believe that additional research is warranted.

References

Agarwal, Vikas, Linlin Ma, and Kevin Mullally, 2018, Managerial multitasking in the mutual fund industry, Working Paper.

Alexander, Gordon J, Gjergji Cici, and Scott Gibson, 2007, Does motivation matter when assessing trade performance? an analysis of mutual funds, *Review of Financial Studies* 20, 125–150.

Amihud, Yakov, 2002, Illiquidity and stock returns: cross-section and time-series effects, *Journal of Financial Markets* 5, 31–56.

Avramov, Doron, Si Cheng, Abraham Lioui, and Andrea Tarelli, 2021, Sustainable investing with ESG rating uncertainty, *Journal of Financial Economics* .

Baghai, Ramin, Bo Becker, and Stefan Pitschner, 2020, The use of credit ratings in financial markets, Working Paper.

Barber, Brad M, Adair Morse, and Ayako Yasuda, 2021, Impact investing, *Journal of Financial Economics* 139, 162–185.

Barber, Brad M, and Terrance Odean, 2008, All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors, *Review of Financial Studies* 21, 785–818.

Benson, Karen L, and Jacquelyn E Humphrey, 2008, Socially responsible investment funds: Investor reaction to current and past returns, *Journal of Banking & Finance* 32, 1850–1859.

Bialkowski, Jedrzej, and Laura T Starks, 2016, SRI funds: Investor demand, exogenous shocks and ESG profiles, Working Paper.

Bollen, Nicolas PB, 2007, Mutual fund attributes and investor behavior, *Journal of Financial and Quantitative Analysis* 42, 683–708.

Bolton, Patrick, and Marcin Kacperczyk, 2021, Do investors care about carbon risk?, *Journal of Financial Economics* 142, 517–549.

Carhart, Mark M, 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.

Chen, Hsiu-Lang, Narasimhan Jegadeesh, and Russ Wermers, 2000, The value of active mutual fund management: An examination of the stockholdings and trades of fund managers, *Journal of Financial and Quantitative Analysis* 35, 343–368.

Cici, Gjergji, Scott Gibson, and Rabih Moussawi, 2010, Mutual fund performance when parent firms simultaneously manage hedge funds, *Journal of Financial Intermediation* 19, 169–187.

Cremers, KJ Martijn, and Antti Petajisto, 2009, How active is your fund manager? a new measure that predicts performance, *Review of Financial Studies* 22, 3329–3365.

Da, Zhi, Joseph Engelberg, and Pengjie Gao, 2011, In search of attention, *Journal of Finance* 66, 1461–1499.

Del Guercio, Diane, Egemen Genc, and Hai Tran, 2018, Playing favorites: Conflicts of interest in mutual fund management, *Journal of Financial Economics* 128, 535–557.

El Ghoul, Sadok, and Aymen Karoui, 2017, Does corporate social responsibility affect mutual fund performance and flows?, *Journal of Banking & Finance* 77, 53–63.

Evans, Richard B, and Rüdiger Fahlenbrach, 2012, Institutional investors and mutual fund governance: Evidence from retail–institutional fund twins, *Review of Financial Studies* 25, 3530–3571.

Fama, Eugene F, and James D MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607–636.

Gârleanu, Nicolae, and Lasse Heje Pedersen, 2013, Dynamic trading with predictable returns and transaction costs, *Journal of Finance* 68, 2309–2340.

Gaspar, Jose-Miguel, Massimo Massa, and Pedro Matos, 2006, Favoritism in mutual fund families? evidence on strategic cross-fund subsidization, *Journal of Finance* 61, 73–104.

Geczy, Christopher C, Robert F Stambaugh, and David Levin, 2021, Investing in socially responsible mutual funds, *Review of Asset Pricing Studies* 11, 309–351.

Goldstein, Itay, Alexandr Kopytov, Lin Shen, and Haotian Xiang, 2021, On ESG investing: Heterogeneous preferences, information, and asset prices, Working Paper.

Grinblatt, Mark, and Sheridan Titman, 1989, Mutual fund performance: An analysis of quarterly portfolio holdings, *Journal of Business* 393–416.

Grinblatt, Mark, and Sheridan Titman, 1993, Performance measurement without benchmarks: An examination of mutual fund returns, *Journal of Business* 47–68.

Hale, Jon, 2021, Sustainable funds us landscape report, *Morningstar, February* .

Hartzmark, Samuel M, and Abigail B Sussman, 2019, Do investors value sustainability? a natural experiment examining ranking and fund flows, *Journal of Finance* 74, 2789–2837.

Hong, Harrison, and Marcin Kacperczyk, 2009, The price of sin: The effects of social norms on markets, *Journal of Financial Economics* 93, 15–36.

Kacperczyk, Marcin, Clemens Sialm, and Lu Zheng, 2008, Unobserved actions of mutual funds, *Review of Financial Studies* 21, 2379–2416.

Kacperczyk, Marcin, Stijn Van Nieuwerburgh, and Laura Veldkamp, 2016, A rational theory of mutual funds' attention allocation, *Econometrica* 84, 571–626.

Nohel, Tom, Z. Jay Wang, and Lu Zheng, 2010, Side-by-side management of hedge funds and mutual funds, *Review of Financial Studies* 23, 2342–2373.

Pastor, Lubos, Robert F Stambaugh, and Lucian A Taylor, 2021, Sustainable investing in equilibrium, *Journal of Financial Economics* 142, 550–571.

Pastor, Lubos, Robert F Stambaugh, and Lucian A Taylor, 2022, Dissecting green returns, *Journal of Financial Economics* 146, 1723–1742.

Pedersen, Lasse Heje, Shaun Fitzgibbons, and Lukasz Pomorski, 2021, Responsible investing: The ESG-efficient frontier, *Journal of Financial Economics* 142, 572–597.

Riedl, Arno, and Paul Smeets, 2017, Why do investors hold socially responsible mutual funds?, *Journal of Finance* 72, 2505–2550.

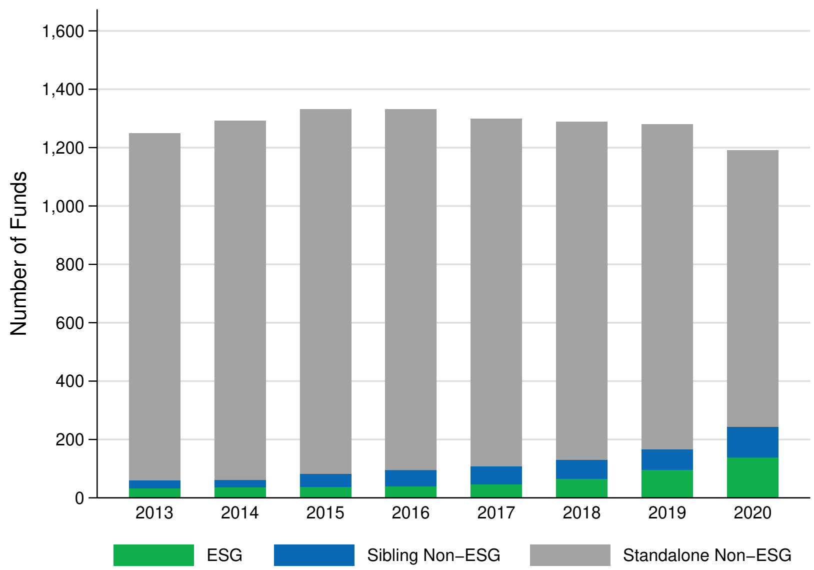
Sirri, Erik R, and Peter Tufano, 1998, Costly search and mutual fund flows, *Journal of Finance* 53, 1589–1622.

