Do Active Fund Managers Exploit Material ESG Information? *

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Abstract – Using a novel dataset containing daily snapshots of firm-level material ESG information, we examine whether active mutual fund managers successfully integrate material ESG information into their portfolio decisions. We find that a typical fund manager over-weights firms with high material ESG score and improves portfolio performance. Fund managers also incorporate material ESG information to cater to investor demand, especially during periods of greater ESG awareness. In the cross-section, ESG-information-investment relation is stronger among funds with better ESG ratings and higher 12b-1 fees. Further, funds located in Democratic states and managers who are less likely to be discriminated exhibit stronger ESG sensitivity.

JEL classifications: G11; G23; G41.

Keywords: ESG integration; materiality; sustainable investing; mutual funds; investment skill; catering.

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1. Introduction

Sustainable investing is one of the fastest growing areas in investments. The incorporation of environmental, social, and governance (ESG) information into investment decisions has been discussed widely, and not just for those investment products that have a sustainable mandate. In a letter to clients, Larry Fink, CEO of BlackRock, stated that "…sustainability should be our new standard for investing". Similarly, the Principles for Responsible Investing (PRI), the world's leading proponent of responsible investing, has attracted more than 3,000 signatories with over 100 trillion dollars in assets under management (AUM) by the end of 2020.

While sustainable and responsible (SR) funds have displayed strong commitments to various sustainable investing strategies, the majority of investment funds do not have explicit ESG mandates.[1] It remains unclear how and to what extent money managers incorporate ESG-information into their portfolio decisions.

According to the PRI reporting framework, sustainable investing strategies can be broadly classified into four categories: screening, thematic, engagement, and integration. Among these strategies, screening and thematic are relatively less applicable to funds that typically focus on mean-variance efficiency.[2] In addition, engagement is shown to be more popular among passive funds (Matos (2020)) and tends to have a low success rate (He et al. (2020)).

In comparison, ESG integration does not require major changes to the investment process and can be readily implemented by funds without sustainable mandates; hence, it is likely to be

[1] The universe of funds with sustainable mandates is still relatively small. For example, Morningstar reports that there are only 392 open-end and exchange-traded sustainable funds available to U.S. investors as of 2020, with a combined AUM under 0.24 trillion. See the 2020 Morningstar Sustainable Funds U.S. Landscape Report: https://www.morningstar.com/lp/sustainable-funds-landscape-report.

[2] For example, Ceccarelli et al. (2021) find that screening and thematic strategies could limit sectoral diversification and increase idiosyncratic volatility of mutual funds. In addition, PRI (2021) also suggests that ESG integration is the only suitable strategy for investors without ESG preferences.

the most practical sustainable investing strategy for a typical asset manager. Supporting this view, PRI (2020) reports that ESG integration is a dominant strategy pursued by U.S. signatories, with 69% of AUM using it as a standalone strategy for investing in listed equity.

In this paper, we investigate whether and to what extent fund managers successfully incorporate ESG integration strategies into their investment decisions. We also examine their motivations for pursuing ESG integration. In the last part of the paper, we test for potential cross-sectional heterogeneity in managerial incentives for ESG integration.

As defined by PRI (2018), ESG integration involves "the explicit and systematic inclusion of ESG issues in investment analysis and investment decisions." Managers pursuing ESG integration would factor ESG information into their portfolio decisions and adjust security weights accordingly. However, examining the degree to which ESG integration influences investment decisions is empirically challenging.

Specifically, ESG integration strategies such as periodic reviews and regular rating updates are often conducted at quarterly or higher frequency. Yet, the annual-frequency ESG ratings commonly used in the literature are unlikely to capture recent ESG information used for integration decisions.

Further, investigating the motives behind ESG integration is difficult. For example, a successful ESG integration strategy involves identifying and assessing material ESG information for return generation. If fund managers implement ESG integration strategies because they have better investment skill, they would only respond to material ESG information and achieve higher returns. However, due to the lack of ESG materiality data, it is difficult to examine fund managers' ability to infer ESG materiality.

To address these challenges, we use a novel daily measure of ESG information constructed by FactSet's Truvalue Labs (TVL) to proxy for information relevant for implementing ESG integration strategies. Specifically, TVL collects firm-specific ESG information from various sources such as mass media, industry publications, and governmental reports. These unstructured ESG data are then aggregated into a continuous daily frequency score (i.e., Pulse score) based on the degree of positivity of each ESG event. A higher Pulse score suggests a more positive corporate ESG profile.

We posit that the Pulse score effectively summarizes fund managers' main information sources for ESG integration.[3] If fund managers actively implement ESG integration strategies, firm-level Pulse score would be correlated with security weights in mutual fund portfolios. In addition, TVL is the first dataset that integrates the Sustainable Accounting Standard Board's (SASB) materiality framework,[4] which allows us to directly examine fund managers' ability to infer ESG materiality.

To test whether a typical asset manager implements ESG integration strategies, we examine the quarterly holdings of all actively managed equity mutual funds in the United States during the 2007 to 2017 period. In regressions that control for a large set of fund and firm attributes, we find a significantly positive relation between firm-level Pulse score and mutual fund holdings. In economic terms, for an average fund-firm pair, a one-standard-deviation increase in Pulse score is associated with between $66,576 and $96,787 extra investment in the next quarter. This evidence indicates that fund managers actively integrate ESG information into their portfolio decisions. We

[3] Consistent with this conjecture, PRI (2018) states that asset managers implementing ESG integration strategies are expected to collect ESG information from company reports, filings, websites, and so on.
[4] The SASB materiality framework is widely used by PRI signatories, which include global leading asset owners and asset managers such as BlackRock, CalPERS, Fidelity, Goldman Sachs, Vanguard, and Morgan Stanley. See https://www.sasb.org/alliance-membership/organizational-members/.

also show that fund managers employ ESG integration strategies by buying stocks with positive ESG information rather than selling stocks with negative ESG information.

Our results remain robust after controlling for different sets of firm-level ESG ratings, suggesting that fund managers perform ESG integration by analyzing timely ESG information. Further, our results are not explained by firm-specific investor sentiment or changes in conventional fundamental signals on firm values.

In the next set of tests, we investigate why fund managers implement ESG integration strategies. Motivated by the evidence in recent studies, we explore two non-mutually exclusive possibilities. First, implementing ESG integration strategies could reflect fund managers' investment skill (e.g., Kacperczyk et al. (2008)). The theoretical model in Pedersen et al. (2021) predicts that compared to ESG-unaware investors, investors who are able to complement mean-variance investment decisions with ESG information could achieve a higher maximum Sharpe ratio. Similarly, industry publications (e.g., PRI (2018)) also argue that ESG integration could lead to higher returns or lower risk if fund managers have skills in identifying and evaluating material ESG information.

To test the skill hypothesis, we start by directly examining fund managers' skill in identifying material ESG information that varies across sectors and industries. Specifically, we construct material and immaterial firm-level Pulse scores using the SASB materiality map. Consistent with the skill hypothesis, we find that fund managers only integrate material ESG information into their portfolio decisions.

Next, we test whether ESG integration is associated with superior return. We estimate fund managers' propensity to trade on ESG information and examine its relation to next-quarter risk-adjusted returns using the Fang et al. (2014) method. Consistent with the skill hypothesis, we find that managers with higher propensity to trade on ESG information earn superior risk-adjusted returns. A one-standard-deviation increase in managerial propensity to integrate ESG information is associated with 1.0% higher Morningstar benchmark-adjusted return in the next quarter relative to the sample mean. Further, we show that the improved portfolio performance is generated through the superior returns of stocks with positive ESG information, and reflects the incorporation of material ESG information into stock prices rather than temporary price pressure.[5]

Beyond reflecting investment skill, implementing ESG integration strategies by fund managers may reflect managerial incentives to attract investor flows. Hartzmark and Sussman (2019) show that mutual fund investors collectively put a positive value on ESG. As ESG events attract investor attention and trigger investor demand (e.g., Barber and Odean (2008), Solomon et al. (2014)), fund managers may actively cater to investor flows by investing in firms with positive ESG events.

To examine this possibility, we focus on the relation between portfolio-level Pulse score and future fund flows. Consistent with the flow catering hypothesis, we find that funds with higher portfolio-level Pulse scores attract more flows. For an average sample fund, a one-standard-deviation increase in portfolio-level Pulse score is associated with $3.7 million higher inflows in the next quarter.

To provide additional evidence on the catering motive, we examine whether managers cater to time-varying ESG demand. Motivated by the methods in Baker and Wurgler (2004) and Naughton et al. (2019), we estimate market-level ESG demand and find that managers respond more strongly to ESG information during high rather than low ESG demand periods.

[5] In unreported test, we also find weak evidence for risk reduction. Fund managers with higher propensity to integrate ESG information into portfolio decisions have lower return standard deviations in the following 6 or 12 months.

We also investigate the effect of the introduction of Morningstar Sustainability Rating on managerial incentives to employ ESG integration strategies. This exogenous event significantly raised investor awareness about sustainable investing. Consequently, capital flows into funds with top-rated ESG performance would be driven by ESG demand to a greater extent after the event (Hartzmark and Sussman (2019)). Consistent with the catering hypothesis, we find that, relative to bottom-rated funds, top-rated funds exhibit an increased propensity to trade on ESG information after this event.

In the last part of the paper, we examine how heterogeneity in fund attributes affects managerial incentives to implement ESG integration strategies. If ESG integration is at least partially explained by the skill hypothesis, then managers who are more skilled in sustainable investing are likely to respond more strongly to ESG information. Similarly, if managerial responses to ESG information are related to catering motives, managers are likely to have stronger incentives to incorporate ESG integration strategies when their catering is more effective.

The existing mutual fund literature demonstrates that managers of Democratic-leaning funds (Hong and Kostovetsky (2012)) and SR funds (Bollen, (2007), Renneboog et al. (2011)) care more about sustainability, and investors of these funds are more sensitive to ESG events. We also expect that catering propensity would be more effective when funds are more salient to investors (Sirri and Tufano, 1998) or among fund managers who are unlikely to be subject to name-induced discrimination (Kumar et al. (2015)).

Motivated by these studies, we posit that managers of Democratic funds, SR funds, salient funds, and funds with "domestic" managers would have stronger incentives to trade on ESG information. Consistent with this conjecture, we find that managers of these funds are more responsive to ESG information. In particular, managers of Democratic and SR funds exhibit both skill and catering motives, while managers of salient funds and those who are unlikely to experience discrimination exhibit a stronger propensity to cater.

Taken together, these findings contribute to a growing finance literature that focuses on sustainable investing. Existing studies have focused on screening (e.g., Bollen (2007), Renneboog et al. (2008), (2011), Hong and Kacperczyk (2009)), engagement (e.g., Dimson et al. (2015), Krueger et al. (2020), Hoepner et al. (2021)), and thematic (e.g., Ceccarelli et al. (2021)) strategies. Using a novel ESG dataset that captures the information set for ESG integration, we extend this literature and demonstrate that mutual fund managers actively and successfully employ ESG integration strategies by increasing the holdings of stocks with positive ESG information.

Our findings also provide new insights into the motives behind sustainable investing. Recent studies (e.g., Riedl and Smeets (2017), Hartzmark and Sussman (2019)) examine the motives from the perspective of mutual fund investors. Our finding complements theirs by investigating the motives from the perspective of fund managers. We demonstrate that investment skill and catering motives jointly induce fund managers to integrate ESG information into their investment decisions.

More broadly, we contribute to the mutual fund literature. Our results provide novel insights into the investment skill of fund managers (e.g., Kacperczyk et al. (2008), Kacperczyk et al. (2014), Pastor et al. (2015)). Specifically, we show that fund managers have skill in discriminating between material and immaterial ESG information. These findings allow us to quantify the economic impact of ESG information more effectively.

Last, we add to the finance literature on the relation between sustainable investing strategies and fund performance (see Matos (2020) for a review). While the existing studies find mixed evidence on other ESG strategies, we demonstrate that fund managers' ESG integration strategies are associated with higher risk-adjusted returns. Our findings that the superior return represents the incorporation of material ESG information into asset prices rather than temporary price pressure shed light on the implications of ESG for firm value (e.g., Edmans (2011), Pastor et al. (2021), Pedersen et al. (2021)).

2. Data and Methods

To examine whether mutual fund managers actively implement ESG integration strategies, we use data from various sources. In this section, we describe all datasets used in the empirical analysis.

2.1. *Mutual fund data*

Our mutual fund data come from three standard databases: Center for Research in Security Prices (CRSP) Survivor Bias-Free Mutual Fund Database, Morningstar, and Refinitiv (formerly known as Thomson Reuters) Mutual Fund Holding Database. We obtain fund returns, total net asset (*TNA*), expenses, loads, and other fund characteristics from CRSP, and collect fund category benchmark portfolio returns from Morningstar. We closely follow the extensive data cleaning process in Pastor et al. (2015) to address data inconsistency issues between the CRSP and Morningstar mutual fund data. Specifically, we merge CRSP and Morningstar data and require funds to have consistent returns and *TNAs* at the share class level in both datasets. Funds with multiple share classes are aggregated into a single fund.[6] We collect quarterly holdings of mutual funds from Refinitiv, and merge holding data with CRSP fund data using MFLINKS.

[6] We sum the *TNA*s of different share classes. For other quantitative fund attributes (e.g., return, expenses, turnover), we take the weighted average using lagged *TNAs* of each share class as weights. For qualitative attributes (i.e., age, investment objective), we use the observation from the oldest share class.

We restrict our sample to actively managed U.S. domestic equity funds. We use the Morningstar category to define fund investment styles, as in Pastor et al. (2015). In addition, we screen fund names and investment styles in CRSP and Morningstar to exclude international, balanced, sector, bond, money market, hedge, target-date, and index funds.[7] Since the reported fund characteristics do not always accurately categorize investment style, we follow Kacperczyk et al. (2008) and delete funds with less than 80% of *TNA* in equity. We further exclude funds with below $5 million *TNA* at the end of the previous quarter.[8]

2.2. *Firm-level ESG information*

We obtain firm-level ESG information from FactSet's TVL. Recent studies show that the TVL data is a timely and consistent measure of firm-level ESG information (e.g., Serafeim and Yoon (2021a)). Using proprietary web-scraping technology, TVL extracts ESG content from over 100,000 sources, including leading news providers, industry-specific publications, social media articles, government agency studies, and reports from watchdog groups and non-governmental organizations. All the sources are vetted by a team of ESG experts. Unlike conventional ESG ratings, TVL excludes company-provided material to mitigate the "greenwash" problem.