Starks, Laura T, Parth Venkat, and Qifei Zhu, 2017, Corporate ESG profiles and investor horizons, Working Paper.

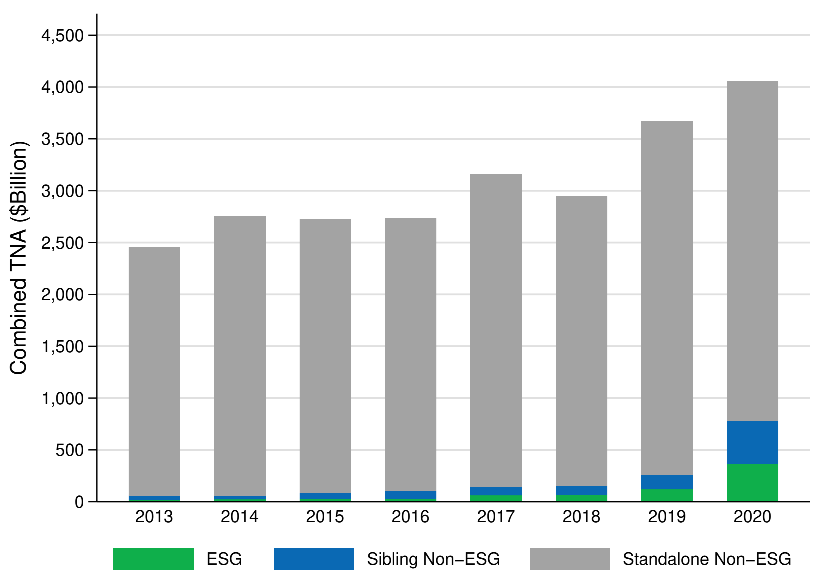
Zhu, Qifei, 2020, The missing new funds, *Management Science* 66, 1193–1204.

FIGURE 1: GROWTH OF ESG FUNDS AND THEIR SIBLINGS

This figure presents the number (Panel A) and the combined TNA (Panel B) of ESG funds, sibling non-ESG funds, and standalone non-ESG funds in our sample. Section 3.2 provides a detailed description of our sample construction procedures.



(A) NUMBER OF FUNDS



(B) COMBINED TNA

TABLE 1: FUND STATISTICS

This table reports, by funds' ESG attributes, the summary statistics for our main fund-level variables. Our sample spans between 2013 and 2020. *ESG*, *SNE*, and *ANE* stand for ESG, sibling non-ESG, and standalone non-ESG funds, respectively. *score* is the value-weighted MSCI KLD ESG score at the fund level. *perflow* measures net fund flow in percentage. *size* is the logarithm of a fund's TNA. Expense ratio (*expratio*) is value-weighted across share classes. A fund's betas (*beta_mkt*, *beta_smb*, *beta_hml*, *beta_umd*) are estimated in 60-month rolling windows. Section 3.2 provides a detailed description of our sample construction procedures.

	ESG		*SNE*		*ANE*	
	Mean	SD	Mean	SD	Mean	SD
score	25.26	11.68	22.15	11.14	20.45	11.45
perflow	0.02	3.49	-0.77	3.35	-0.58	3.42
size	5.42	1.77	6.05	1.75	6.08	1.87
expratio	1.03	0.31	0.98	0.28	1.02	0.32
beta_mkt	1.00	0.09	1.00	0.09	1.00	0.09
beta_smb	0.19	0.32	0.22	0.32	0.25	0.35
beta_hml	-0.02	0.23	-0.02	0.24	-0.01	0.25
beta_umd	-0.01	0.10	0.01	0.08	0.00	0.09

TABLE 2: ESG SPILLOVERS

This table reports the regression result for ESG spillovers. Our baseline specification in column (1) is given by: $score_{i,t+1} = \alpha + \beta_1 ESG_{i,t} + \beta_2 SNE_{i,t} + \sum_k \gamma_k Controls^k_{i,t} + u_i + \epsilon_{i,t}$. $score_{i,t+1}$ is the value-weigted ESG score for fund i in month $t+1$. $ESG_{i,t}$ and $SNE_{i,t}$ indicate if fund i is an ESG fund or a sibling non-ESG fund in month t. In column (2), dummy variables $SNE\_3y+/SNE\_2y/SNE\_1y/SNE\_0y$ equals 1 if a fund is a non-ESG sibling fund and has been co-managed with ESG funds for 3+/2∼3/1∼2/0∼1 years, respectively. SNE_-1y is equal to 1 if the fund is currently a standalone non-ESG fund but will become a non-ESG sibling fund within one year. In column (3), our sample includes only non-ESG sibling funds, and $score\_ESG$ represents the ESG score of a fund's co-managed ESG funds. Control variables include fund size, fund age, expense ratio, turnover ratio. Fund fixed effects are controlled. Standard errors are clustered at the fund level. t-statistics are in parentheses. ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

	ESG Score		
	(1)	(2)	(3)
ESG	3.42***	3.44***	
	(5.75)	(5.68)	
SNE	1.04**		
	(2.17)		
SNE_3y+		1.50**	
		(2.57)	
SNE_2y		1.20*	
		(1.85)	
SNE_1y		1.19	
		(1.50)	
SNE_0y		0.60	
		(1.00)	
SNE_-1y		0.14	
		(0.33)	
score_ESG			0.40***
			(6.76)
Controls	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
Obs	120,230	120,230	4,458
R2	0.88	0.88	0.95

TABLE 3: HOLDING STATISTICS

This table reports the probability for stocks held by non-ESG sibling funds to be simultaneously held by their ESG siblings. In each month, we sort all stocks held by non-ESG sibling funds into 10 deciles according to their ESG scores. For each stock-fund observation, we create a dummy that equals 1 if the stock is held by the fund's co-managed ESG funds in that month. We then average the dummies across funds for a given stock to construct the overlap probability.

Decile	ESG Score	Overlap
1 (Low)	-1.53	24.73%
2	3.02	24.99%
3	7.98	31.35%
4	9.71	31.45%
5	12.78	28.52%
6	16.24	32.30%
7	20.92	34.69%
8	27.42	41.35%
9	37.15	49.07%
10 (High)	56.86	58.14%

TABLE 4: STOCK-PICKING ABILITIES OF NON-ESG SIBLING FUNDS

This table investigates how the high and low ESG stocks acquired by ESG, sibling non-ESG, and standalone non-ESG funds perform differently. We identify large non-flow-induced buy trades using the following criteria: 1) the change in dollar position of the stock exceeds 0.2% of the fund's TNA; 2) the fund is either having a net outflow or the percentage increase in the stock position is 10 times larger than the net fund inflow. We exclude stocks with a price less than $5 or a market capitalization in the bottom 10% using NYSE breakpoints. We run the following regression: $hpa_{j,t} = \alpha_0 + \sum_{q=1}^{5} \beta_q SNE\_quintile_{j,t}^{q} + \sum_{q=1}^{5} \phi_q ANE\_quintile_{j,t}^{q} + \sum_{q=2}^{5} \delta_q ESG\_quintile_{j,t}^{q} + \sum_k \gamma_k Controls_{j,t}^{k} + v_t + \epsilon_{j,t}$. $hpa_{j,t}$ is the (cumulative) four-factor alpha of trade j placed at time t, assuming that the stock is held for 1 month (Panel A), 1 quarter (Panel B), or 1 year (Panel C). In each period, we sort all trades into 5 quintiles according to the ESG score of their underlying stocks. $SNE\_quintile_{j,t}^{q}/ANE\_quintile_{j,t}^{q}/ESG\_quintile_{j,t}^{q}$ equals 1 if the underlying stock of trade j by a sibling non-ESG/standalone non-ESG/ESG fund falls into quintile q. Control variables include size, book-to-market, momentum, and the Amihud ratio. We keep only funds who disclose their holdings at the monthly frequency in Panel A. We report average holding-period alphas as $\{\beta_q + \alpha_0\}_{q=1}^{5}$, $\{\phi_q + \alpha_0\}_{q=1}^{5}$, and $\{\alpha_0, \delta_q + \alpha_0\}_{q=2}^{5}$. We use Wald-test to test for the significance of the difference between regression coefficients in the last two columns. ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

	Holding-period Alpha				
ESG Score	*SNE*	*ANE*	*ESG*	*SNE−ANE*	*SNE−ESG*
	Panel A: 1 Month				
Quintile 1 (Low)	-0.13%	-0.20%	0.04%	0.07%	-0.17%
Quintile 2	-0.51%	-0.31%	-0.20%	-0.20%	-0.31%
Quintile 3	-0.15%	-0.12%	-0.23%	-0.03%	0.08%
Quintile 4	-0.07%	-0.10%	-0.06%	0.02%	-0.01%
Quintile 5 (High)	0.21%	-0.11%	0.03%	0.32%**	0.18%
	Panel B: 1 Quarter				
Quintile 1 (Low)	-0.37%	-0.40%	-0.32%	0.03%	-0.05%
Quintile 2	-1.45%	-0.86%	-0.61%	-0.59%**	-0.84%**
Quintile 3	-0.56%	-0.16%	-0.29%	-0.40%	-0.27%
Quintile 4	-0.06%	-0.38%	-0.14%	0.32%*	0.08%
Quintile 5 (High)	0.46%	-0.25%	-0.25%	0.71%***	0.71%***
	Panel C: 1 Year				
Quintile 1 (Low)	-1.72%	-1.23%	0.00%	-0.50%	-1.72%**
Quintile 2	-4.54%	-3.00%	-2.91%	-1.54%***	-1.63%*
Quintile 3	-2.67%	-1.71%	-2.73%	-0.96%	0.06%
Quintile 4	-1.24%	-1.01%	-0.19%	-0.23%	-1.05%*
Quintile 5 (High)	1.12%	-0.41%	-0.14%	1.53%***	1.25%**

TABLE 5: UNDERPERFORMANCE OF NON-ESG SIBLING FUNDS

This table reports the regression result for fund performance. Panel A restricts the sample to sibling ESG and non-ESG funds, and considers the following specification: $Perf_{i,t+1} = \alpha + \beta_1 SNE_{i,t} + \sum_k \gamma_k Controls^k_{i,t} + \epsilon_{i,t}$. Panel B considers the full sample and the following specification: $Perf_{i,t+1} = \alpha + \beta_1 SNE_{i,t} + \beta_2 ESG_{i,t} + \sum_k \gamma_k Controls^k_{i,t} + \epsilon_{i,t}$. The left panel measures the fund performance using the Carhart four-factor alpha, i.e., $alpha_{i,t+1}$. The right panel measures the fund performance using the gross return, i.e., $grossret_{i,t+1}$. $ESG_{i,t}$ and $SNE_{i,t}$ indicate if fund i is an ESG fund or a sibling non-ESG fund in month t. Control variables include fund size, fund age, expense ratio, turnover ratio, and fund style fixed effects. We also control for loadings on market, size, value, and momentum factors on the right panel. Columns (1) and (3) perform Fama-MacBeth regressions, in which standard errors are adjusted by the Newey-West procedure with a lag of 3 periods. Columns (2) and (4) perform pooled OLS regressions with time fixed effects included. We cluster the standard errors at the fund level. t-statistics are in parentheses. ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

	Alpha(%)		Gross Return(%)	
	Fama-MacBeth	Pooled OLS	Fama-MacBeth	Pooled OLS
	(1)	(2)	(3)	(4)
Panel A: Co-management Sample				
SNE	-0.06*	-0.08**	-0.05*	-0.09*
	(-1.84)	(-2.27)	(-1.81)	(-1.79)
Controls	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Time FE	/	Yes	/	Yes
Obs	6,880	6,880	6,880	6,880
R2	0.41	0.17	0.70	0.89
Panel B: Full Sample				
SNE	-0.03**	-0.04**	-0.03**	-0.05**
	(-2.02)	(-2.41)	(-1.99)	(-2.25)
ESG	0.00	0.03	-0.00	0.03
	(0.19)	(1.28)	(-0.04)	(1.18)
Controls	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Time FE	/	Yes	/	Yes
Obs	120,233	120,233	120,233	120,233
R2	0.19	0.10	0.51	0.86