To measure the information content of an article, TVL classifies events in each article into sustainability categories following the SASB 26-category codified framework, and applies natural language processing to quantify the semantic tone for all relevant firms that appeared in the article. These firms are assigned Pulse scores on relevant sustainability categories to quantify their

[7] Our empirical analysis includes nine Morningstar categories (i.e., investment styles) : US fund large blend, US fund large growth, US fund large value, US fund mid-cap blend, US fund mid-cap growth, US fund mid-cap value, US fund small blend, US fund small growth, and US fund small value. These nine Morningstar categories correspond to the following six CRSP investment objective codes (*crsp_obj_cd*): EDCI, EDCM, EDCS, EDYB, EDYG, and EDYI.
[8] Some studies (e.g., Elton et al. (2001), Chen et al. (2004)) require funds to have at least $15 million *TNA*. Our results remain similar if we drop funds with *TNA* below $15 million.

category-specific performance. The Pulse score has a value ranging from 0 to 100, which captures both the direction and magnitude of impacts generated by ESG events. Scores above (below) 50 indicate a positive (negative) impact from an ESG event while a score of 50 suggests a neutral impact.

At the end of each day, each firm is assigned an all-category Pulse score by volume weighting Pulse scores on individual sustainability categories over the day using category article volume as weight. In addition, to identify material ESG categories across firms, TVL classifies each firm into an industry using the SASB Sustainable Industry Classification System (SICS), which can then be merged with the SASB materiality map.[9]

We rescale Pulse scores to lie between -0.5 (most negative) and 0.5 (most positive), with 0 indicating a neutral impact. To ensure that firms have enough coverage, we exclude firms that are covered by fewer than five unique articles in the past twelve months (i.e., require firms to have at least one article per quarter). The Pulse score is available from 2007.

Figure 1 shows the all-category Pulse score of Apple during the June to December 2017 period. We find that all the peaks and troughs in the series coincide with firm-specific ESG events. For example, the peak in June is related to the firm's issuance of $1 billion corporate green bonds for renewable energy after the Trump administration's Paris climate exit. In comparison, the sharp decrease in Pulse score in December is mainly associated with the iPhone battery scandal. To ensure transparency in Pulse score, TVL includes the articles and corresponding SASB categories that drive the change. We find that the Pulse score covers publicly available information from mass media (e.g., Bloomberg, CNBC, Fox News, and The Wall Street Journal) that has been shown to

[9] The SASB materiality map defines materiality of the 26 general ESG issue categories for 11 SICS sectors and 77 SICS industries, see https://materiality.sasb.org/.

attract investor attention (e.g., Barber and Odean (2008)) and affect investors' trading behavior (e.g. Tetlock (2007)).

2.3. *Conventional ESG ratings*

To ensure the Pulse score contains value-relevant ESG information beyond conventional ESG measures, we include three sets of ESG ratings that are widely used in the finance literature. First, we collect ESG scores from MSCI KLD, which report ESG performance in seven dimensions: Community, Diversity, Environment, Employee, Product, Human Rights, and Governance. To ensure KLD scores are comparable across firms and over time, we use the Deng et al. (2013) method to construct adjusted KLD scores (ESG_{KLD}). Second, we obtain overall ESG scores from Sustainalytics ($ESG_{Sustainalytics}$), which are available from August 2009. Third, we measure firm-level ESG performance using Refinitiv ESG scores (formerly known as Asset4). Following Dyck et al. (2019), we equal weight scores in the environmental, social, and governance pillars to construct an overall Refinitiv score ($ESG_{Refinitiv}$).

2.4. *Other data sources and summary statistics*

We collect stock price and return information from CRSP and obtain accounting information and short interest from Compustat. We collect sell-side analyst recommendations from Refinitiv's Institutional Brokers Estimate System (I/B/E/S). We obtain risk factors from French's data library. We collect data on state-level Presidential election outcomes from Dave Leip's Atlas of U.S. Presidential Elections and collect the partisan composition of the state governor and legislature from Ballotpedia. Our final sample consists of 1,734,426 fund-firm-quarter observations during the 2007 to 2017 period, covering 1,870 unique funds and 1,519 unique stocks (share code of 10 or 11). Table A1 in the Internet Appendix reports the detailed breakdown of sample firms by the Fama and French 12-industry classification. We find that our sample has reasonable coverage of the 12 industries.

Panel A of Table 1 reports the detailed definitions of all variables used in the empirical analysis, while Panel B reports the summary statistics. An average fund in our sample has a *TNA* of $1,752 million and holds 341 shares in a typical firm.

3. Do Fund Managers Implement ESG Integration Strategies?

3.1. *Holding regression estimates: Baseline results*

To examine whether fund managers incorporate ESG information into their portfolio decisions, we estimate the following regression at the fund-firm-quarter level:

$$ln(D/TNA)_{i,j,t} = \beta_0 + \beta_1 Pulse_{j,t-1} + \gamma X_{i,t-1} + \theta W_{j,t-1} + \alpha_i + \tau_j + \delta_t + \varepsilon_{i,j,t.} \qquad (1)$$

The dependent variable $ln(D/TNA)_{i,j,t}$, is the natural logarithm of the market value of firm j owned by fund i in quarter t, divided by the total net assets of fund i in quarter t. We take the natural logarithm to control for the skewness in *D/TNA*.

The main variable of interest is the time-series average of all-category Pulse scores of firm j in quarter t-1 ($Pulse_{j,t-1}$), which captures the average degree of positivity of ESG information on firm j in quarter t-1.[10] We conjecture that *Pulse* summarizes firm-level ESG information from the sources that are used by mutual fund managers for ESG integration. If fund managers actively engage in ESG integration strategies, we expect β_1 to be significantly positive.

Our primary set of control variables includes both fund and firm attributes. Specifically, X_i is a vector of fund characteristics, including fund size, expense ratio, turnover ratio, fund age, and a dummy variable for loaded funds. In addition, we control for fund returns by including

[10] Our results are insensitive to using the end-of-quarter values of the all-category Pulse scores. These unreported results are available upon request.

performance rank (i.e., the rank of a fund's average return in the past twelve months relative to all other funds in the same Morningstar category) and squared performance rank, as in Kumar et al. (2015). W_j is a vector of stock characteristics, including firm size, stock turnover ratio, and book-to-market ratio, as in Fang et al. (2014). We lag all control variables by one quarter.

To mitigate potential concerns about omitted variables, fund (α_i) and firm (τ_j) fixed effects are included to account for any time-invariant or persistent unobserved factors at the fund and firm levels, respectively. Year-quarter fixed effects (δ_t) are included to control for the effects of market-wide shocks on mutual fund holdings. Standard errors are triple-clustered at the fund, firm, and year-quarter levels.

Panel A of Table 2 reports the baseline holding regression results. Consistent with fund managers actively integrating ESG information into portfolio decisions, we find that the coefficient of *Pulse* is significantly positive across all specifications. After controlling for fund and stock characteristics, a one-standard-deviation increase in *Pulse* is associated with between 0.140 × 0.027 = 0.38% and 0.140 × 0.038 = 0.53% increase in mutual fund holdings, or between $66,576 and $96,787 additional investment of an average fund-firm pair from the sample mean.[11]

Columns 1 and 2 include different combinations of year-quarter, firm, and fund fixed effects. In addition, we control for fund-firm fixed effects in Column 3 and show that within the same fund-firm pair, a fund manager increases holdings when the firm has more positive ESG information. This finding also suggests that our results are not explained by unobservable heterogeneity in fund managers' preferences across firms. In Columns 4 and 5, we control for Year-quarter × Fama French 49 industry (FF49) and Year-quarter × Style fixed effects and find

[11] The economic magnitude is estimated using sample average *D/TNA* of 1.04% and *TNA* of $1,752 million (see Panel B of Table 1). For instance, the 0.53% increase from mean *D/TNA* amounts to a 0.55-basis-point increase in *D/TNA*, or $96,787 (0.000055234×1752.31).

consistent results. This evidence indicates that our results are not explained by unobservable variations at the industry or investment style level over time. Taken together, our findings in Panel A suggest that fund managers actively engage in ESG integration strategies.

In Panel B of Table 2, we conduct an extensive set of robustness tests to ensure our holding regression estimates are robust to different specifications. For brevity, we only report the estimates of the main variables of interest.

In Columns 1 and 2, we find that our results remain unchanged if we require firms to be covered by at least ten articles in the past twelve months or exclude funds with fewer than ten stocks. In Columns 3 and 4, to ensure that our holding regression results are not driven by firms with increased share prices following positive ESG information (e.g., Serafaim (2020)), we use the log number of a firm's shares held by a fund (*ln(Shares)*) and the log of the proportion of a firm's shares held by a fund (*ln(Shares/CSHO)*) as alternative dependent variables. Our results still hold. Further, our results are robust to alternative fixed effects (Columns 5 and 6) and different standard error clustering (Columns 7 to 9).

3.2. *Estimates with conventional ESG ratings and investor sentiment controls*

In Panel C of Table 2, we examine whether *Pulse* has incremental explanatory power on fund managers' investment decisions over conventional firm-level ESG ratings. We consider three sets of widely used ESG ratings in the literature: MSCI KLD, Sustainalytics, and Refinitiv ESG ratings. If *Pulse* does not proxy for value-relevant information for ESG integration beyond conventional ESG ratings, the explanatory power of *Pulse* would disappear after including these conventional ratings. In Columns 1 to 6, we find that coefficients of *Pulse* remain statistically and economically significant after controlling for conventional ESG ratings. In contrast, conventional

ESG measures do not show any significant influence on quarterly fund holdings, potentially due to low frequency and lag in the information contained in these ratings.

For further robustness, we also control for firm-specific investor sentiment to examine whether the Pulse score is simply capturing general investor sentiment. Motivated by Berkman et al. (2012) and Aboody et al. (2018), we use overnight returns ($RET_{Overnight}$) to proxy for firm-specific investor sentiment. We also use the natural log of the proportion of negative financial words in 10-K reports (*ln(Fin-Neg)*) to capture the negative sentiment generated by corporate financial reports, as in Loughran and McDonald (2011).[12]

The results from these tests are summarized in Columns 7 to 10 in Panel C. We find that the positive relation between *Pulse* and mutual fund holdings remains robust after controlling for investor sentiment. Columns 7 and 9 show that the coefficient estimates of $RET_{Overnight}$ are significantly positive, suggesting that fund managers actively respond to firm-specific investor sentiment. In comparison, in Columns 8 and 10, we find that the coefficient estimates of *ln(Fin-Neg)* are negatively associated with *ln(D/TNA)* but not *ln(Shares/CSHO)*. This evidence suggests that negative sentiment from financial reports is more likely to affect stock prices rather than fund holdings.

3.3. *Estimates with controls for fundamentals*

Next, we investigate whether *Pulse* contains material ESG information beyond changes in conventional fundamental information that affect firm value. We employ two sets of fundamental proxies: processed and unprocessed fundamental information. The existing literature demonstrates

[12] We obtain the negative word count for the 10-K reports from the Notre Dame Software Repository for Accounting and Finance, available at https://sraf.nd.edu/. We are grateful to Tim Loughran and Bill McDonald for making these data publicly available.

that short sellers (Engelberg et al. (2012)) and financial analysts (Kim and Verrecchia (1994)) have better skills in processing public firm-specific information (e.g., earnings announcement). Therefore, their activities are likely to contain superior information about firm-level fundamentals. In addition, Lin et al. (2014) show that mutual fund managers adjust stock holdings based on information processed by savvy market participants, especially when public information is noisy. Motivated by these studies, we include short interest and consensus analyst recommendation as our proxies for processed fundamental information. Higher short interest and pessimistic analyst recommendation represent more negative forecasts on a firm's fundamentals.[13]

In addition, we include a large set of commonly used fundamental variables as our proxies for unprocessed fundamental information: leverage, Tobin's Q, return on assets, research and development expenditure over total assets, capital expenditure over total assets, and cash holdings over net assets. If *Pulse* does not capture complementary material information to conventional fundamentals for investment decision-making, the explanatory power of *Pulse* would disappear after controlling for these fundamental signals.

The results of these tests are summarized in Panel D of Table 2. In Columns 1 and 3, we show that the coefficients of *Pulse* remain statistically and economically significant after controlling for processed fundamental information. Consistent with the existing literature, short interest and pessimistic consensus recommendation are negatively associated with mutual fund holdings. Our results remain quantitatively similar when we further control for unprocessed fundamental information, as shown in Columns 2 and 4.

[13] The I/B/E/S database assigns 1 for "strong buy" and 5 for "strong sell". Therefore, a higher value indicates a more pessimistic analyst recommendation. Following the existing literature, we exclude stocks that are covered by fewer than five analysts.

In Columns 5 to 8, we control for fundamental information using an alternative approach. Specifically, in Columns 5 and 7 (6 and 8), we regress our baseline *Pulse* on processed (both processed and unprocessed) fundamental information and use the residuals as fundamental-adjusted Pulse scores $Pulse_{Adj1}$ ($Pulse_{Adj2}$). Our results remain unchanged. Collectively, these findings suggest that *Pulse* contains material ESG information beyond fundamental information commonly used by fund managers.

3.4. *Estimates with buying and selling as dependent variables*

In the last set of tests in Section 3, we investigate whether fund managers implement ESG integration strategies by buying stocks with positive ESG information or selling stocks with negative ESG information. We use *ln(Buy/TNA)* and *ln(Sell/TNA)* to proxy for the buying and selling activities of fund managers. Specifically, $ln(Buy/TNA)_{i,j,t}$ ($ln(Sell/TNA)_{i,j,t}$) equals the natural logarithm of the positive (negative) change in the market value of firm *j* owned by fund *i* in quarter *t* from quarter *t-1*, divided by the total net assets of fund *i* in quarter *t*, or zero otherwise. We re-estimate equation (1) using these two proxies as the dependent variables.

The results of these tests are reported in Table 3. In Columns 1 to 3, we find a positive relation between *Pulse* and *ln(Buy/TNA)*. In contrast, Columns 4 to 6 show that there is no significant relation between *Pulse* and *ln(Sell/TNA)*. This finding suggests that fund managers are likely to integrate ESG information into their portfolio decisions by increasing holdings of firms with positive information, rather than decreasing holdings of firms with negative information. Our results also provide insights into the findings in Serafeim and Yoon (2021b), who show that stock price reaction to ESG news is larger for positive news.

Taken together, our holding regression results in Section 3 demonstrate that fund managers actively implement ESG integration strategies by over-weighting stocks with positive ESG information. Our results are robust to different variations to the main specification.

4. Why Do Fund Managers Implement ESG Integration?

Our findings so far raise a natural question: why do fund managers implement ESG integration strategies? In this section, we examine two potential hypotheses. The first hypothesis posits that fund managers have skill in integrating material ESG information to achieve higher risk-adjusted returns, and the second hypothesis posits that fund managers adopt ESG integration strategies to cater to investors' ESG demand. These hypotheses are not mutually exclusive, and each could affect our results to certain degree.