TABLE 6: FLOW-PERFORMANCE SENSITIVITY

This table reports the flow-performance sensitivity for funds by their ESG attributes. We estimate the flow-performance sensitivity by the following regression: $flow_{i,t+1} = \alpha_0 + \alpha_1 SNE_{i,t} + \alpha_2 ESG_{i,t} + \sum_{h\in\{ANE,SNE,ESG\}} \sum_{s\in\{+,-\}} \beta_{hs} I^{hs}_{i,t} alpha_{i,t} + \sum_k \gamma_k Controls^k_{i,t} + v_t + \epsilon_{i,t}$. We use the Carhart four-factor alpha to measure performance. In the left panel, the dependent variable is the percentage net fund flow $perflow$, computed as the difference between TNA growth rates and gross fund returns. In the right panel, the dependent variable is the dollar value net fund flow $dollarflow$, computed as the product of the percentage fund flow and the fund TNA at the end of the previous month. $ANE_{i,t}$, $SNE_{i,t}$, and $ESG_{i,t}$ indicate if fund i is a standalone non-ESG fund, a sibling non-ESG fund, or an ESG fund in month t. The dummy variable $s = +(-)$ indicates if $alpha_{i,t}$ is above (below) the sample median in month t. $I^{hs}_{i,t}$ are a series of dummies—for instance, $I^{SNE,+}_{i,t} = 1$ if fund i is a sibling non-ESG fund and gets an alpha above median in month t. Control variables include fund size, fund age, expense ratio, and turnover ratio. Time fixed effects are included. Standard errors are clustered at the fund level. t-statistics are in parentheses. Wald-test are used to test the difference of estimated coefficients. F-statistics for Wald test are in parentheses in the last row. ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

	Flow (%)		Flow ($million)	
	Above Median	Below Median	Above Median	Below Median
β_{ANE}	0.25	0.18	1.73	1.81
	(9.80)	(9.26)	(4.90)	(5.87)
β_{SNE}	0.22	0.20	0.53	0.09
	(1.72)	(2.43)	(0.39)	(0.08)
β_{ESG}	0.53	0.15	7.98	-0.49
	(4.69)	(1.98)	(3.26)	(-0.44)
$\beta_{ESG} - \beta_{SNE}$	0.32*	-0.04	7.45***	-0.57
	(3.50)	(0.15)	(7.21)	(0.14)

TABLE 7: STRATEGIC TIMING OF TRADING OF ILLIQUID STOCKS

This table reports the trading lead-lag relationships for 132 pairs of ESG and non-ESG siblings which disclose their portfolios at a monthly frequency. We construct a sample of non-flow-induced large trades with the following procedure. For buy (sell) trades, we require: 1) the change in dollar position of the stock exceeds 0.2% of the fund's TNA; 2) the fund is either having an outflow (inflow) or the percentage increase (decrease) in the stock position is 10 times larger than the net fund inflow (outflow). We exclude stocks with a price less than \$5 or a market capitalization in the bottom 10% using NYSE breakpoints. When observing sibling non-ESG fund i buying (selling) stock n in month t, we create a dummy equal to 1 if i's co-managed ESG funds buy (sell) n in month $t-1$. Averaging the dummy across n, i, and t gives *ESG Lead*. When observing ESG fund i buying (selling) stock n in month t, we create a dummy equal to 1 if i's co-managed non-ESG funds buy (sell) n in month $t-1$. Averaging the dummy across n, i, and t gives *SNE Lead*. We sort all buys and sells into 2 groups according to the underlying stock's liquidity, using the average daily Amihud ratio and the average daily dollar trading volume over the past 12 months. The first group includes trades with top 20% illiquidity, and the second group includes the rest 80% of trades. T-tests are performed on the difference between *ESG Lead* and *SNE Lead*, i.e., on *Diff*. ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

		Buys			Sells		
		ESG Lead	*SNE Lead*	Diff.	*ESG Lead*	*SNE Lead*	Diff.
Amihud	Illiquid 20%	13.69%	9.78%	3.91%***	12.02%	6.36%	5.66%***
	Rest 80%	9.92%	10.35%	-0.42%	7.97%	8.67%	-0.69%
Volume	Illiquid 20%	14.47%	11.39%	3.08%**	11.27%	6.67%	4.61%***
	Rest 80%	9.73%	9.93%	-0.20%	8.16%	8.58%	-0.43%

TABLE 8: IPO ALLOCATIONS: EVIDENCE FROM HOLDINGS DATA

This table reports how IPO allocations differ across ESG funds and sibling non-ESG funds. For a stock issued in month t, we use a fund's first portfolio disclosure between months t and $t+1$ from Morningstar to determine if it has participated in the IPO. We define *Allocate Shares* to be the number of shares of the IPO stock appearing in the disclosure. *Offering* is defined as the product of the *Allocate Shares* and the offering price. *Offering to TNA* is the *Offering* divided by the fund's TNA in month $t-1$. We calculate the 1^{st}*-day return* as the percentage difference between the 1^{st}-day closing price and the offering price. *Underpricing Dollar* is the product of the 1^{st}*-day return* and the *Allocate Shares*. *Underpricing Dollar to TNA* is the *Underpricing Dollar* divided by the fund's TNA in month $t-1$. We compute *Monthly Total Underpricing to TNA* by first summing up *Underpricing dollar* across all the deals participated by a fund in month t and then dividing it by the fund TNA at $t-1$. We use T-tests for the difference between group averages and non-parametric K-sample tests for the difference between group medians. ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

	ESG	*SNE*	Diff.
Panel A: IPOs with ESG and Sibling Non-ESG Participation			
Number of Deals	138	476	
Avg Offering to TNA	0.77%	0.19%	0.59%***
Med Offering to TNA	0.37%	0.08%	0.28%***
Avg 1^{st}-day Return	54.44%	46.73%	7.71%
Med 1^{st}-day Return	43.98%	33.74%	10.24%*
Avg Underpricing Dollar to TNA	0.27%	0.07%	0.20%***
Med Underpricing Dollar to TNA	0.14%	0.02%	0.12%***
Panel B: Participating Funds			
Number of Funds	39	85	
Avg Monthly Total Underpricing to TNA (bps)	3.13	1.46	1.67**

TABLE 9: IPO ALLOCATIONS: EVIDENCE FROM DAILY EXCESS RETURNS

This table compares daily excess returns of ESG and non-ESG siblings on IPO days. The specification is given by: $alpha_{i,t} = \alpha + \beta_1 ESG_{i,t} + \sum_k \gamma_k Controls^k_{i,t} + v_t + \epsilon_{i,t}$. $alpha_{i,t}$ is the Carhart four-factor alpha of fund i in day t. Our sample is restricted to days in which the total *IPO Dollar Underpricing* across deals is positive and to pairs of non-ESG and ESG siblings. The left (right) panel includes days with a total *IPO Dollar Underpricing* falling into the top 50% (20%) of our sample. Control variables include fund size, fund age, expense ratio, and turnover ratio. We control for fund style and day fixed effects. Standard errors are clustered at the fund and day level. t-statistics are in parentheses. ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

	Daily Alpha (bps)			
	Top 50% Profitability		Top 20% Profitability	
	(1)	(2)	(3)	(4)
ESG	0.82**	0.83*	1.77***	1.77**
	(2.01)	(1.90)	(2.78)	(2.48)
Controls	No	Yes	No	Yes
Style FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Obs	24,078	24,078	11,348	11,348
R2	0.12	0.12	0.11	0.11

Appendix

A Data

A.1 Fund Screening

We construct a sample of diversified actively managed open-ended U.S. domestic equity funds following the methodology of Kacperczyk, Sialm, and Zheng (2008). Firstly, we select funds with one of the following Lipper Classification Code: EIEI, G, LCCE, LCGE, LCVE, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE, or SCVE. For funds with missing Lipper Classification Code, we select funds with one of the following Strategic Insights Objective Code: AGG, GMC, GRI, GRO, ING, or SCG. For funds where both codes are missing, we keep those with Wiesenberger Objective Codes equal to G, G-I, GCI, LTG, MCG, or SCG or with Policy Code equal to CS. For the remaining funds, we require a lifetime average equity investment between 80% to 105%. Lastly, we drop passive funds using the CRSP index fund flags. For funds with missing index fund flag, we remove those whose names contain “Index”, “S&P”, and “ETF”.

Following the literature (e.g., Cremers and Petajisto, 2009), we restrict our sample to fund-month observations where stock holdings that can be matched with the CRSP monthly stock data account for at least 67% of the reported TNA of that month. In addition, we require that the sum of equity weights with an MSCI ESG rating accounts for at least 67% of the CRSP-matched portfolio. We restrict our fund-holding observations to common stocks (CRSP share codes 10 or 11) listed on NYSE, AMEX, or Nasdaq. Holding observations are dropped if the stock price, CUSIP, or the number of shares held is missing. We also require funds to hold at least 10 stocks in their portfolio, have their investment style within the three-by-three size/value category grid, and disclose their portfolios more frequently than a quarterly basis. To merge the fund share class between Morningstar and CRSP, we use the 9-digit CUSIP and the ticker of the share class. We keep only share classes that can be one-to-one matched between Morningstar

(SecID) and CRSP (CRSP_FundNo) through either the 9-digit CUSIP or the ticker. We merge the variables from CRSP with those from SEC filings using the ticker of a fund's share class.

Our ESG dictionary includes the following keywords (ignoring the case of letters): "esg", "csr", "socially", "social and governance", "social responsibility", "social values", "social impact", "governance factors", "corporate governance", "corporate responsibility", "governance criterion", "governance guidelines", "environmental", "responsible investment", "responsible investing", "responsibility factors", "sri", "environmental, social and governance", "environmental, social, and governance", "corporate social responsibility", "social responsible invest", "ethical invest", "ethically invest", "ethnicity", "sustainable invest", "responsible invest", "controversial", "military", "firearm", "weapon", "alcohol", "tobacco", "casino", "gambling", "gaming", "nuclear", "emission","pollute", and "pollution".

A.2 Reported Holdings under Different Frequencies

On the Morningstar Direct platform, some funds report their holdings at a monthly frequency while others report them at a lower frequency such as every two, three, or six months. We only include in our analyses funds that report at least on a quarterly basis.

We use the subsample of funds that disclose their holdings at the monthly frequency when analyzing the 1-month holding-period alpha of stock picks in Panel A of Table 4 and the strategic timing of trading of illiquid stocks in Table 7.

For the rest of our analyses where holdings are involved, we use the full sample of Morningstar Direct holdings data. For Table 2, we compute the portfolio-average ESG scores whenever a fund discloses its portfolio holdings and extrapolate the scores forward until there is an update of its holdings. For Table 3, we extrapolate holdings. For Table 8, we utilize the closest reporting in a two-month window following the IPO, irrespective of funds' reporting frequency, to pin down IPO allocations.

B Robustness

B.1 ESG Spillovers and Underperformance: Difference-in-Differences

In this section, we conduct a difference-in-differences (DID) analysis to show how the ESG score and overall performance of non-ESG funds evolve before and after being co-managed with ESG funds. In particular, we match each sibling non-ESG fund and its standalone predecessor prior to co-management (treated) with a standalone non-ESG fund (matched) based on fund size, expense ratio, and risk profiles. We then compute the difference between their average ESG scores and alphas, and investigate how such difference evolves around co-management.

Specifically, for each treated fund i in year t, we first construct a sample consisting of all funds which remain to be standalone non-ESG funds throughout our sample period and have no missing observations in year t, and then choose the best match out of it. Our strategy follows Bollen (2007) and Starks, Venkat, and Zhu (2017). We keep fund j in the sample if (1) its age is between $age_i \pm 3$ and (2) the gap between i and j's expense ratios is within one cross-sectional standard deviation in year t. We then compute the distance $dist_{i,j}$ for each j by:

$$dist_{i,j} = \left(\frac{TNA_i - TNA_j}{\sigma_{TNA}}\right)^2 + \sum_k \left(\frac{\beta_{i,k} - \beta_{j,k}}{\sigma_k}\right)^2 \tag{B1}$$

where TNA_j is fund j's TNA and σ_{TNA} is the standard deviation of all TNAs in the same year. $\beta_{j,k}$ represents fund j's loading on factor k of Carhart four factors, and σ_k is the standard deviation of all β_k's in the same year. For treated fund i in year t, we match it with the fund j that exhibits the smallest $dist$.

Column (1) in Table C1 presents our DID result regarding the fund ESG score. In particular, within a 24-month window around the point where the treated fund starts to be co-managed with ESG funds, we run the following regression:

$$Diff_{i,t+1} = \alpha + \beta_1 SNE_{i,t} + \sum_k \gamma_k Controls_{i,t}^k + u_i + \epsilon_{i,t},$$

where for dependent variable, we use the difference in ESG scores between the treated fund i and its matched fund. $SNE_{i,t} = 1$ if fund i is a sibling non-ESG fund in month t. We control for fund size, fund age, expense ratio, turnover ratio, and fund fixed effects. We cluster the standard errors at the fund level. The coefficient for SNE is significantly positive, suggesting that the difference in ESG scores widens after the co-management. This is consistent with our results in Table 2.

In column (2), we conduct the DID analysis on fund performance by replacing the dependent variable with the difference in Carhart four-factor alphas between treated and matched funds. While we have shown in the main text that sibling non-ESG funds underperform the standalone non-ESG funds, our DID result suggests that such an underperformance becomes more salient after co-management. In Appendix B.8, we in fact show that the predecessors of sibling non-ESG funds do not underperform. All these results echo each other in supporting our hypotheses about shifted investor attention.

—Insert Table C1 about here—

B.2 Underperformance of Non-ESG Sibling Funds: Portfolio Regressions

In the main text, we have established the underperformance of sibling funds via Fama-MacBeth regressions and pooled regressions with fixed effects, controlling for various fund characteristics. In this section, we resort to an alternative strategy by forming long-short portfolios based on funds' ESG attributes.