4.1. *Fund manager skill*

4.1.1. Materiality and ESG integration

We start by investigating whether fund managers have skills to infer ESG materiality. According to Freiberg et al. (2020), the materiality of ESG categories varies systematically across sectors and industries. In addition, Khan et al. (2016) find that firms with good sustainability ratings outperform those with poor ratings only when the sustainability categories are material to firm value. Similarly, since ESG integration strategies can be used by investors focusing on mean-variance efficiency, an efficient ESG integration strategy is less likely to incorporate immaterial ESG information (PRI (2021)). If fund managers have skill in implementing ESG integration strategies, we would expect them to only respond to ESG information that is material to firm value.

To test this hypothesis, we merge firm-level Pulse scores with the SASB materiality map using SICS, and classify each of the 26 SASB sustainability categories as material or immaterial to firm value. We then construct volume-weighted material and immaterial Pulse scores (*Pulse*$_{Material}$ and *Pulse*$_{Immaterial}$) for each firm using the Pulse scores on individual sustainability categories and corresponding category article volumes. By construction, *Pulse*$_{Material}$ and *Pulse*$_{Immaterial}$ are computed using Pulse scores on non-overlapping sustainability categories. Importantly, the SASB materiality framework is developed in 2018. Therefore, during our sample period, fund managers need to use their skill to infer ESG materiality.

We re-estimate the baseline holding regression by replacing *Pulse* with *Pulse*$_{Material}$ and *Pulse*$_{Immaterial}$ as the main independent variables. Table 4 reports the results. Consistent with the skill hypothesis, we find that when *Pulse*$_{Material}$ and *Pulse*$_{Immaterial}$ are included separately (Columns 1 to 2 and 4 to 5), only *Pulse*$_{Material}$ has explanatory power on next-quarter mutual fund holdings. In addition, in Columns 3 and 6, we include both *Pulse*$_{Material}$ and *Pulse*$_{Immaterial}$ and find similar results. This evidence suggests that fund managers are skilled in distinguishing firm-specific material ESG information from immaterial information and only incorporate material information into their ESG integration decisions.

4.1.2. ESG integration and risk-adjusted returns

In the next set of tests, we investigate the relation between ESG integration and mutual fund performance. If ESG integration is motivated by better investment skill, we would expect a positive relation between fund managers' propensity to integrate ESG information and future risk-adjusted returns.

We follow the Fang et al. (2014) method to estimate fund managers' propensity to integrate ESG information (*Propensity*), and examine the cross-sectional relation between *Propensity* and future fund returns.[14] At the beginning of each quarter, we sort all mutual funds into *Propensity* quintiles. Managers in Quintile 5 (1) have the highest (lowest) propensity to integrate ESG information into their portfolio decisions.

We consider excess returns, style-adjusted returns, Morningstar benchmark-adjusted returns, CAPM-adjusted returns, Carhart (1997) four-factor adjusted returns, and Fama and French (2015) five-factor adjusted returns as risk-adjusted return measures. Standard errors are adjusted using the Newey and West (1987) method with eight lags.

Panel A of Table 5 reports the time-series averages of cross-sectional returns. Consistent with the literature (e.g., Gruber (1996), Fama and French (2010)), we find that actively managed equity funds in the U.S. earn negative alphas. However, the return differences between managers with the highest and lowest propensity to integrate ESG information are positive and statistically significant across almost all risk-adjusted return measures. For example, the quarterly four-factor alpha of managers with the highest propensity to implement ESG integration strategies is higher than that of managers with the lowest propensity by 16 bps (64 bps per annum), which is comparable to the magnitude of skill-related outperformance documented in Pastor et al. (2015).

Panel B of Table 5 presents results using an alternative approach, where we regress risk-adjusted fund returns on lagged *Propensity*, fund attributes, and different combinations of fixed effects. We use both excess returns and Morningstar benchmark-adjusted returns as dependent variables, and include the same set of fund attributes as in equation (1). We report coefficient estimates using Fama-MacBeth (1973) regressions.[15] Standard errors are adjusted using the Newey and West (1987) method with eight lags.

[14] See Section A in the Internet Appendix for more detail on *Propensity* estimation.
[15] Our results remain similar if we use pooled OLS regressions.

Consistent with the skill hypothesis, we find that *Propensity* is positively associated with next-quarter returns. In Column 4, a one-standard-deviation increase in *Propensity* is associated with a 0.443 × 0.072 × 100 = 3.2 bps increase in Morningstar benchmark-adjusted return, corresponding to a 1.0% increase relative to the sample mean (mean = 3.11 percentage points).

4.1.3. Source of superior returns and impact on asset prices

Our results so far have established that responding to positive ESG information leads to an improvement in overall portfolio performance. In the last set of skill hypothesis tests, we examine whether the improved risk-adjusted return is generated through the superior performance of firms with positive ESG information or other firms in the portfolio. Specifically, we estimate the Fama-MacBeth (1973) cross-sectional regressions. The dependent variable is the next-quarter stock return and the main explanatory variable is the interaction term between *Pulse* and change in aggregate mutual fund ownership ($\Delta Share/CSHO_{t-1}$). We include the same sets of stock attributes in equation (1) as well as industry fixed effects.

Results are presented in Panel A of Table 6. In Column 1, we find that the coefficient of the interaction term is positively significant (at the 10% level), which suggests that the superior risk-adjusted returns are likely to be generated through buying stocks with positive ESG information. In addition, Column 1 in Panel B reports the Fama-MacBeth regression estimates separately for three subsamples sorted by *Pulse*. The main variable of interest is $\Delta Share/CSHO_{t-1}$. We find that the positive relation between change in mutual fund holdings and next-quarter stock return mainly comes from stocks with the most positive ESG information.

We also investigate whether the superior risk-adjusted return reflects permanent price change or temporary price pressure. If fund managers have skill in analyzing ESG information, they could better infer the intrinsic value of related stocks (e.g., Pedersen et al. (2021)). The superior risk-adjusted return reflects the incorporation of material information into asset prices. In contrast, if the higher risk-adjusted return is due to temporary buying pressure, we would expect it to revert in the long run.

We estimate the Fama-MacBeth regressions using returns in quarters 2 to 4 as dependent variables. Consistent with fund managers' ESG integration strategies facilitating information incorporation into asset prices, we find no evidence of return reversals in the following three quarters (Columns 2 to 4 in both Panels of Table 6) .[16]

In light of the results in Table 3, the evidence in Section 4.1 suggests that fund managers have skill in implementing ESG integration strategies into their portfolio decisions. They earn superior risk-adjusted returns by buying stocks with positive ESG information. Their use of material ESG information makes the prices of portfolio firms more informative.

4.2. *Catering to ESG demand*

4.2.1. ESG integration and investor flow

Next, we investigate whether fund managers adopt ESG integration strategies to cater to the ESG demand of mutual fund investors. Hartzmark and Sussman (2019) find that fund investors perceive ESG as a positive fund attribute. They show that funds with good Morningstar Sustainability Ratings attract more investor flows without having better return performance. If mutual fund investors are attracted to stocks with positive ESG information and allocate capital

[16] In unreported tests, we also find no evidence of return reversal in quarters 5 to 8.

into funds that hold these stocks, then fund managers are likely to integrate ESG information to cater to investors' taste for ESG attributes.[17]

To test this catering hypothesis, we examine whether investor flows are responsive to fund managers' trading on ESG information. Specifically, we regress next-quarter fund flow on portfolio-level Pulse score and a large set of control variables that have been shown to explain flows:

$$Flow_{i,s,t} = \beta_0 + \beta_1 Pulse_{Portfolio\ i,t-1} + \theta X_{i,t-1} + \tau_{s,t} + \varepsilon_{i,s,t}\ , \tag{2}$$

The dependent variable is fund flow in quarter t. $X_{i,t-1}$ is a vector of baseline fund attributes and flows in quarter t-1, while $\tau_{s,t}$ denotes Year-quarter × Style fixed effects. Standard errors are double clustered at the fund and year-quarter levels.

The main variable of interest is the portfolio-level Pulse score of a mutual fund ($Pulse_{Portfolio}$), computed as value-weighted all-category Pulse scores of all firms in a mutual fund portfolio. Since the disclosure of fund holdings could take up to 45 days, we construct $Pulse_{Portfolio}$ in quarter t-1 using portfolio weights at the end of quarter t-2 to ensure holding information is known to investors. In addition, to address the possibility that investors are not aware of the full list of fund holdings, we also construct an alternative portfolio-level Pulse score using only the Pulse scores of the fund's top ten holdings ($Pulse_{Top10}$).[18] If the catering hypothesis holds, we expect $Pulse_{Portfolio}$ and $Pulse_{Top10}$ to be positively associated with future investor flows.

[17] Fund managers might also cater to ESG demand by changing fund names (e.g., Cooper et al. (2005)). However, after the introduction of Rule 35d-1 by the SEC in 2001, investment companies are prohibited from using deceptive or misleading names.

[18] Motivated by Cremers and Petajisto (2009), we require funds to have at least 50% of *TNA* in firms covered by Truvalue Labs and KLD to ensure that $Pulse_{Portfolio}$ and $Pulse_{Top10}$ are representative of a fund portfolio's overall activeness in ESG integration.

Table 7 reports the flow regression estimates. Consistent with the catering hypothesis, we find that funds with more positive portfolio-level Pulse scores attract more flows. In economic terms, a one-standard-deviation increase in $Pulse_{Portfolio}$ (i.e., 0.034) in Column 2 is associated with 23.6 basis points (bps) or \$3.7 million higher flows in the next quarter. In addition, we find a slightly larger economic magnitude if the portfolio-level Pulse score is measured using the more salient top ten holdings. In economic terms, a one-standard-deviation increase in $Pulse_{Top10}$ (i.e., 0.051) in Column 5 is associated with 22.5 bps or \$3.8 million higher flows in the next quarter.[19] Further, Columns 3 and 6 present the estimates for the flow regressions that include fund fixed effects. We find that the positive relation between portfolio Pulse score and future fund flows also exists within-fund.

4.2.2. Catering to time-varying ESG demand

In the next set of tests, we examine whether fund managers' ESG integration strategies are related to investors' time-varying ESG demand. Naughton et al. (2019) show that firms improve ESG performance during periods when investors place a valuation premium on ESG performance. Similarly, during periods of strong ESG demand, fund managers could have stronger incentives to adopt ESG integration strategies.

To test this conjecture, we follow the approach in Baker and Wurgler (2004) and Naughton et al. (2019) to estimate the market-level ESG premium, and categorize our sample into high and low ESG demand periods.[20] Specifically, we define a year as a high (low) ESG demand period if its ESG premium is above (below) the median value of all previous observations. If fund managers

[19] The dollar value increase in quarterly net flows are estimated using an average one-quarter-lagged *TNA* of \$1,564.8 million (\$1,696.9 million) for the $Pulse_{Portfolio}$ ($Pulse_{Top10}$) sample.

[20] See Section B in the Internet Appendix for more detail on market-level ESG premium estimation.

cater to investors' ESG demand, they are likely to respond more strongly to ESG information during periods of high market-level ESG demand.

Table 8 reports the holding regression results of high and low ESG demand periods. Consistent with the catering hypothesis, we find that managers have stronger incentives to adopt ESG integration strategies when investors have stronger ESG demand. A one-standard-deviation increase in *Pulse* in Column 2 is associated with $exp^{(0.143 \times 0.030)} - 1$ = 0.43% higher mutual fund holdings (*Shares/CSHO*) for an average fund-firm pair. In contrast, managers have weaker incentives to integrate ESG information during periods with low ESG demand.

4.2.3. Catering to increased ESG demand

In the last set of catering hypothesis tests, we use the introduction of the Morningstar Sustainability Rating as a quasi-natural experiment to examine whether fund managers have stronger incentives to integrate ESG information into their portfolio decisions following an unexpected increase in ESG demand. In March 2016, Morningstar released the Sustainability Rating that categorized over 20,000 mutual funds into a simple rating between one and five globes. The globe ratings are prominently displayed on each fund's Morningstar page after the event.

We exploit the fact that the event created a plausibly exogenous ESG salience shock to the mutual fund sector that significantly increases investors' awareness of sustainable investing and reduces the efforts required for identifying funds with top-rated ESG performance. After the event, flows into top-rated funds would be driven by ESG demand to a greater extent (Hartzmark and Sussman (2019)). If catering to ESG demand is an underlying motive, managers of top-rated funds would be more motivated to implement ESG integration strategies after the event compared to managers of bottom-rated funds.

To test our conjecture, we classify top- (bottom-) rated funds into the treatment (control) group, and estimate the following difference-in-differences regression model:

$$
\begin{aligned}
Holding_{i,s,j,k,t} = {} & \beta_0 + \beta_1 Pulse_{j,t-1} + \beta_2 Pulse_{j,t-1} \times TOP_{i,j} + \beta_3 Pulse_{j,t-1} \times POST_t \\
& + \beta_4 TOP_{i,j} \times POST_t + \beta_5 Pulse_{j,t-1} \times TOP_{i,j} \times POST_t \\
& + X\beta' + \alpha_{i,j} + \tau_{k,t} + \delta_{s,t} + \varepsilon_{i,s,j,k,t}, \qquad (3)
\end{aligned}
$$

where i denotes a fund, s denotes an investment style, j denotes a firm, k denotes a Fama-French 49 industry, and t denotes a year-quarter. We use both *ln(D/TNA)* and *ln(Shares/CSHO)* as the dependent variables. $TOP_{i,j}$ is a dummy variable that equals one for funds with top-rated ESG performance, or zero for bottom-rated funds. Similar to the method used in constructing Morningstar globe ratings, we calculate the ESG rating of a mutual fund portfolio using value-weighted KLD scores of portfolio firms, and define top- (bottom-) rated funds as those with the top (bottom) tercile $ESG_{KLD,Portfolio}$ scores at the end of 2015q4. Funds with middle tercile $ESG_{KLD,Portfolio}$ scores are excluded from the analysis. In total, we have 299 (284) funds in the treatment (control) group. $POST_t$ is a post-event dummy variable that equals one from 2016q2 to 2017q4, or zero before 2016q1.[21] The event quarter (2016q1) is dropped from the analysis.

Our main variable of interest is β_5 (i.e., the difference-in-differences estimator), which captures the post-minus-pre-event difference in managers' propensity to implement ESG integration strategies between the top- and bottom-rated funds. We use Column 5 in Panel A of Table 2 as our baseline specification, and further include interactions between the fund and firm attributes with $TOP_{i,j}$, $POST_t$, and $TOP_{i,j} \times POST_t$ dummy variables ($X\beta'$). Standard errors are triple-clustered at the fund, firm, and year-quarter levels.

[21] Note that the standalone terms of $TOP_{i,j}$ and $POST_t$ are absorbed by the fixed effects.

Table 9 reports the results. Consistent with the catering hypothesis, we find that the coefficient estimates of the triple-interaction term ($Pulse_{j,t-1}$ × $TOP_{i,j}$ × $POST_t$) are positively significant across all specifications. In Column 1, the implied coefficient for *Pulse* increases by 10.1 percentage points for top-rated funds relative to bottom-rated funds after the event, which is equivalent to a 10.6% increase in *D/TNA*.[22] Figure 2 plots the difference-in-differences estimates surrounding the event using *ln(Shares/CSHO)* as the holding measure along with the 90% confidence intervals. Visual inspection shows that the propensity to implement ESG integration strategies increases significantly for top-rated funds relative to bottom-rated funds immediately following the introduction of the globe ratings.