In particular, at the end of each month, we divide all funds into two equal groups according to their size. We first construct value- and equal-weighted returns separately for ESG, sibling non-ESG, and standalone non-ESG funds within each size group, and then compute simple averages across groups. We compute differences in average returns between sibling and standalone non-ESG funds and regress them on the Carhart four factors. Similarly, we also regress the return differences between sibling non-ESG funds and ESG funds on the Carhart four factors.

Table C2 reports our results. If we value (equal)-weight stocks within each size group, the portfolio that longs standalone non-ESG funds and shorts sibling non-ESG funds is able to deliver a monthly alpha of 0.08% (0.05%) with a *t*-value of 2.94 (2.23). Similarly, the portfolio that longs ESG funds and shorts sibling non-ESG funds also delivers a large alpha. These findings are consistent with our results in the main text—that is, sibling non-ESG funds underperform both standalone non-ESG funds and ESG funds in our sample.

—Insert Table C2 about here—

B.3 Funds with No More than 3 Managers

In our main sample, we classify a non-ESG fund to be a sibling as long as one member of its management team manages an ESG fund at the same time. It is natural to expect a stronger spillover effect if the management team is small and thus each member can play a big role. In this Appendix, we restrict our sample to funds managed by no more than 3 managers.

The left panel of Table C3 replicates our analyses about ESG spillovers in Table 2. According to column (1), the ESG score of sibling non-ESG funds is on average 2.2 points higher than that of standalone non-ESG funds. Such a difference is larger than the counterpart in Table 2. The right panel replicates our analyses regarding the underperformance of non-ESG sibling funds in column (1) and (2) in Panel A of Table 5. We find that sibling non-ESG funds underperform sibling ESG funds by about 13 basis points per month using Fama-MacBeth regression, which is again larger than the baseline counterpart. Overall, the results support the conjecture that when managers play a bigger role, adding an ESG fund to their responsibility generates a larger spillover effect.

—Insert Table C3 about here—

B.4 Alternative Samples of Trades

In our analyses in Section 4.2 and Section 6.1, we focused on trades larger than 0.2% of the fund's AUM. We also considered a trade, in the same direction as the contemporaneous fund flow, to not be flow-induced if it is percentage-wise 10 times larger than the fund flow. To identify more informative trades, we now experiment with an alternative size cutoff of 0.3% of the fund's AUM, and an alternative flow cutoff of 20 times the net fund flow.

Table C4 revisits our results in Section 4.2, which remain robust under these alternative cutoffs. Compared to ESG and standalone non-ESG funds, non-ESG sibling funds outperform in picking high ESG stocks while underperform in picking low ESG stocks.

—Insert Table C4 about here—

Table C5 revisits our results in Section 6.1. We again find our results robust—that is, ESG funds tend to lead their non-ESG siblings in trading illiquid stocks, especially when selling.

—Insert Table C5 about here—

B.5 Does ESG Score Explain Fund Performance?

In Section 5, we show that sibling non-ESG funds underperform their ESG siblings. However, if high ESG stocks outperform low ESG stocks in our sample period, ESG funds might outperform their non-ESG siblings in a mechanical way rather than through cross-fund subsidization. In the main text, we fail to find a performance difference between ESG and standalone non-ESG funds, which alleviates such concern. To rule out this competing hypothesis more formally, we regress the fund alpha onto the fund ESG score. In particular, our specification follows Table 5 except that we replace dummies that represent funds' ESG attributes, i.e., ESG and SNE, with fund ESG scores, i.e., $score$. Our results are presented in Table C6. The coefficient of the ESG score is not significant, indicating that the performance difference between ESG and non-ESG siblings that we have documented cannot be fully attributed to that between high and low ESG stocks.

—Insert Table C6 about here—

Moreover, as reported in Table C7, we do not find a significantly positive relationship between the performance of individual stocks and their ESG scores in our sample.

—Insert Table C7 about here—

B.6 Comparing Standalone and Sibling ESG Funds

For some of our main analyses, we pool all ESG funds together regardless of whether or not an ESG fund is co-managed with non-ESG funds. It is interesting to investigate if ESG funds that are co-managed with non-ESG funds behave differently from standalone ESG funds, due to for instance attention allocation and cross-fund subsidization.

In Table C8, we include into the sample all ESG funds, and regress fund ESG score and performance onto a dummy variable *Standalone* which is equal to 1 if the fund is not co-managed with any non-ESG funds in a given month. Various specifications lead to similar conclusions. According to columns (1) and (2), the average ESG score of standalone ESG funds is higher than that of ESG funds co-managed with non-ESG funds. However, such a difference is statistically insignificant. Results from columns (3) to (6) show that standalone ESG funds perform relatively worse than sibling ESG funds, even though such difference again lacks statistical significance. In our baseline analyses, we do not specifically differentiate between standalone and sibling ESG funds, even though our analyses about cross-fund spillovers based on sibling pairs effectively make a distinction.

—Insert Table C8 about here—

B.7 Strategic Timing of Trades of Illiquid Stocks: Logit Regressions

In Section 6.1, we have shown that ESG funds lead non-ESG funds in both buying and selling of illiquid stocks by computing conditional probability—that is, conditional on observing a significant trade by one fund, the probability of observing a similar trade by its siblings in the previous month. In this section, we employ Logit regressions, which allow us to control for a series of stock characteristics.

With the sample of trades by sibling pairs of ESG and non-ESG funds used in Section 6.1, we run a Logit regression:

$$I(SibLead_{j,t-1}) = \alpha + \beta_1 SNE_{j,t} + \sum_k Controls^k_{j,t} + \epsilon_{j,t}$$

where the independent variable $SNE_{j,t}$ indicates if a trade j in month t is executed by a sibling non-ESG fund. The dependent variable $I(SibLead_{j,t-1})$ is a dummy that is equal to 1 if the fund's sibling trades the same stock in month $t-1$ along the same direction. We control for size, book-to-market, and momentum of the stock underlying trade j. We expect a positive coefficient of $SNE_{j,t}$ for illiquid stocks—that is, trades of illiquid stocks by sibling non-ESG funds are more likely to be led by their ESG siblings than vice versa.

The estimation results are provided in Table C9. In column (1), we estimate the Logit regression in our sample of top 20% Amihud illiquidity, and find that buy trades of sibling non-ESG funds are more likely to be led by buy trades of their ESG siblings than vice versa. As a placebo test, the coefficient of $SNE_{j,t}$ is insignificant in the liquid sample. Columns (3) and (4) perform Logit regressions on the sell side, with the results being slightly stronger. These results are consistent with those in the main text.

—Insert Table C9 about here—

B.8 ESG Spillovers and Underperformance: Further Analyses

We provide additional results on ESG spillovers and sibling non-ESG funds' underperformance that complement our results in the main text. In our baseline analyses, we have shown that non-ESG sibling funds underperform and suggested cross-fund subsidization as a possible explanation. We now show that the predecessors of sibling non-ESG funds do not underperform. At that point, there is no incentive to cross subsidize. This echoes our result in the main text that non-ESG siblings do not tend to have a higher ESG score prior to the co-management.