The difference-in-differences regression results suggest that managers of top-rated funds have increased incentives to integrate ESG information after the ESG salience shock, which amplifies the valuation of sustainable investing by mutual fund investors.

Overall, the evidence in Section 4.2 supports the catering hypothesis. We find that flow catering is an important motivation for fund managers to implement ESG integration strategies, especially during periods of stronger ESG demand. Collectively, the results in Section 4 demonstrate that both investment skill and investor demand affect fund managers' ability to integrate ESG information into their portfolio decisions.

[22] To ensure that the parallel trends assumption holds, we include two pre-event dummy variables to identify the periods that are one to four quarters ($Pre^{(-1\ to\ -4)}$) and five to eight quarters ($Pre^{(-5\ to\ -8)}$) before the event quarter, and interact the two pre-event dummies with $Pulse_{j,t-1}$, $TOP_{i,j}$, and fund and firm attributes, respectively. Consistent with the parallel trends assumption, we find that the coefficients of these interaction terms are all statistically insignificant. For robustness, we also re-estimate equation (3) using a propensity score matched sample, and perform several placebo tests. The results from these tests are summarized in Section C in the Internet Appendix.

5. Which Funds Have Stronger Incentives to Implement ESG Integration Strategies?

Our results so far establish that fund managers actively integrate ESG information into portfolio decisions, and their ESG integration strategies can at least be partially explained by two non-mutually exclusive motives: investment skill and flow catering. In the last section of our empirical analysis, we examine how heterogeneity in fund attributes affects managerial incentives to employ ESG integration strategies. Specifically, if investment skill motivates ESG integration, we would expect managers who are experienced in sustainable investing to respond more strongly to ESG information. Similarly, if catering induces managers to respond to ESG information, we would expect them to respond more strongly if their clients are more sensitive to ESG information.

Motivated by the existing literature, we examine the following fund attributes: (i) political orientation, (ii) ESG orientation, (iii) fund salience, and (iv) manager name. We re-estimate holding, return, and flow regressions for funds sorted by these attributes. Specifically, we use Column 5 in Panel A of Table 2 as the baseline specification for holding regressions, and consider both *ln(D/TNA)* and *ln(Shares/CSHO)* as the dependent variable. We use Column 4 in Panel B of Table 4 (Column 6 of Table 6) as the baseline specification for return (flow) regressions.[23]

5.1. *Political orientation*

In the first set of tests, we examine whether the state-level political environment affects fund managers' incentives to implement ESG integration strategies. The existing literature demonstrates that compared to Republicans, Democrats care more about ESG (e.g., Di Giuli and Kostovetsky (2014)). As local political values shape the ESG preferences of local investors, the

[23] For brevity, we only report results using *Ben-adj RET* ($Pulse_{,Top10}$) as the main dependent (independent) variable for return (flow) regressions. Our results are similar if we use *Excess RET* ($Pulse_{,Portfolio}$) as the main dependent (independent) variable.

demand for ESG is likely to be stronger among investors located in Democratic states. To cater to ESG demand, managers of funds headquartered in Democratic states would have stronger incentives to integrate ESG information. In addition, since Democratic-leaning managers are more experienced in sustainable investing (Hong and Kostovetsky (2012)), they could integrate material ESG information to achieve higher returns.

To test this conjecture, we use two methods to identify a state's political environment. First, a state is classified as a Democratic state if a Democrat won the most recent Presidential election in that state. Alternatively, we measure the state government composition as 0.5 × indicator equals to one if the governor is a Democrat + 0.25 × indicator equals to one if Democrats control the majority seats in state legislature upper chamber + 0.25 × indicator equals to one if Democrats control the majority seats in state legislature lower chamber, as in Di Giuli and Kostovetsky (2014). We define a state as Democratic-leaning if the state government composition value is greater than 0.5. Since large funds are less likely to be affected by local political values (Hong and Kostovetsky, 2012), we focus on funds with below-median *TNAs*.

Panel A of Table 10 (Table 11) presents the holding (return and flow) regression results. Consistent with our conjecture, we find that managers of funds headquartered in Democratic states respond more strongly to ESG information, regardless of the definition of political orientation. Further, their ESG integration strategies are associated with superior risk-adjusted returns and higher investor flows in the next quarter. In comparison, managers of funds located in Republican-leaning states are less responsive to ESG information.

5.2. *ESG orientation*

In the next set of tests, we examine whether the ESG orientation of mutual funds affects managerial incentive to engage in ESG integration. With more experience in sustainable investing, managers of SR funds are likely to be more skillful in interpreting ESG information when compared to those of non-SR funds. In addition, with stronger ESG awareness, investors of SR funds are more sensitive to ESG information. Therefore, we expect managers of SR funds to have stronger incentives to implement ESG integration strategies.

To test this conjecture, we evaluate a fund's ESG orientation by the value-weighted KLD scores of its portfolio firms. Following Cao et al. (2020), we define funds with above- (below-) median portfolio-level ESG scores (i.e., $ESG_{KLD,Portfolio}$) in the previous quarter as SR (non-SR) funds. Panel B of Table 10 (Table 11) reports the holding (return and flow) regression estimates of SR and non-SR funds. As expected, we find that managers of SR funds have stronger incentives to integrate ESG information, and their ESG integration strategies are related to both investment skill and ESG demand. In comparison, managers of non-SR funds have weaker incentives to incorporate ESG information.

5.3. *Mutual fund salience*

Next, we examine whether the salience of mutual funds affects managers' incentives to adopt ESG integration strategies. Sirri and Tufano (1998) find that performance on important fund attributes exerts the greatest influence on investor decisions when funds are salient to investors. In addition, Hartzmark and Sussman (2019) show that investors collectively consider ESG as an important fund attribute when allocating capital to mutual funds. Since catering to investors' ESG demand is expected to be more effective among salient funds, managers of salient funds are likely to have stronger incentives to trade on ESG information.

To test this conjecture, we follow Sirri and Tufano (1998) and measure a fund's salience by its 12b-1 fee. Specifically, we sort funds into two groups using the median 12b-1 fee in the previous quarter. Funds with above-median 12b-1 fees are more salient to investors. We report the holding regression estimates in Panel B of Table 9. Consistent with our expectation, the positive relation between *Pulse* and holdings only exists among salient funds. In addition, salient funds that respond more strongly to ESG information attract more investor flows (Column 6 in Panel B of Table 11). However, we find no evidence of superior return for salient fund managers with higher propensity to trade on ESG information (Column 5 in Panel B of Table 11). Our findings suggest that salient fund managers employ ESG integration strategies mainly for catering purposes.

5.4. *Manager name*

In the last set of tests, we examine whether name-induced stereotypes by investors affect managers' incentives to implement ESG integration strategies. Kumar et al. (2015) find that U.S. fund managers with local-sounding (i.e., American or "domestic") names experience higher cash inflows (lower cash outflows) following good (bad) performance compared with managers with foreign-sounding names. If ESG integration is perceived as managers' efforts to improve ESG performance, such an investment strategy would be more rewarding for "domestic" managers. Therefore, we expect these managers to have stronger incentives to adopt ESG integration strategies.

To test this conjecture, we use hand-collected data on a subsample of individual-managed funds and define a manager name as foreign ("domestic") if over (fewer than) 75% of survey respondents consider the name as foreign-sounding, as in Kumar et al. (2015). Panel C of Table 10 reports the holding regression results. Consistent with our expectation, we find that managers with "domestic" names are more responsive to ESG information. The results remain robust if we change the foreign name threshold to 67%. In comparison, managers with foreign-sounding names are less motivated to implement ESG integration strategies. In Panel C of Table 11, we also find some weak evidence that "domestic" managers' ESG integration attracts investor flows. However, this relation is marginally insignificant, potentially due to a small sample and lack of statistical power.

Taken together, our results in Section 5 demonstrate that investment skill and flow catering jointly motivate managers to trade on ESG information. Funds with skillful managers and ESG-sensitive clienteles exhibit stronger propensity to engage in ESG integration strategies.

6. Summary and Conclusions

In this paper, we examine whether and to what extent do active fund managers implement ESG integration strategies in their portfolio decisions. Specifically, we use a novel measure to proxy for ESG information that is relevant for integration decision-making. We find that fund managers increase the holdings of firms with positive ESG information to actively implement ESG integration strategies.

Examining the motives behind ESG integration, we show that fund managers are skilled in identifying and accessing material ESG information. Fund managers' ESG integration strategies could generate superior risk-adjusted returns and facilitate the incorporation of material ESG information into asset prices. In addition, fund managers also adopt ESG integration strategies to attract investor flows, especially during periods of stronger ESG demand.

The heterogeneity in fund attributes also affects managerial propensity to engage in ESG integration. Specifically, we show that managers who are more experienced in sustainable investing respond more strongly to ESG information. Stronger ESG integration propensity is also associated with ESG-sensitive clienteles. Further, managers who benefit more from flow catering also have stronger propensity to trade on ESG information.

Taken together, our findings contribute to the growing literature on sustainable and responsible investing. Our paper adds a new dimension to this literature by demonstrating that fund managers skillfully integrate material ESG information to complement their investment decisions and this sustainable investing strategy attracts investor flows.

In future work, it may be interesting to examine whether and how other professional investors consider ESG integration strategies in their investment decisions. For instance, unlike active fund managers who are able to alter their portfolio holdings considerably, passive fund managers who face greater constraints may implement ESG integration strategies differently. It would also be interesting to examine whether equity analysts successfully integrate ESG information into their earnings forecasts.

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Figure 1
Pulse score of Apple Inc.

This figure displays the Pulse score of Apple Inc. from June 2017 to December 2017. The dotted line plots the daily all-category Pulse score, annotated with ESG event announcements and corresponding SASB categories. The bar chart presents the volume of unique articles, and the solid line plots the exponentially weighted moving average of Pulse scores, with a 6-month half-life to smooth out the Pulse score. Source: Truvalue Labs.

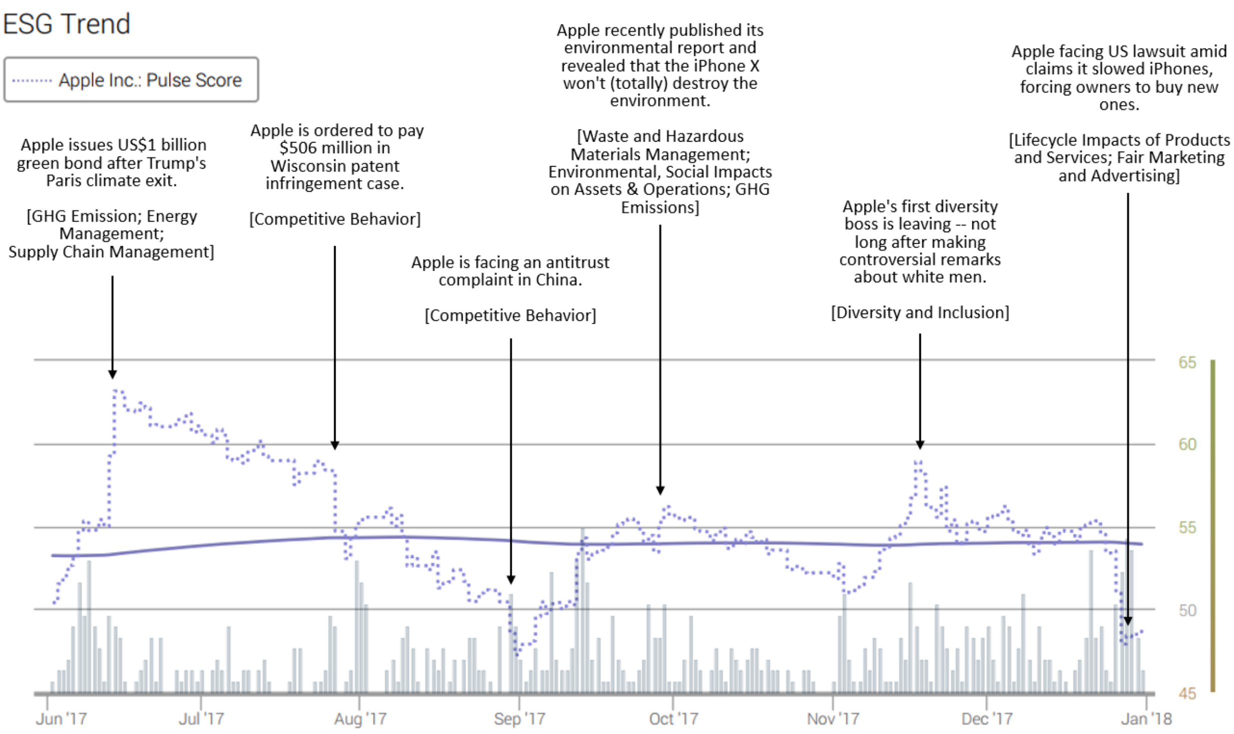

Figure 2
Graphical Illustration of the Difference-in-Differences Estimates

This figure plots the evolution of the relation of firm-level Pulse score and mutual fund holdings between funds with top- and bottom-rated ESG performance around the introduction of Morningstar Sustainability Rating in 2016q1. We define top- and bottom-rated funds as those with the top (bottom) tercile portfolio ESG ratings ($ESG_{KLD,Portfolio}$) in 2015q4. We estimate difference-in-differences regressions that interact firm-level Pulse score and the fund and firm attributes with the top-rated fund dummy variable, as well as pre-event, and post-event dummy variables to explain holdings (measured by *ln(Shares/CSHO)*). The difference-in-differences regressions include fund-firm pair, fund-style-time, and industry-time fixed effects. The event quarter, 2016q1, is excluded from the analysis. Standard errors are triple-clustered at the fund, firm, and year-quarter levels. We plot the difference-in-differences estimates, i.e., those estimates for the three-way interacted term between the firm-level Pulse score, the top-rated fund dummy, and the post-event dummies, along with their 90% confidence intervals (dotted line) in the figure.