Columns (1) and (2) of Table C10 follow the specification of columns (1) and (2) of Table 2 except that we change the dependent variable from fund ESG score to fund alpha. Our results show that the performance of sibling non-ESG funds deteriorates after co-management and does not tend to be different from typical standalone non-ESG funds prior to it. These results are consistent with our DID results in Appendix B.1 that fund performance gap widens after co-management.

—Insert Table C10 about here—

The size of ESG funds could potentially influence how managers allocate their attention between sibling ESG and non-ESG funds. If the ESG fund under co-management is larger, managers would naturally pay more attention to high ESG stocks in the first stage of the investment process and therefore include more high ESG stocks into their non-ESG portfolios at the end. To test this hypothesis, we add into the specification of column (3) in Table 2 an additional independent variable—the size of the co-managed ESG funds. As reported in column (3) of Table C10, coefficient for $size\_ESG$ is significantly positive, which is consistently our theory of limited attention.

C Tables for Appendix

TABLE C1: ESG SPILLOVERS AND UNDERPERFORMANCE: DIFFERENCE-IN-DIFFERENCES

This table investigates how the ESG score and performance of sibling non-ESG funds change around co-management using difference-in-differences. In each year, for a sibling non-ESG fund and its predecessor (treated), we match it with a non-ESG fund that remains to be standalone throughout our sample period (matched) according to fund size, age, expense ratio, and risk profiles. Within a 24-month window around the point where the treated fund starts to be co-managed with ESG funds, we run the following regression: $Diff_{i,t+1} = \alpha + \beta_1 SNE_{i,t} + \sum_k Controls^k_{i,t} + u_i + \epsilon_{i,t}$. For dependent variable, we use the difference in ESG scores in column (1) and that in Carhart four-factor alphas in column (2) between the treated and the matched funds. $SNE_{i,t} = 1$ if fund i is a sibling non-ESG fund in month t. We control for fund size, fund age, expense ratio, turnover ratio, and fund fixed effects. We cluster the standard errors at the fund level. t-statistics are in parentheses. ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

	Diff: ESG score	*Diff*: Alpha (%)
	(1)	(2)
SNE	0.90**	-0.09*
	(1.99)	(-1.71)
Controls	Yes	Yes
Fund FE	Yes	Yes
Obs	5,545	5,545
R2	0.58	0.04

TABLE C2: UNDERPERFORMANCE OF NON-ESG SIBLING FUNDS: PORTFOLIO REGRESSIONS

This table establishes the underperformance of non-ESG sibling funds using long-short portfolio regressions. At the end of each month and for each ESG attributes, we sort funds into two groups by their sizes, i.e., $small$ and big. We first construct the value- or equal-weighted returns of ESG funds (E), sibling non-ESG funds (S), and standalone non-ESG funds (A) within each group. The return gaps between standalone and sibling non-ESG funds ($ANE - SNE$) are given by: $0.5 \times (small/A + big/A) - 0.5 \times (small/S + big/S)$. The return gaps between ESG and sibling non-ESG funds ($ESG - SNE$) are given by: $0.5 \times (small/E + big/E) - 0.5 \times (small/S + big/S)$. We regress the returns gaps on the Carhart four factors. t-statistics are in parentheses. ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

	Value-weight Return (%)		Equal-weight Return (%)	
	(1) $ANE - SNE$	(2) $ESG - SNE$	(3) $ANE - SNE$	(4) $ESG - SNE$
Alpha	0.08***	0.11*	0.05**	0.08*
	(2.94)	(1.96)	(2.23)	(1.89)
MKT	-0.02**	-0.03*	-0.00	-0.01
	(-2.43)	(-1.90)	(-0.58)	(-1.09)
SMB	-0.06***	-0.14***	0.04***	-0.05***
	(-5.80)	(-6.41)	(3.70)	(-3.13)
HML	0.03**	0.01	0.02**	-0.01
	(2.46)	(0.55)	(2.24)	(-0.59)
UMD	-0.01	-0.02	-0.00	-0.03**
	(-1.38)	(-1.03)	(-0.42)	(-2.06)
Obs	95	95	95	95
R2	0.39	0.39	0.24	0.14

TABLE C3: EXCLUDING FUNDS MANAGED BY MORE THAN 3 MANAGERS

This table replicates our main analyses with a subsample of funds managed by no more than 3 fund managers. The left panel presents the ESG spillover results, with specifications following Table 2. The right panel presents the underperformance of sibling funds results, with a specification following the Panel A of Table 5. t-statistics are in parentheses. ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

	ESG Score		Alpha (%)	
	(1) Full Sample	(2) Sibling Sample	(3) Fama-MacBeth	(4) Pooled OLS
ESG	4.00***			
	(5.21)			
SNE	2.18**		-0.13***	-0.07*
	(2.09)		(-3.08)	(-1.86)
score_ESG		0.50***		
		(9.75)		
Controls	Yes	Yes	Yes	Yes
Fixed Effect	Fund	Fund	Style	Style+Time
Obs	90,355	1,521	2,583	2,583
R2	0.88	0.97	0.65	0.21

TABLE C4: STOCK-PICKING ABILITIES: ALTERNATIVE SAMPLES OF TRADES

This table replicates our empirical analyses in Table 4 with alternative criteria to construct the sample of buy trades. Panel A requires: 1) the position increase for a stock exceeds 0.3% of the fund's TNA in month t; 2) the fund is either having an outflow or the percentage increase of the stock is 10 times larger than the inflow in month t. Panel B requires: 1) the position increase for a stock exceeds 0.2% of the fund's TNA in month t; 2) the fund is either having an outflow or the percentage increase of the stock is 20 times larger than the inflow in month t. For detailed definition of variables, please refer to Table 4. ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

		Holding-period Alpha				
Period	ESG Score	SNE	ANE	ESG	SNE−ANE	SNE−ESG
Panel A: 0.3% AUM, 10 times flow						
1 Quarter	Q1 (Low)	-0.64%	-0.39%	-0.30%	-0.26%	-0.34%
	Q5 (High)	0.54%	-0.25%	-0.36%	0.79%***	0.90%***
1 Year	Q1 (Low)	-1.97%	-1.10%	0.50%	-0.87%	-2.47%***
	Q5 (High)	1.94%	-0.40%	-0.23%	2.34%***	2.17%***
Panel B: 0.2% AUM, 20 times flow						
1 Quarter	Q1 (Low)	-0.39%	-0.41%	-0.28%	0.02%	-0.11%
	Q5 (High)	0.43%	-0.22%	-0.29%	0.65%***	0.73%**
1 Year	Q1 (Low)	-1.83%	-1.29%	-0.19%	-0.55%	-1.64%*
	Q5 (High)	1.18%	-0.35%	-0.08%	1.53%***	1.26%**