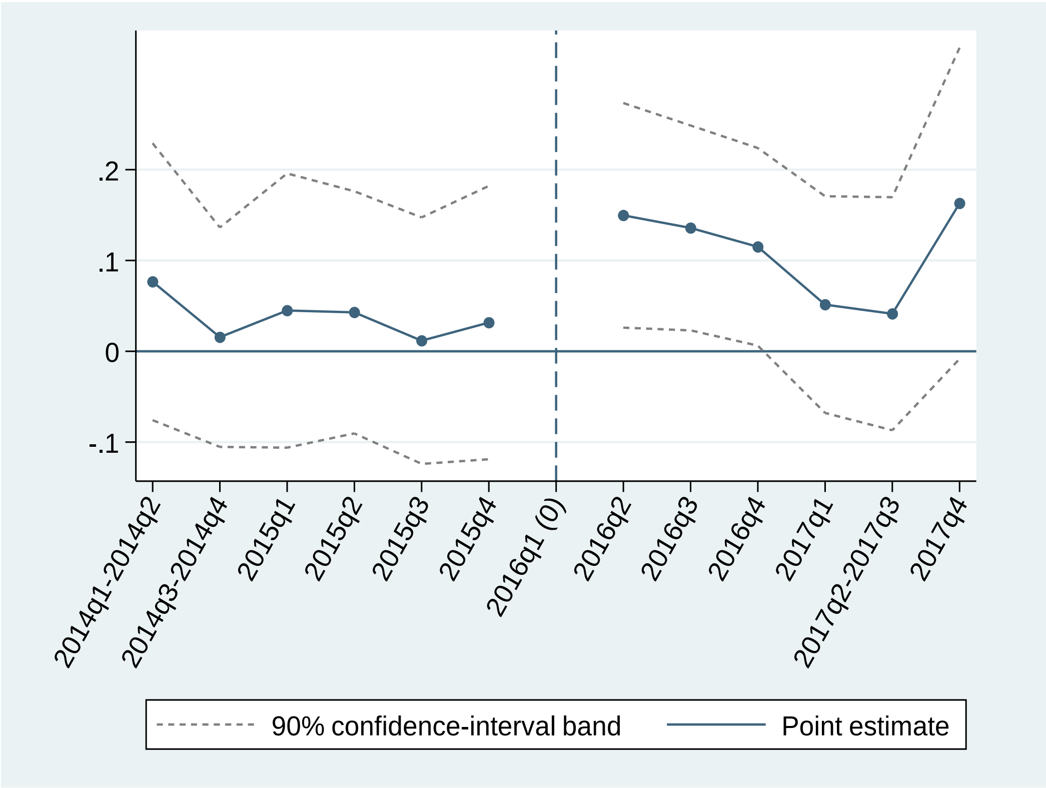

Table 1
Variable definitions and summary statistics

This table presents the main variables used in the empirical analysis. Panel A reports the definitions and data sources used to estimate these variables. Panel B presents the summary statistics of variables at the fund-firm-quarter level. The main sample period is from 2007q1 to 2017q4.

Panel A: Definitions and sources of main variables

Variable name	Definition	Source
Main dependent variables		
ln(D/TNA)	Natural log of dollar amount invested in a stock divided by the fund's total net assets.	CRSP, Refinitiv
ln(Shares/CSHO)	Natural log of a firm's shares held by a mutual fund divided by the firm's total outstanding shares.	CRSP, Refinitiv
ln(Buy/TNA) or ln(Sell/TNA)	Natural log of increased (decreased) dollar amount invested in a stock from the previous quarter divided by the fund's total net assets, or zero otherwise.	CRSP, Refinitiv
Flow	Quarterly fund flow, computed as $(TNA_{i,t} - TNA_{i,t-1})/TNA_{i,t-1} - RET_{i,t}$, where $TNA_{i,t}$ denotes fund i's total net assets in quarter t and $RET_{i,t}$ denotes fund i's return in quarter t. *TNA* and *RET* are required to have consistent value in CRSP and Morningstar.	CRSP, Morningstar
Main independent variables		
Pulse	Quarterly Pulse score, computed as time-series average of daily all-category Pulse scores in quarter *t*-1, where daily all-category Pulse scores are constructed using ESG information related to all 26 SASB sustainability categories. The quarterly Pulse scores are rescaled to lie between -0.5 (most negative impact) and +0.5 (most positive impact), with 0 indicating a neutral impact.	FactSet TVL
$Pulse_{Material}$	Quarterly material Pulse score, computed as time-series average of daily material Pulse scores in quarter *t*-1, where daily material Pulse scores are constructed as volume-weighted Pulse scores on material sustainability categories. The quarterly material Pulse scores are rescaled to lie between -0.5 (most negative impact) and +0.5 (most positive impact), with 0 indicating a neutral impact.	FactSet TVL
$Pulse_{Immaterial}$	Quarterly immaterial Pulse score, computed as time-series average of daily immaterial Pulse scores in quarter *t*-1, where daily immaterial Pulse scores are constructed as volume-weighted Pulse scores on immaterial sustainability categories. The quarterly immaterial Pulse scores are rescaled to lie between -0.5 (most negative impact) and +0.5 (most positive impact), with 0 indicating a neutral impact.	FactSet TVL
$Pulse_{Portfolio}$	Pulse score of a mutual fund portfolio, computed by aggregating *Pulse* of all invested firms in quarter *t*-1, using the invested value in quarter *t*-2 as weight since holding disclosure could take up to 45 days.	FactSet TVL, Refinitiv
$Pulse_{Top10}$	Pulse score of a mutual fund portfolio, computed by aggregating *Pulse* of the top ten holdings in quarter *t*-1, using the invested value in quarter *t*-2 as weight since holding disclosure could take up to 45 days.	FactSet TVL, Refinitiv

Table 1- Continued

Fund control variables		
PR	Performance rank of a fund in the past twelve months, relative to all other funds in the same Morningstar category, scaled to lie between 0 (worst performance) and 1 (best performance).	CRSP, Morningstar
PR^2	Performance rank squared.	CRSP, Morningstar
ln(Age)	Fund age, computed as the natural logarithm of the number of months since a fund's inception.	CRSP
ln(TNA)	Natural log of a fund's total net assets in million USD.	CRSP, Morningstar
Expense	A fund's quarterly expense ratio in %.	CRSP
$Turnover_{Fund}$	A fund's quarterly turnover ratio in %.	CRSP
Load	A dummy variable equals one (zero) if the fund has (does not have) load fees.	CRSP
ln(ME)	Natural log of a firm's market capitalization in million US dollars.	CRSP
Stock control variables		
$Turnover_{Stock}$	Stock turnover ratio, computed as the total number of shares traded in each quarter, divided by the firm's quarter-end total outstanding shares.	CRSP
ln(BM)	Natural log of book-to-market ratio, where book-to-market ratio is computed as the book value of equity divided by market value of equity.	CRSP, Compustat
$RET_{Overnight}$	Overnight return, computed as the average daily overnight stock returns over a quarter, multiplied by 60. Daily overnight stock returns are calculated as opening price minus closing price of the previous trading day, all divided by the closing price of the previous trading day.	CRSP
ln(Fin-Neg)	Natural log of the proportion of negative words in the total word count of a firm's 10-K report for the fiscal year ended in calendar year *t*-1, using the Loughran and McDonald (2011) word dictionary.	Notre Dame SRAF
Short	Detrended and standardized short interest index in quarter *t*-1, where short interest index is computed as the number of shares on short divided by total outstanding shares, as in Rapach, Ringgenberg, and Zhou (2016).	Compustat
Recommendation	I/B/E/S median analyst recommendation in quarter *t*-1. Analyst recommendation ranges from 1 to 5, with 1 = "strong buy", 2 = "buy", 3 = "hold", 4 = "underperform", and 5 = "sell".	Refinitiv
ESG ratings		
ESG_{KLD}	KLD score of a firm, constructed using annual ESG ratings in seven categories (i.e., Community, Diversity, Environment, Employee, Product, Human Rights, and Governance) in year *t*-1, and adjusted following the Deng, Kang, and Low (2013) method.	MSCI
$ESG_{KLD,Portfolio}$	KLD score of a mutual fund portfolio, computed by aggregating invested firms' KLD scores in year *t*-1, using the invested value in each firm in quarter *t*-1 as weight.	MSCI, Refinitiv
$ESG_{Refinitiv}$	Refinitiv ESG score of a firm, computed by equal weighting annual environmental, social, and corporate governance pillar scores in year *t-1*.	Refinitiv
$ESG_{Sustainalytics}$	Sustainalytics ESG score of a firm, computed as the average monthly Sustainalytics ESG scores in quarter *t*-1.	Sustainalytics

Table 1-Continued

Panel B: Summary statistics

	Fund-firm-quarter	Mean	Std. Dev	25 pctl	Median	75 pctl
D/TNA	1,734,426	0.010	0.011	0.002	0.007	0.014
Shares/CSHO	1,734,426	0.001	0.003	0.000	0.000	0.001
Shares (in '000)	1,734,426	341	1,385	10	47	211
Buy/TNA	1,734,426	0.001	0.002	0.000	0.000	0.000
Sell/TNA	1,734,426	-0.001	0.003	-0.001	0.000	0.000
Pulse	1,734,426	0.034	0.140	-0.054	0.027	0.121
$Pulse_{Materiality}$	1,678,355	0.035	0.156	-0.069	0.033	0.141
$Pulse_{Immaterial}$	1,678,355	0.025	0.126	-0.048	0.020	0.099
PR	1,734,426	0.513	0.262	0.300	0.514	0.730
PR^2	1,734,426	0.332	0.275	0.090	0.264	0.533
Age (months)	1,734,426	190	128	107	168	239
ln(Age)	1,734,426	5.020	0.725	4.673	5.124	5.476
TNA (in $ million)	1,734,426	1,752	3,582	127	485	1,615
ln(TNA)	1,734,426	6.098	1.788	4.847	6.184	7.387
Expense	1,734,426	0.003	0.001	0.002	0.003	0.003
$Turnover_{Fund}$	1,734,426	0.181	0.151	0.083	0.148	0.238
Load	1,734,426	0.574	0.494	0.000	1.000	1.000
ME	1,734,426	41,017	69,258	4,168	13,000	40,440
ln(ME)	1,734,426	9.491	1.596	8.335	9.473	10.608
$Turnover_{Stock}$	1,734,426	0.642	0.440	0.357	0.515	0.773
$ln(Turnover_{Stock})$	1,734,426	-0.620	0.576	-1.030	-0.665	-0.258
BM	1,734,426	0.500	0.371	0.235	0.394	0.677
ln(BM)	1,734,426	-0.984	0.825	-1.447	-0.932	-0.390

Table 2
Effects of firm-level ESG information on mutual fund holdings

This panel reports the estimates of quarterly fund holdings regressed on firm-level Pulse score and various control variables, at the portfolio-holding level (i.e., a fund-firm-quarter panel). All variables are defined in Table 1. The dependent variable is the log of the proportion of a fund's total net asset invested in a stock (*ln(D/TNA)*). The main independent variable is *Pulse*. All independent variables, except for the loaded fund identifier (*Load*), are lagged by one quarter. The sample period is from 2007q1 to 2017q4. The *t*-statistics (reported in parentheses) are computed using triple-clustered standard errors at the fund, firm, and year-quarter levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Baseline results

	ln(D/TNA)				
	(1)	(2)	(3)	(4)	(5)
Pulse	0.038**	0.037***	0.027***	0.030***	0.034***
	(2.280)	(3.277)	(2.858)	(3.014)	(3.333)
PR	-2.516***	-0.082	-0.044	-0.044	-0.057
	(-6.731)	(-1.351)	(-1.110)	(-1.106)	(-1.406)
PR^2	2.493***	0.061	0.019	0.017	0.013
	(6.814)	(1.165)	(0.518)	(0.477)	(0.366)
ln(Age)	0.107*	0.113**	0.073*	0.070	0.051
	(1.813)	(2.439)	(1.691)	(1.642)	(1.256)
ln(TNA)	-0.091***	-0.069***	-0.062***	-0.061***	-0.055***
	(-3.415)	(-4.540)	(-4.321)	(-4.274)	(-4.066)
Expense	289.006***	9.906	-6.550	-6.589	-8.236
	(4.375)	(0.402)	(-0.263)	(-0.264)	(-0.367)
$Turnover_{Fund}$	-0.588**	-0.103	-0.022	-0.023	-0.050
	(-2.376)	(-0.926)	(-0.275)	(-0.290)	(-0.642)
Load	0.201*	0.017	-0.025	-0.025	-0.036
	(1.824)	(0.192)	(-0.329)	(-0.320)	(-0.508)
ln(ME)	0.524***	0.396***	0.468***	0.446***	0.471***
	(18.324)	(18.166)	(19.945)	(19.027)	(19.467)
$ln(Turnover_{Stock})$	-0.061***	-0.044***	-0.041***	-0.030**	-0.023*
	(-3.123)	(-3.177)	(-3.059)	(-2.483)	(-1.954)
ln(BM)	-0.079***	-0.063***	-0.046***	-0.055***	-0.045***
	(-4.692)	(-5.099)	(-3.445)	(-4.394)	(-3.590)
Firm FE	Yes	Yes			
Fund FE		Yes			
Fund-Firm FE			Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes		
Year-quarter×FF49 FE				Yes	Yes
Year-quarter×Style FE					Yes
Observations	1,734,426	1,734,426	1,734,426	1,734,426	1,734,426
Adj. R^2	0.306	0.668	0.850	0.851	0.852

Table 2-Continued

This panel reports robustness checks for the baseline results in Panel A. All variables are defined in Table 1. Column 1 excludes firms that are covered by fewer than ten articles in the past twelve months. Column 2 excludes fund-quarter observations in which funds held fewer than ten stocks at the beginning of a quarter. Columns 3 to 4 present results using alternative stock holding measures as dependent variables: *ln(Shares)* (Column 3), and *ln(Shares/CSHO)* (Column 4). Column 5 further augments the baseline model with fund-family-time fixed effects. In Column 6, industry-time fixed effects are constructed using an alternative 2-digit SIC industry classification. Columns 7, 8, and 9 present results with alternative standard errors, clustered at (i) the firm and year-quarter levels, (ii) fund and year-quarter levels, and (iii) at the fund-firm pair and year-quarter levels. We use the same set of fund- and firm-level control variables as in Panel A (suppressed for brevity). The sample period is from 2007q1 to 2017q4. The *t*-statistics (reported in parentheses) are computed using triple-clustered standard errors at the fund, firm, and year-quarter levels, unless stated otherwise. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel B: Robustness tests

Alternative	Sample		Holdings variables		FEs and industry classification		Standard errors clustering		
	Article volume≥10	*Min. number of holdings≥10*	*ln(Shares)*	*ln(Shares/CSHO)*	Year-quarter×Family FE	2-digit SIC industries FE	Firm and Year-quarter	Fund and Year-quarter	Fund-Firm pair, and Year-quarter
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Pulse	0.036**	0.036***	0.035**	0.027***	0.034***	0.035***	0.034***	0.034***	0.034***
	(2.647)	(3.716)	(2.122)	(3.541)	(3.387)	(3.832)	(3.303)	(3.556)	(3.520)
Fund controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter×FF49 FE	Yes	Yes	Yes	Yes	Yes		Yes	Yes	Yes
Year-quarter×Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter×Family FE					Yes				
Year-quarter×SIC2 FE						Yes			
Observations	1,399,088	1,649,805	1,734,426	1,734,426	1,732,291	1,734,426	1,734,426	1,734,426	1,734,426
Adj. R^2	0.845	0.852	0.916	0.927	0.860	0.852	0.852	0.852	0.852

Table 2-Continued

This panel reports additional test results after controlling for firm-level ESG ratings (Columns 1 to 6) and investor sentiment (Columns 7 to 10), respectively. All variables are defined in Table 1. Dependent variables (stated above each column) include *ln(D/TNA)* and *ln(Shares/CSHO)*. The main independent variable is *Pulse*. Firm-level ESG ratings include ESG_{KLD}, $ESG_{Sustainalytics}$, *and* $ESG_{Refinitiv}$. Columns 7 and 9 include overnight returns ($RET_{Overnight}$) to control for firm-specific investor sentiment. Columns 8 and 10 include the log of the proportion of negative words in the total word count of a firm's 10-K report (*ln(Fin-Neg)*) to control for the negative investor sentiment generated by firm-level financial reports. We use Column 5 of Panel A as the baseline specification. The sample period is from 2009q1 to 2017 q4 in Columns 2 and 5, or from 2007q1 to 2017q4 in other columns. The *t*-statistics (reported in parentheses) are computed using triple-clustered standard errors at the fund, firm, and year-quarter levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel C: Controlling for firm-level ESG rating and firm-specific investor sentiment

	ln(D/TNA)			*ln(Shares/CSHO)*			*ln(D/TNA)*		*ln(Shares/CSHO)*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Pulse	0.026***	0.047***	0.038***	0.025***	0.033***	0.031***	0.032***	0.035***	0.026***	0.032***
	(2.736)	(3.608)	(3.409)	(3.806)	(3.546)	(4.037)	(3.219)	(3.204)	(3.413)	(3.971)
ESG_{KLD}	0.003			-0.004						
	(0.065)			(-0.118)						
$ESG_{Sustainalytics}$		0.001			-0.001					
		(0.627)			(-0.666)					
$ESG_{Refinitiv}$			0.001			-0.000				
			(1.087)			(-0.305)				
$RET_{Overnight}$							0.152***		0.102***	
							(6.885)		(4.693)	
ln(Fin-Neg)								-0.047*		-0.000
								(-1.890)		(-0.000)
Fund Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter×FF49 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter×Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,667,199	1,135,187	1,450,329	1,667,199	1,135,187	1,450,329	1,734,426	1,525,893	1,734,426	1,525,893
Adj. R^2	0.850	0.851	0.843	0.927	0.930	0.926	0.852	0.855	0.927	0.927

Table 2-Continued

This panel reports additional test results after controlling for firm-level fundamentals. All variables are defined in Table 1. Dependent variables (stated above each column) include *ln(D/TNA)* and *ln(Shares/CSHO)*. The main independent variable is *Pulse*. Columns 1 and 3 include short interest (*Short*) and consensus analyst recommendation (*Recommendation*) to account for processed fundamental information by savvy market participants. Columns 2 and 4 further include leverage, Tobin's Q, return on assets, research and development expenditure over total assets, capital expenditure over total assets, and cash holdings over net assets to account for unprocessed fundamental information. Columns 5 to 8 replace *Pulse* with fundamental-adjusted Pulse scores as the main independent variables ($Pulse_{Adj1}$ and $Pulse_{Adj2}$), where $Pulse_{Adj1}$ ($Pulse_{Adj2}$) are the residuals obtained by regressing *Pulse* on processed (both processed and unprocessed) fundamental controls. We use Column 5 of Panel A as the baseline specification. The sample period is from 2007q1 to 2017q4. The *t*-statistics (reported in parentheses) are computed using triple-clustered standard errors at the fund, firm, and year-quarter levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel D: Controlling for fundamentals

	ln(D/TNA)		*ln(Shares/CSHO)*		*ln(D/TNA)*		*ln(Shares/CSHO)*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pulse	0.036***	0.036***	0.026***	0.027***				
	(3.134)	(3.217)	(3.273)	(3.433)				
Short	-0.006*	-0.005	-0.001	-0.000				
	(-1.783)	(-1.548)	(-0.283)	(-0.032)				
Recommendation	-0.018***	-0.018***	-0.006	-0.006				
	(-3.007)	(-3.018)	(-1.244)	(-1.235)				
$Pulse_{Adj1}$					0.035***		0.026***	
					(3.126)		(3.280)	
$Pulse_{Adj2}$						0.034***		0.027***
						(2.991)		(3.433)
Fundamental Controls		Yes		Yes		Yes		Yes
Fund Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter×FF49 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter×Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,607,193	1,590,916	1,607,193	1,590,916	1,607,193	1,590,916	1,607,193	1,590,916
Adj. R^2	0.844	0.844	0.927	0.927	0.843	0.844	0.927	0.927

Table 3
Effects of firm-level ESG information on mutual fund buying and selling

This table reports the effects of firm-level Pulse scores on buying and selling of mutual funds. All variables are defined in Table 1. In Columns 1 to 3, the dependent variable is *ln(Buy/TNA)*. In Columns 4 to 6, the dependent variable is *ln(Sell/TNA)*. The main independent variable is *Pulse*. We use the same set of fund- and firm-level control variables as in Panel A of Table 2 (suppressed for brevity). Coefficients are multiplied by 1,000. The sample period is from 2007q1 to 2017q4. The *t*-statistics (reported in parentheses) are computed using triple-clustered standard errors at the fund, firm, and year-quarter levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	ln(Buy/TNA)			*ln(Sell/TNA)*		
	(1)	(2)	(3)	(4)	(5)	(6)
Pulse	0.064**	0.062*	0.067**	-0.007	0.013	0.011
	(2.223)	(1.907)	(2.304)	(-0.220)	(0.388)	(0.355)
Fund Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes			Yes		
Fund FE	Yes			Yes		
Fund-Firm FE		Yes	Yes		Yes	Yes
Year-quarter FE	Yes	Yes		Yes	Yes	
Year-quarter×FF49 FE			Yes			Yes
Year-quarter×Style FE			Yes			Yes
Observations	1,734,426	1,734,426	1,734,426	1,734,279	1,734,279	1,734,279
Adj. R^2	0.110	0.122	0.130	0.127	0.153	0.157

Table 4
Materiality and ESG integration

This table reports the effects of firm-level material and immaterial Pulse scores on stock holdings of mutual funds. All variables are defined in Table 1. Dependent variables (stated above each column) include *ln(D/TNA)* and *ln(Shares/CSHO)*. The main independent variables are volume-weighted material and immaterial Pulse scores ($Pulse_{Material}$ and $Pulse_{Immaterial}$) constructed using the SASB materiality map. In Columns 1 to 2 and 4 to 5, we include $Pulse_{Material}$ and $Pulse_{Immaterial}$ separately. In Columns 3 and 6, we include both $Pulse_{Material}$ and $Pulse_{Immaterial}$. We use the same set of fund- and firm-level control variables as in Panel A of Table 2 (suppressed for brevity). The sample period is from 2007q1 to 2017q4. The *t*-statistics (reported in parentheses) are computed using triple-clustered standard errors at the fund, firm, and year-quarter levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	ln(D/TNA)			*ln(Shares/CSHO)*		
	(1)	(2)	(3)	(4)	(5)	(6)
$Pulse_{Material}$	0.053***		0.052***	0.038***		0.037***
	(3.867)		(3.788)	(3.638)		(3.510)
$Pulse_{Immaterial}$		0.018	0.012		0.017	0.013
		(1.221)	(0.835)		(1.452)	(1.106)
Fund Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter×FF49 FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter×Style FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,678,355	1,678,355	1,678,355	1,678,355	1,678,355	1,678,355
Adj. R^2	0.850	0.850	0.850	0.926	0.926	0.926

Table 5
ESG integration and risk-adjusted returns

This table summarises the test results related to fund managers' skill in integrating ESG information into their portfolio decisions. All variables are defined in Table 1. Panel A reports the performance estimates of funds sorted by managerial propensity to trade on ESG information (*Propensity*), where *Propensity* is estimated following the Fang et al. (2014) method. Managers in group 5 (group 1) are predicted to have the highest (lowest) propensity to trade on ESG information. Column 1 reports the *TNA*-weighted average *Propensity*. In Columns 2 to 7, we report six different risk-adjusted quarterly returns (coefficients are multiplied by 100): excess returns, style-adjusted return, Morningstar benchmark-adjusted returns, and abnormal returns estimated using the CAPM, Carhart (1997) four-factor, and the Fama and French (2015) five-factor models. The sample period is from 2007q1 to 2017q4. The *t*-statistics (reported in parentheses) are computed using Newey-West (1987) adjusted standard errors (with eight lags). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Sorting results

Rank	*Propensity* (1)	*Excess RET* (2)	*Style-adj RET* (3)	*Ben-adj RET* (4)	*CAPM α* (5)	*C4 α* (6)	*FF5 α* (7)
1 (Low)	-0.697	2.418**	0.092***	-0.280***	-0.409***	-0.451***	-0.354***
		(2.087)	(3.369)	(-3.106)	(-3.386)	(-5.217)	(-3.437)
2	-0.237	2.440**	0.062	-0.332***	-0.335***	-0.420***	-0.366***
		(2.112)	(0.868)	(-6.347)	(-3.022)	(-6.015)	(-3.143)
3	-0.014	2.381**	0.046	-0.349***	-0.397***	-0.482***	-0.399***
		(2.038)	(0.738)	(-6.865)	(-3.588)	(-5.242)	(-2.939)
4	0.191	2.480**	0.135***	-0.252***	-0.300**	-0.352***	-0.246**
		(2.187)	(5.805)	(-3.038)	(-2.159)	(-6.266)	(-2.544)
5 (High)	0.574	2.594**	0.172***	-0.207*	-0.225	-0.289***	-0.204**
		(2.332)	(6.191)	(-1.882)	(-1.090)	(-2.766)	(-2.224)
5-1	1.272	0.176**	0.080**	0.072	0.185*	0.162***	0.150*
		(2.325)	(2.035)	(1.489)	(1.725)	(3.478)	(1.926)

Table 5-Continued

This panel reports the estimates from Fama-MacBeth (1973) regressions. We regress quarterly excess returns (*Excess RET*) or Morningstar benchmark-adjusted returns (*Ben-adj RET*) on fund managers' propensity to trade on ESG information (*Propensity*), fund age, fund size, expense ratio, turnover ratio, and a loaded fund dummy variable. All independent variables, except for the loaded fund identifier (*Load*), are lagged by one quarter. The sample period is from 2007q1 to 2017q4. We report the time-series average of the estimated cross-sectional R^2. All coefficients are multiplied by 100. The *t*-statistics (reported in parentheses) are computed using Newey-West (1987) adjusted standard errors (with eight lags). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel B: Fama-MacBeth estimates

	Excess RET		*Ben-adj RET*	
	(1)	(2)	(3)	(4)
Propensity	0.090***	0.083***	0.079**	0.072**
	(3.097)	(3.054)	(2.414)	(2.260)
ln(Age)		0.022		0.031
		(0.713)		(0.968)
ln(TNA)		0.005		0.003
		(0.503)		(0.278)
Expense		-1.494***		-1.559***
		(-6.302)		(-5.415)
$Turnover_{Fund}$		-0.000		-0.000
		(-0.154)		(-0.148)
Load		-0.005		0.000
		(-0.084)		(0.002)
Style FE	Yes	Yes	Yes	Yes
Observations	19,246	19,246	19,246	19,246
Avg. R^2	0.390	0.411	0.133	0.164

Table 6
ESG integration and future stock returns

This table reports the effects of mutual funds' ESG integration strategy on future stock returns estimated using Fama-MacBeth (1973) regressions. The dependent variable is t-quarter ahead stock returns where t=1 to 4. Panel A reports the full sample results where the main independent variable is *Pulse* interacted with change in a stock's total mutual fund ownership (*ΔShare/CSHO*). Panel B presents the coefficient estimates of *ΔShare/CSHO* of three subsamples sorted by firm-level Pulse scores. Both panels include the same set of firm-level control variables as in Panel A of Table 2 (suppressed for brevity). The sample period is from 2007q1 to 2017q4. We report the time-series average of the estimated cross-sectional R^2. All coefficients are multiplied by 100. The t-statistics (reported in parentheses) are computed using Newey-West (1987) adjusted standard errors (with eight lags). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Full sample estimates

	Quarter 1 (1)	Quarter 2 (2)	Quarter 3 (3)	Quarter 4 (4)
Pulse × ΔShare/CSHO	0.435*	-0.048	-0.094	0.479*
	(1.863)	(-0.176)	(-0.419)	(1.767)
Pulse	0.007	0.041	-0.088	-0.114
	(0.188)	(0.686)	(-1.481)	(-1.525)
ΔShare/CSHO	-0.007	-0.008	-0.006	-0.006
	(-1.249)	(-1.154)	(-0.907)	(-1.428)
ln(ME)	-0.002	-0.002	-0.002	-0.003*
	(-1.078)	(-1.309)	(-1.354)	(-1.911)
ln($Turnover_{Stock}$)	-0.000	-0.002	-0.000	0.002
	(-0.088)	(-0.418)	(-0.113)	(0.479)
ln(BM)	0.005	0.003	0.002	0.000
	(1.058)	(0.721)	(0.445)	(0.074)
Industry FE	Yes	Yes	Yes	Yes
Observations	46,210	44,413	42,680	41,010
Avg. R^2	0.161	0.162	0.158	0.161

Panel B: Subsamples estimates sorted by firm-level Pulse scores

Pulse Rank	Quarter 1 (1)	Quarter 2 (2)	Quarter 3 (3)	Quarter 4 (4)
1 (Low)	-0.164	0.105	-0.192**	0.016
	(-1.294)	(0.837)	(-2.159)	(0.123)
2	-0.069	0.039	-0.107*	-0.042
	(-0.975)	(0.440)	(-1.720)	(-0.338)
3 (High)	0.278***	0.103	0.013	-0.067
	(2.741)	(0.697)	(0.145)	(-0.988)