TABLE C5: STRATEGIC TIMING OF TRADING: ALTERNATIVE SAMPLES OF TRADES

This table replicates our empirical analyses in Table 7 with alternative criteria to construct the sample of trades. For buy (sell) trades, Panel A requires: 1) the position increase for a stock exceeds 0.3% of the fund's TNA in month t; 2) the fund is either having an outflow (inflow) or the percentage increase (decrease) of the stock is 10 times larger than the inflow (outflow) in month t. For buy (sell) trades, Panel B requires: 1) the position increase for a stock exceeds 0.2% of the fund's TNA in month t; 2) the fund is either having an outflow (inflow) or the percentage increase (decrease) of the stock is 20 times larger than the inflow (outflow) in month t. For detailed definition of variables, please refer to Table 7. ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

	Buys			Sells		
	ESG Lead	*SNE Lead*	Diff.	*ESG Lead*	*SNE Lead*	Diff.
Panel A: 0.3% AUM, 10 time flow						
High Amihud 20%	10.69%	7.62%	3.07%**	8.50%	4.91%	3.59%***
Rest 80%	7.26%	8.53%	-1.28%*	6.39%	7.35%	-0.97%
Panel B: 0.2% AUM, 20 times flow						
High Amihud 20%	12.50%	8.60%	3.90%***	11.81%	5.52%	6.29%***
Rest 80%	9.61%	9.67%	-0.06%	6.89%	7.43%	-0.54%

TABLE C6: DOES ESG SCORE EXPLAIN UNDERPERFORMANCE OF NON-ESG SIBLINGS?

This table shows the relationship between fund performance and fund ESG scores. We employ the same empirical specifications as those in Table 5 except that we replace the dummies of fund ESG attributes (SNE in the co-management sample; ESG and SNE in the full sample) with the fund ESG score (*score*). t-statistics are in parentheses. ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

	Alpha(%)			
	Co-management Sample		Full Sample	
	Fama-MacBeth	Pooled OLS	Fama-MacBeth	Pooled OLS
	(1)	(2)	(3)	(4)
score	0.01	-0.00	0.00	0.00
	(0.82)	(-0.20)	(0.23)	(1.16)
Controls	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Time FE	/	Yes	/	Yes
Obs	6,880	6,880	120,233	120,233
R2	0.43	0.17	0.20	0.10

TABLE C7: ESG SCORES AND STOCK RETURNS

This table shows the Carhart four-factor alpha for stocks with different ESG scores. We exclude stocks with a price less than \$5 or a market capitalization in the bottom 10% using NYSE breakboints. We sort stocks into 5 portfolios by their ESG scores at the end of month $t-1$ and compute alphas using value-weighted returns in month t. t-statistics are in parentheses.

	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	H−L
Alpha (%)	0.00	-0.07	0.05	0.04	0.05	0.04
	(0.03)	(-0.43)	(0.52)	(0.41)	(0.97)	(0.23)

Table C8: Comparing standalone and sibling ESG funds

This table compares standalone and sibling ESG funds regarding their portfolio ESG scores and performance. We focus on the sample of ESG funds only. $Standalone$ is a dummy variable equal to 1 if a fund is an ESG fund not co-managed with any non-ESG funds. Columns (1) and (2) compare the ESG scores. Columns (3)-(6) compare the fund performance. We control for fund size, fund age, expense ratio, turnover ratio in (2)-(4). We also control for loadings on market, size, value, and momentum factors in (5) and (6). t-statistics are in parentheses. ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

	ESG Score		Alpha (%)		Gross Return (%)	
	(1) OLS	(2) OLS	(3) FMB	(4) OLS	(5) FMB	(6) OLS
Standalone	2.27	1.52	-0.04	-0.07**	-0.04	-0.09
	(1.18)	(0.95)	(-1.05)	(-2.01)	(-0.97)	(-1.48)
Controls	No	Yes	Yes	Yes	Yes	Yes
Fixed Effect	/	/	Style	Style+Time	Style	Style+Time
Obs	5,068	5,068	5,068	5,068	5,068	5,068
R2	0.01	0.31	0.45	0.14	0.73	0.88

Table C9: Strategic Timing of Trading of Illiquid Stocks: Logit Regression

This table reports Logit regression estimates regarding the strategic timing of trading illiquid stocks. For the sample of trades used in Table 7, we run the following regression: $I(SibLead_{j,t-1}) = \alpha + \beta_1 SNE_{j,t} + \sum_k Controls^k_{j,t} + \epsilon_{j,t}$. $SNE_{j,t}$ indicates if a trade j in month t is by a sibling non-ESG fund. $I(SibLead_{j,t-1})$ is a dummy that is equal to 1 if the fund's sibling trades the same stock in month $t-1$ along the same direction. We control for stock size, book-to-market, and momentum. In columns (1) and (3), we use the sample of buys and sells with top 20% Amihud ratio, respectively. In columns (2) and (4), we use the rest 80% of buys and sells. We use robust standard errors. z-statistics are in parentheses. ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

	$I(SibLead_{j,t-1})$			
	Buys		Sells	
	(1) Illiquid 20%	(2) Rest 80%	(3) Illiquid 20%	(4) Rest 80%
$SNE_{j,t}$	0.32**	-0.01	0.62***	-0.08
	(2.24)	(-0.19)	(3.71)	(-0.99)
Controls	Yes	Yes	Yes	Yes
Obs	2,095	8,296	1,931	8,031
Pseudo R2	0.01	0.01	0.02	0.01

TABLE C10: ESG SPILLOVERS AND UNDERPERFORMANCE: FURTHER ANALYSES

This table shows two results that are complementary to our baseline results about sibling non-ESG funds' underperformance and ESG spillovers. In column (1)/(2), we employ the same empirical specification as that in column (1)/(2) of Table 2 except that we change the dependent variable from fund ESG score to Carhart four-factor alpha. In column (3), we employ the same empirical specification as that in column (3) of Table 2 except that we add the size of co-managed ESG funds (*size_ESG*) as an additional independent variable. t-statistics are in parentheses. ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

	Alpha(%)		ESG Score
	(1)	(2)	(3)
ESG	-0.04	-0.05	
	(-0.93)	(-1.00)	
SNE	-0.09***		
	(-2.95)		
SNE_3y+		-0.10***	
		(-2.62)	
SNE_2y		0.00	
		(0.06)	
SNE_1y		-0.07	
		(-1.39)	
SNE_0y		-0.14***	
		(-3.21)	
SNE_-1y		-0.04	
		(-1.23)	
score_ESG			0.45***
			(10.78)
size_ESG			1.62***
			(6.84)
Controls	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
Obs	120,230	120,230	4,458
R2	0.02	0.02	0.95