Table 7
ESG integration and investor flow

This table examines the relation between fund portfolio Pulse score and investor flow. All variables are defined in Table 1. The dependent variable is quarterly flow (*Flow*). Columns 1 to 3 use $Pulse_{Portfolio}$ as the main independent variable, while Columns 4 to 6 use $Pulse_{Top10}$. Columns 1, 2, 4, and 5 include fund style and time interacted fixed effects, while Columns 3 and 6 further include fund fixed effects. The sample period is from 2007q1 to 2017q4. The *t*-statistics (reported in parentheses) are computed using double-clustered standard errors at the fund and year-quarter levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Flow					
	(1)	(2)	(3)	(4)	(5)	(6)
$Pulse_{Portfolio}$	0.113***	0.069***	0.064**			
	(3.079)	(2.733)	(2.256)			
$Pulse_{Top10}$				0.068***	0.044**	0.043**
				(2.800)	(2.452)	(2.250)
PR		0.059***	0.035***		0.055***	0.042***
		(6.096)	(3.023)		(5.669)	(3.369)
PR^2		0.004	0.016		0.008	0.010
		(0.365)	(1.325)		(0.759)	(0.798)
ln(Age)		-0.011***	-0.036***		-0.012***	-0.043***
		(-7.242)	(-3.954)		(-6.802)	(-3.943)
ln(TNA)		-0.002***	-0.025***		-0.002***	-0.026***
		(-3.367)	(-8.483)		(-3.069)	(-7.728)
Expense		-2.157*	0.494		-1.213	0.303
		(-1.866)	(0.142)		(-0.929)	(0.070)
$Turnover_{Fund}$		-0.019***	0.000		-0.026***	-0.005
		(-2.821)	(0.003)		(-3.712)	(-0.495)
$Flow_{t-1}$		0.318***	0.188***		0.310***	0.178***
		(21.395)	(12.113)		(18.253)	(10.216)
Load		0.003	-0.001		0.003	-0.001
		(1.440)	(-0.202)		(1.217)	(-0.064)
Fund FE			Yes			Yes
Year-quarter×Style FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,039	28,039	28,039	20,599	20,599	20,599
Adj. R^2	0.020	0.188	0.262	0.017	0.179	0.254

Table 8
Catering to time-varying ESG demand

This table reports the effects of firm-level Pulse score on stock holdings of mutual funds during high and low ESG demand periods. All variables are defined in Table 1. Dependent variables (stated above each column) include *ln(D/TNA)* and *ln(Shares/CSHO)*. The main independent variable is *Pulse*. We define a year as a high (low) ESG demand period if the market-level ESG premium is above (below) the median value of all previous observations, where market-level ESG premium is estimated using the Naughton, Wang, and Yeung (2019) method. We use the same set of fund- and firm-level control variables as in Panel A of Table 2 (suppressed for brevity). The sample period is from 2007q1 to 2017q4. The *t*-statistics (reported in parentheses) are computed using triple-clustered standard errors at the fund, firm, and year-quarter levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	High ESG demand		Low ESG demand	
	ln(D/TNA)	*ln(Shares/CSHO)*	*ln(D/TNA)*	*ln(Shares/CSHO)*
	(1)	(2)	(3)	(4)
Pulse	0.035***	0.030***	0.015	0.006
	(3.227)	(3.140)	(0.918)	(0.529)
Fund Controls	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
Fund-Firm FE	Yes	Yes	Yes	Yes
Year-quarter×FF49 FE	Yes	Yes	Yes	Yes
Year-quarter×Style FE	Yes	Yes	Yes	Yes
Observations	935,179	935,179	799,247	799,247
Adj. R^2	0.874	0.934	0.862	0.936

Table 9
Catering to increased ESG demand

This table reports the difference-in-differences estimates of mutual fund holdings regressed on *Pulse* interacted with *TOP*, *PRE*, and *POST* dummy variables, using the introduction of Morningstar Sustainability Rating in March 2016 (i.e., 2016q1) as an exogenous event. Dependent variables (stated above each column) include *ln(D/TNA)* and *ln(Shares/CSHO)*. *TOP* is a dummy variable that equals one for funds in the top $ESG_{KLD,Portfolio}$ tercile in 2015q4 (i.e., treatment funds), or zero otherwise. *POST* is a post-event dummy variable that equals one after 2016q1, or zero otherwise. We include two pre-event dummy variables that identify the periods that are one to four quarters or five to eight quarters before the event quarter, respectively. $PRE^{(-1\ to\ -4)}$ ($PRE^{(-5\ to\ -8)}$) equals one during the 2015q1 to 2015q4 (2014q1 to 2014q4) period, or zero otherwise. We use the same set of fund- and firm-level control variables as in Panel A of Table 2. We also include interactions between control variables and treatment, pre-event, and post-event dummy variables (suppressed for brevity). We exclude the event quarter (i.e., 2016q1) from the analysis. The *t*-statistics (reported in parentheses) are computed using triple-clustered standard errors at the fund, firm, and year-quarter levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	ln(D/TNA)			*ln(Shares/CSHO)*		
	(1)	(2)	(3)	(4)	(5)	(6)
Pulse	0.016	0.022	0.028	0.013	0.012	0.017
	(0.837)	(0.000)	(1.106)	(0.761)	(0.587)	(0.698)
Pulse × *TOP*	0.038	0.034	0.032	0.022	0.020	0.011
	(1.419)	(1.179)	(0.961)	(0.902)	(0.769)	(0.350)
Pulse × *POST*	-0.042	-0.045	-0.051	-0.040	-0.038	-0.042
	(-1.470)	(-1.546)	(-1.566)	(-1.382)	(-1.177)	(-1.214)
TOP × *POST*	0.005	0.284	0.142	-0.319	-0.366	-0.319
	(0.014)	(0.554)	(0.248)	(-0.804)	(-0.711)	(-0.552)
Pulse × *TOP* × *POST*	0.103**	0.105**	0.106**	0.095**	0.097**	0.106**
	(2.297)	(2.260)	(2.145)	(2.292)	(2.081)	(2.133)
Pulse × $PRE^{(-1\ to\ -4)}$		-0.022	-0.029		0.005	-0.002
		(-0.459)	(-0.537)		(0.125)	(-0.051)
TOP × $PRE^{(-1\ to\ -4)}$		0.409	0.324		0.096	0.174
		(1.363)	(0.816)		(0.294)	(0.397)
Pulse × *TOP* × $PRE^{(-1\ to\ -4)}$		0.015	0.019		0.011	0.025
		(0.273)	(0.303)		(0.219)	(0.385)
Pulse × $PRE^{(-5\ to\ -8)}$			-0.027			-0.021
			(-0.604)			(-0.484)
TOP × $PRE^{(-5\ to\ -8)}$			-0.132			0.175
			(-0.464)			(0.521)
Pulse × *TOP* × $PRE^{(-5\ to\ -8)}$			0.006			0.045
			(0.093)			(0.668)
Interaction between fund and firm controls, *TOP*, and *POST*	Yes	Yes	Yes	Yes	Yes	Yes
Interaction between fund and firm controls, *TOP*, and $PRE^{(-1\ to\ -4)}$		Yes	Yes		Yes	Yes
Interaction between fund and firm controls, *TOP*, and $PRE^{(-5\ to\ -8)}$			Yes			Yes
Fund-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter×FF49 FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter×Style FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	815,889	815,889	815,889	815,889	815,889	815,889
Adj. R^2	0.854	0.854	0.854	0.922	0.922	0.922

Table 10
Heterogeneous fund attributes and ESG integration: Holding regression estimates

This panel reports the effects of firm-level Pulse score on stock holdings of mutual funds headquartered in Democratic-leaning or Republican-leaning states. All variables are defined in Table 1. Dependent variables (stated above each column) include *ln(D/TNA)* and *ln(Shares/CSHO)*. The main independent variable is *Pulse*. In Columns 1 to 4, we define a state as Democratic-leaning if a Democrat won the most recent Presidential election in that state. In Columns 5 to 8, we define a state as Democratic-leaning if the state government composition value is above 0.5, where state government composition is calculated as 0.5 × indicator equals to one if the governor is a Democrat + 0.25 × indicator equals to one if Democrats control the majority seats in state legislature upper chamber + 0.25 × indicator equals to one if Democrats control the majority seats in state legislature lower chamber, as in Di Giuli and Kostovetsky (2014). We use the same set of fund- and firm-level control variables as in Panel A of Table 2 (suppressed for brevity). The sample period is from 2007q1 to 2017q4. The *t*-statistics (reported in parentheses) are computed using triple-clustered standard errors at the fund, firm, and year-quarter levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Political orientation

	Presidential Election				State Government			
	Democratic		Republican		Democratic		Republican	
	ln(D/TNA)	*ln(Shares/CSHO)*	*ln(D/TNA)*	*ln(Shares/CSHO)*	*ln(D/TNA)*	*ln(Shares/CSHO)*	*ln(D/TNA)*	*ln(Shares/CSHO)*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pulse	0.023*	0.021**	0.004	-0.011	0.025*	0.023**	0.008	0.002
	(1.887)	(2.220)	(0.227)	(-0.668)	(1.960)	(2.284)	(0.621)	(0.192)
Fund controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter×FF49 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter×Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	731,359	731,359	118,665	118,665	506,375	506,375	343,649	343,649
Adj. R^2	0.878	0.917	0.837	0.956	0.887	0.923	0.893	0.937

Table 10-Continued

This panel reports the effects of firm-level Pulse score on stock holdings of funds with high or low ESG ratings (Columns 1 to 4), and high or low 12b-1 fees (Columns 5 to 8). All variables are defined in Table 1. Dependent variables (stated above each column) include *ln(D/TNA)* and *ln(Shares/CSHO)*. The main independent variable is *Pulse*. We categorize a fund as an SR (non-SR) fund if it has above- (below-) median portfolio ESG ratings (i.e., $ESG_{KLD,Portfolio}$) in the previous quarter. A fund is considered to be a salient fund if it has above median 12b-1 fees in the previous quarter. We use the same set of fund- and firm-level control variables as in Panel A of Table 2 (suppressed for brevity). The sample period is from 2007q1 to 2017q4. The *t*-statistics (reported in parentheses) are computed using triple-clustered standard errors at the fund, firm, and year-quarter levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel B: ESG orientation and mutual fund salience

	Mutual fund ESG ratings				Mutual fund salience			
	SR funds		Non-SR funds		High 12b-1 fees		Low 12b-1 fees	
	ln(D/TNA)	*ln(Shares/CSHO)*	*ln(D/TNA)*	*ln(Shares/CSHO)*	*ln(D/TNA)*	*ln(Shares/CSHO)*	*ln(D/TNA)*	*ln(Shares/CSHO)*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pulse	0.065***	0.040***	0.010	0.022**	0.040***	0.031***	0.018	0.009
	(3.882)	(3.150)	(0.847)	(2.144)	(2.958)	(2.885)	(1.326)	(0.757)
$ESG_{KLD,Portfolio}$	-0.030	-0.140	-0.020	-0.173				
	(-0.101)	(-0.491)	(-0.060)	(-0.530)				
12b-1					67.166	106.149	678.028**	848.986***
					(1.315)	(1.605)	(2.607)	(2.927)
Fund Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter×FF49 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter×Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	700,905	700,905	656,834	656,834	588,598	588,598	591,474	591,474
Adj. R^2	0.874	0.932	0.882	0.945	0.825	0.942	0.842	0.917

Table 10-Continued

This panel reports the effects of firm-level Pulse score on stock holdings of mutual funds with "domestic" and foreign-sounding managers. All variables are defined in Table 1. Dependent variables (stated above each column) include *ln(D/TNA)* and *ln(Shares/CSHO)*. The main independent variable is *Pulse*. In Columns 1 to 4, we define a fund manager name as foreign ("domestic") if over (fewer than) 75% of survey respondents consider the name as foreign-sounding, as in Kumar et al. (2015). In Columns 5 to 8, we use 67% as an alternative threshold to classify fund manager names. We use the same set of fund- and firm-level control variables as in Panel A of Table 2 (suppressed for brevity). The sample period is from 2007q1 to 2017q4. The *t*-statistics (reported in parentheses) are computed using triple-clustered standard errors at the fund, firm, and year-quarter levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel C: Manager names

	Foreign>75%				Foreign>67%			
	Domestic		Foreign		Domestic		Foreign	
	ln(D/TNA)	*ln(Shares/CSHO)*	*ln(D/TNA)*	*ln(Shares/CSHO)*	*ln(D/TNA)*	*ln(Shares/CSHO)*	*ln(D/TNA)*	*ln(Shares/CSHO)*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pulse	0.041**	0.033*	0.018	0.003	0.040*	0.032*	-0.013	-0.033
	(2.031)	(1.843)	(0.352)	(0.074)	(1.935)	(1.749)	(-0.231)	(-0.565)
Fund controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter×FF49 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter×Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	267,232	267,232	22,351	22,351	261,715	261,715	27,868	27,868
Adj. R^2	0.827	0.936	0.854	0.957	0.831	0.939	0.85	0.948

Table 11
Heterogeneous fund attributes and ESG integration: Return and flow regression estimates

This panel examines the effects of fund portfolio Pulse score on risk-adjust returns and investor flows of funds headquartered in Democratic-leaning or Republican-leaning states. All variables are defined in Table 1. Dependent variables (stated above each column) include Morningstar benchmark-adjusted return (*Ben-adj RET*) and quarterly flow (*Flow*). Fama-MacBeth (1973) return regressions (odd columns) use *Propensity* as the main independent variable, while flow regressions (even columns) use $Pulse_{Top10}$ as the main independent variable. In Columns 1 to 4, we define a state as Democratic-leaning if a Democrat won the most recent Presidential election in that state. In Columns 5 to 8, we define a state as Democratic-leaning if the state government composition value is above 0.5, where state government composition is calculated as 0.5 × indicator equals to one if the governor is a Democrat + 0.25 × indicator equals to one if Democrats control the majority seats in state legislature upper chamber + 0.25 × indicator equals to one if Democrats control the majority seats in state legislature lower chamber, as in Di Giuli and Kostovetsky (2014). We use the same set of control variables as in Panel B of Table 5 (Table 7) for return (flow) regressions (suppressed for brevity). The sample period is from 2007q1 to 2017q4. The *t*-statistics (reported in parentheses) are computed using Newey-West (1987) adjusted standard errors (with eight lags) in Fama-MacBeth return regressions, or double-clustered standard errors at the fund and year-quarter levels in flow regressions. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Political orientation

	Presidential Election				State Government			
	Democratic		Republican		Democratic		Republican	
	Ben-adj RET	*Flow*	*Ben-adj RET*	*Flow*	*Ben-adj RET*	*Flow*	*Ben-adj RET*	*Flow*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Propensity	0.091***		0.084		0.145***		0.034	
	(2.746)		(0.263)		(3.855)		(0.424)	
$Pulse_{Top10}$		0.068**		0.087		0.083*		0.052
		(2.122)		(1.513)		(1.851)		(1.386)
Fund controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter×Style FE		Yes		Yes		Yes		Yes
Style FE	Yes		Yes		Yes		Yes	
Observations	7,738	7,745	1,611	1,871	5,415	5,263	3,934	4,353
Adj. R^2	0.200	0.176	0.443	0.179	0.222	0.181	0.277	0.160

Table 11-Continued

This panel examines the effects of fund portfolio Pulse score on risk-adjust returns and investor flows of funds with different ESG ratings (Columns 1 to 4), and different 12b-1 fees (Columns 5 to 8). All variables are defined in Table 1. Dependent variables (stated above each column) include Morningstar benchmark-adjusted return (*Ben-adj RET*) and quarterly flow (*Flow*). Fama-MacBeth (1973) return regressions (odd columns) use *Propensity* as the main independent variable, while flow regressions (even columns) use $Pulse_{Top10}$ as the main independent variable. We categorize a fund as an SR (non-SR) fund if it has above- (below-) median portfolio ESG ratings (i.e., $ESG_{KLD,Portfolio}$) in the previous quarter. A fund is considered to be a salient fund if it has above median 12b-1 fees in the previous quarter. We use the same set of control variables as in Panel B of Table 5 (Table 7) for return (flow) regressions (suppressed for brevity). The sample period is from 2007q1 to 2017q4. The *t*-statistics (reported in parentheses) are computed using Newey-West (1987) adjusted standard errors (with eight lags) in Fama-MacBeth return regressions, or double-clustered standard errors at the fund and year-quarter levels in flow regressions. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel B: ESG orientation and mutual fund salience

	Mutual fund ESG ratings				Mutual fund salience			
	SR funds		Non-SR funds		High 12b-1 fees		Low 12b-1 fees	
	Ben-adj RET	*Flow*	*Ben-adj RET*	*Flow*	*Ben-adj RET*	*Flow*	*Ben-adj RET*	*Flow*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Propensity	0.093*		0.029		-0.004		0.035	
	(1.731)		(0.572)		(-0.092)		(0.617)	
$Pulse_{Top10}$		0.074**		0.007		0.068**		-0.005
		(2.627)		(0.383)		(2.514)		(-0.191)
Fund controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter×Style FE		Yes		Yes		Yes		Yes
Style FE	Yes		Yes		Yes		Yes	
Observations	11,090	12,288	8,156	8,352	7,147	7,567	7,168	7,485
Adj. R^2	0.165	0.184	0.229	0.186	0.212	0.186	0.236	0.189

Table 11-Continued

This panel examines the effects of fund portfolio Pulse score on risk-adjust returns and investor flows of funds with "domestic" and foreign-sounding managers. All variables are defined in Table 1. Dependent variables (stated above each column) include Morningstar benchmark-adjusted return (*Ben-adj RET*) and quarterly flow (*Flow*). Fama-MacBeth (1973) return regressions (odd columns) use *Propensity* as the main independent variable, while flow regressions (even columns) use $Pulse_{Top10}$ as the main independent variable. In Columns 1 to 4, we define a fund manager name as foreign ("domestic") if over (fewer than) 75% of survey respondents consider the name as foreign-sounding, as in Kumar et al. (2015). In Columns 5 to 8, we use 67% as an alternative threshold to classify fund manager names. We use the same set of control variables as in Panel B of Table 5 (Table 7) for return (flow) regressions (suppressed for brevity). The sample period is from 2007q1 to 2017q4. The *t*-statistics (reported in parentheses) are computed using Newey-West (1987) adjusted standard errors (with eight lags) in Fama-MacBeth return regressions, or double-clustered standard errors at the fund and year-quarter levels in flow regressions. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel C: Manager names

	Foreign>75%				Foreign>67%			
	Domestic		Foreign		Domestic		Foreign	
	Ben-adj RET	*Flow*	*Ben-adj RET*	*Flow*	*Ben-adj RET*	*Flow*	*Ben-adj RET*	*Flow*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Propensity	0.115		-0.451		0.101		-0.720*	
	(0.828)		(-1.689)		(0.714)		(-1.871)	
$Pulse_{Top10}$		0.071		0.046		0.074		-0.008
		(1.457)		(0.876)		(1.529)		(-0.116)
Fund controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter×Style FE		Yes		Yes		Yes		Yes
Style FE	Yes		Yes		Yes		Yes	
Observations	3,016	3,404	331	281	2,958	3,341	389	344
Adj. R^2	0.336	0.143	0.988	0.440	0.338	0.143	0.954	0.469

Internet Appendix

A. *Fund manager propensity estimation*

We follow the Fang et al. (2014) method to estimate fund managers' propensity to implement ESG integration strategies. Specifically, for each fund and in each quarter t, we estimate a cross-sectional regression using an eight-quarter rolling window (quarter t-7 to t) at the portfolio holding level as follows:

$$ln(D/TNA)_{i,j,t} = \beta_0 + \beta_{i,t}Pulse_{j,t-1} + \theta_{i,t}W_{j,t-1} + \varepsilon_{i,j,t}\,. \tag{A1}$$

The dependent variable is the natural logarithm of the market value of firm j owned by fund i in quarter t, divided by the total net assets of fund i in quarter t. The main independent variable is the average Pulse score of firm j in quarter t-1 ($Pulse_{j,t-1}$). $W_{j,t-1}$ is a vector of lagged stock characteristics, including firm size, stock turnover ratio, and book-to-market ratio. Standard errors are clustered at the firm level.

$\beta_{i,t}$ captures the average propensity of fund i to trade stocks using ESG information over the eight-quarter period (quarters t-7 to t) for quarter t. Following Fang, Peress, and Zheng (2014), our main propensity measure used in Sections 4 and 5 ($Propensity_{i,t}$) is calculated as a precision-weighted shrinkage estimator based on β_i and variance of β_i over the previous four quarters (quarters t-3 to t):

$$Propensity_{it} = \frac{1}{\left(\frac{1}{\sigma_{it}^2}+\frac{1}{\sigma_{it-1}^2}+\frac{1}{\sigma_{it-2}^2}+\frac{1}{\sigma_{it-3}^2}\right)} \times \left(\frac{\beta_{it}}{\sigma_{it}^2}+\frac{\beta_{it-1}}{\sigma_{it-1}^2}+\frac{\beta_{it-2}}{\sigma_{it-2}^2}+\frac{\beta_{it-3}}{\sigma_{it-3}^2}\right), \tag{A2}$$

where $\sigma^2_{i,t-q}$ is the variance of the estimated coefficient $\beta_{i,t-q}$. The mean (median) value of *Propensity* in our fund-quarter panel dataset is -0.042 (-0.020), with a standard deviation of 0.443. We use one-quarter lagged propensity scores in all related tests in Sections 4 and 5.

B. Market-level ESG premium estimation

We construct market-level ESG premium and categorize our sample into high and low ESG demand periods based on the approach employed in Baker and Wurgler (2004). Specifically, we regress firm-level KLD score on firm attributes that have been shown to affect a firm's ESG policy:

$$KLD_{j,s,t} = \beta_0 + \beta_1 W_{j,t-1} + \varepsilon_{j,s,t}\,, \tag{A3}$$

where $W_{j,t-1}$ is a vector of firm attributes including asset turnover, advertisement over net sales, cash over total assets, operating cash flows over total assets, leverage, profit margin, R&D, and log total assets, industry fixed effects, and a time trend dummy, as in Naughton et al. (2019).

The residual $\varepsilon_{j,s,t}$ in this regression is considered as the unexplained ESG component (abnormal ESG). In each year, we rank all stocks based on abnormal ESG and construct the market-level ESG premium as the difference in log(average market-to-book ratio) between the highest and lowest abnormal ESG quintiles. A year is classified into a high (low) ESG demand period if its ESG premium is above (below) the median ESG premium of all previous years.

C. Difference-in-differences robustness tests

While the trends before the Morningstar event in Figure 2 appear to be parallel, top- and bottom-rated funds could have different attributes. Table A2 in the Appendix shows that relative to bottom-rated funds, top-rated funds are larger and have lower expense and turnover ratios. To mitigate the concerns that our results could be confounded by these systematic differences, we perform propensity score matching and match funds on these attributes.

Specifically, using the fund-quarter sample up to 2015q4, we estimate a logistic regression to predict the likelihood of a fund being a top-rated fund as a function of the lagged baseline fund characteristics and year-quarter fixed effects. We then match each top-rated fund with a bottom-rated fund using fitted propensity scores in 2015q4, and require the absolute difference in propensity scores to be smaller than 0.01. This matching procedure yields 219 pairs of matched funds. Columns 5 to 8 of Table A2 in the Appendix show that the differences in fund attributes in our matched sample become statistically insignificant.

Columns 1 and 2 in Table A3 report the difference-in-differences regression estimates for the matched sample. We find that the coefficient of the three-way interaction term $Pulse_{j,t-1} \times TOP_{i,j} \times POST_t$ continues to be positively significant, while the differences in trends before the event remain insignificant.

For further robustness, we perform placebo tests using two placebo quarters before the true Morningstar event: 2014q4 or 2013q4. The two placebo quarters are arbitrarily chosen to ensure that at least four quarters exist after the placebo events. To avoid contamination from the true event, the sample period of placebo tests ends in 2015q4. Columns 3 to 6 of Table A3 report the placebo test results. We find that the placebo difference-in-differences estimates become statistically insignificant, while the trends of managers' propensity to implement ESG integration strategies remain similar for the top- and bottom-rated funds before the two placebo quarters.

Overall, the robustness test results support the catering hypothesis. We find that managers have stronger incentives to adopt ESG integration strategies if their clients have increased demand for ESG.

Table A1
Sample distribution by Fama and French 12 industries

This table reports the distribution of our fund-firm-quarter panel sample by Fama and French 12 industries. The number of observations and the unique number of funds and firms in each of the 12 industries are reported.

Fama and French 12 industries	Observations	Unique # of funds	Unique # of firms
Consumer Nondurables	107,665	1,678	84
Consumer Durables	39,691	1,379	38
Manufacturing	169,822	1,756	155
Oil, Gas, and Coal Extraction and Production	81,502	1,519	61
Chemicals and Allied Products	70,161	1,587	54
Business Equipment	318,551	1,825	260
Telephone and Television Transmission	52,497	1,332	36
Utilities	80,696	1,283	59
Wholesale, Retail, and Some Services	190,701	1,763	149
Healthcare, Medical Equipment, and Drugs	144,001	1,709	202
Finance	290,250	1,792	232
Other	188,889	1,792	189
Total	1,734,426	1,870	1,519

Table A2
Covariate balance for difference-in-differences tests

This table reports average fund and firm characteristics for the treatment and control groups in 2015q4 (one quarter before the introduction of Morningstar Sustainability Rating). The data used for estimating these sample statistics are at the holdings level. Columns 1 to 4 present statistics for the unmatched sample, while Columns 5 to 8 present statistics for the sample in which funds are matched using propensity score matching techniques. Columns 3 and 7 report the differences between group means, while Columns 4 and 8 report the corresponding *t*-statistics. The *t*-statistics are computed using double-clustered standard errors at the fund and firm levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Unmatched funds				Matched funds			
	2015q4				*2015q4*			
Fund number	299	283			222	221		
Fund-firm obs.	N=17,764	N=15,742			N=12,187	N=12,957		
	Treat	Control	Diff	*t*-stat	Treat	Control	Diff	*t*-stat
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PR	0.591	0.560	0.031	1.099	0.575	0.560	0.015	0.471
PR^2	0.410	0.372	0.038	1.122	0.396	0.368	0.028	0.790
ln(Age)	5.263	5.110	0.153	1.576	5.218	5.203	0.015	0.171
ln(TNA)	6.635	5.934	0.701***	3.217	6.405	6.061	0.344	1.542
Expense	0.002	0.003	-0.000***	-3.596	0.003	0.003	-0.000	-0.606
$Turnover_{Fund}$	0.147	0.174	-0.027**	-1.99	0.155	0.170	-0.016	-0.961
Load	0.532	0.617	-0.085	-1.292	0.601	0.594	0.007	0.091
ln(ME)	10.150	7.927	2.223***	16.353	10.150	7.924	2.225***	14.718
$ln(Turnover_{Stock})$	-0.724	-0.618	-0.106***	-3.217	-0.727	-0.622	-0.105***	-3.025
ln(BM)	-1.243	-0.964	-0.279***	-4.351	-1.229	-0.965	-0.263***	-3.877

Table A3
Difference-in-differences robustness tests

This table presents robustness checks for the difference-in-differences tests using the introduction of Morningstar Sustainability Rating in March 2016 (i.e., 2016q1) as an exogenous event. Dependent variables (stated above each column) include *ln(D/TNA)* and *ln(Shares/CSHO)*. *TOP* is a dummy variable that equals one for funds in the top $ESG_{KLD,Portfolio}$ tercile in 2015q4 (i.e., treatment funds), or zero otherwise. *POST* is a post-event dummy variable that equals one after 2016q1, or zero otherwise. We include two pre-event dummy variables that identify the periods that are one to four quarters ($PRE^{(-1\ to\ -4)}$) or five to eight quarters ($PRE^{(-5\ to\ -8)}$) before the event quarter, respectively. Columns 1 and 2 presents results from estimating specifications 3 and 6 in Table 8 on a sample of matched funds. We construct the matched fund sample by regressing the likelihood of a fund being in the top $ESG_{KLD,Portfolio}$ tercile (as opposed to being in the bottom tercile) in 2015q4 on fund attributes and time fixed effects over the sample period before the event. Fund attributes used for matching are reported in Table A2. We match a treatment fund (i.e., funds in the top $ESG_{KLD,Portfolio}$ tercile) with a control fund from the bottom $ESG_{KLD,Portfolio}$ tercile with the closest propensity score, and exclude matched fund pairs if the absolute differences in propensity scores exceed 0.01. Columns 3 and 4 (5 and 6) present the results of placebo tests using 2014q4 (2013q4) as the event quarter. We exclude the event quarter (i.e., 2016q1) from the analysis. The *t*-statistics (reported in parentheses) are computed using triple-clustered standard errors at the fund, firm, and year-quarter levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Matched funds		Placebo tests (sample ended in 2015q4)			
			Placebo event=2014q4		Placebo event=2013q4	
	ln(D/TNA)	*ln(Shares/CSHO)*	*ln(D/TNA)*	*ln(Shares/CSHO)*	*ln(D/TNA)*	*ln(Shares/CSHO)*
	(1)	(2)	(3)	(4)	(5)	(6)
Pulse × *TOP* × *POST*	0.121*	0.144**	-0.021	0.002	-0.041	-0.010
	(1.920)	(2.363)	(-0.277)	(0.030)	(-0.502)	(-0.125)
Pulse × *TOP* × $PRE^{(-1\ to\ -4)}$	0.044	0.068	-0.089	-0.004	-0.029	-0.017
	(0.608)	(0.985)	(-1.142)	(-0.050)	(-0.317)	(-0.240)
Pulse × *TOP* × $PRE^{(-5\ to\ -8)}$	0.042	0.088	-0.022	-0.003	-0.028	-0.043
	(0.566)	(1.205)	(-0.300)	(-0.048)	(-0.374)	(-0.619)
Interaction between fund and firm controls, *TOP*, and *POST*	Yes	Yes	Yes	Yes	Yes	Yes
Interaction between fund and firm controls, *TOP*, and $PRE^{(-1\ to\ -4)}$	Yes	Yes	Yes	Yes	Yes	Yes
Interaction between fund and firm controls, *TOP*, and $PRE^{(-5\ to\ -8)}$	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter×FF49 FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter×Style FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	466,263	466,263	582,583	582,583	585,334	585,334
Adj. R^2	0.877	0.932	0.853	0.926	0.854	0.926