

# Mutual fund trading, fund flows, and ESG portfolios

Rui Albuquerque, Yrjö Koskinen, and Raffaele Santioni\*

June 5, 2025

## Abstract

This paper studies how ESG and conventional mutual funds trade stocks during the COVID-19 crash. Both fund types trade individual stocks similarly: net purchases of ESG stocks are less sensitive than other stocks to fund flows pre crash, but sensitivities increase for all stocks during the crash. In contrast, ESG funds' aggregate net purchases are less sensitive than those of conventional funds during the crash. This difference is due to ESG funds' portfolio tilt toward the less flow-sensitive ESG stocks. There is no evidence of an ESG clientele effect in trading decisions, as both fund types trade individual stocks similarly.

Keywords: ESG, mutual funds, trading, clientele effect, fund flows, COVID-19

JEL classifications: G01, G12, G23, G32, M14

---

\*Rui Albuquerque, rui.albuquerque@bc.edu, Carroll School of Management, Boston College, ECGI, and CEPR. Yrjö Koskinen, yrjo.koskinen@ucalgary.ca, Haskayne School of Business, University of Calgary, and ECGI. Raffaele Santioni, raffaele.santioni@bancaditalia.it, Bank of Italy. We thank Tim Adam, Massimiliano Affinito, Dimitrios Gounopoulos, Alexei Orlov, Raghu Rau, Jonathan Reuter, Luca Zucchelli, Alex Wagner, and participants at seminars at Fundação Getúlio Vargas, University of Bath, University of Calgary, University of Mississippi, University of Oregon, Canadian Sustainable Finance Network, the 2021 IFABS conference at Oxford, the Conference on “The Role of Institutional Investors in International Corporate Governance” at the University of Hamburg, the 2022 Financial Markets and Corporate Governance Conference, and the 2024 Public Investors Conference in Singapore for comments. We thank Morningstar for access to proprietary holdings data, and Emanuela Bassi, Michele Cicconetti, and Sara Silano for invaluable advice. An earlier version of the manuscript circulated with the title of “Mutual Fund Trading, Greenwashing, and ESG Clientele.” Albuquerque is grateful for financial support from the Foundation for Science and Technology under grant PTDC/EGE-OGE/30314/2017. Koskinen acknowledges financial support from the BMO Professorship in Sustainable and Transition Finance. The views expressed in this article are those of the authors and do not necessarily represent the views of the institutions with which they are affiliated, Morningstar or its content providers.

# I Introduction

We study how U.S. actively managed environmental, social, and governance (ESG) and conventional mutual funds trade stocks during the COVID-19 market crash. The crash in February and March of 2020 was unexpected and unrelated to economic conditions. It led to large and unanticipated outflows from most mutual funds (Pastor and Vorsatz (2020)). This paper uses this quasi-natural experiment to examine whether ESG and conventional funds trade similarly or whether there are systematic differences in how they respond to unanticipated fund flows originating from their different clienteles. We address this question by studying funds' trading decisions in their aggregate portfolios and by examining how they trade ESG and non-ESG stocks.

We present a benchmark model of trading, where funds allocate flows into their portfolios according to their optimal share allocation (Lou (2012)), which we refer to as the constant-portfolio-share hypothesis. If the hypothesis is not rejected, the sensitivity of net purchases to fund flows across ESG and conventional funds should not differ. An alternative hypothesis, which we refer to as the clientele hypothesis, is that ESG funds attract traditional investors who are only interested in the risk and return of their asset holdings in addition to ESG investors who also have nonpecuniary motives for holding ESG stocks (Pastor, Stambaugh, and Taylor (2021) and Pedersen, Fitzgibbons, and Pomorski (2021)). After a negative stock market shock, ESG investors are less likely than other investors to sell their holdings in ESG funds, all else equal. Consequently, ESG funds' clientele becomes more ESG-oriented. If ESG funds cater to their clientele's preferences, they are more likely to hold their ESG stocks and to sell non-ESG ones when experiencing outflows compared to conventional funds.

From the benchmark model, we derive an empirical regression model of net stock purchases. The sensitivity of net purchases of ESG and non-ESG stocks to fund flows, which we refer to as trading sensitivity, should equal one, according to the constant-portfolio share hypothesis. Naturally, changes in expected returns occurring with the crash can lead to changes in the optimal

portfolio allocation. We show in our model that a difference-in-differences estimation contrasting ESG and conventional mutual funds can identify ESG fund managers' trading associated with fund flows that is unrelated to the expected financial performance of stocks.

Our main data source is a proprietary dataset from Morningstar with monthly portfolio holdings. The sample is from January 2019 to March 2020. Monthly data allow us to identify February and March of 2020 as the stock market crash months and to study fund trading at a higher frequency than the normally used quarterly data. The data consist of 1,699 unique U.S. equity active mutual funds with total net assets of \$2.6 trillion as of December 2018, representing about 400,000 stock positions. We use two classifications for ESG funds: Morningstar's Globe 5 sustainability rating (the highest Globe sustainability rating) and Morningstar's Low Carbon Designation. The separate interest in low-carbon funds is justified, as these funds appear to have their own clientele (Ceccarelli, Ramelli, and Wagner (2023)), and are the closest we have to the E category in ESG, the main aspect of ESG that matters to climate-conscious investors. Consistent with the possibility of different clienteles, only 4.5% of the funds in our sample have both a Low Carbon Designation and a Globe 5 rating. We use a lagged classification of mutual funds as ESG-oriented (treated sample) and conventional (control sample) and treat these groups as exogenous in our analysis because the COVID-19 crash was unexpected and, being a health crisis, unrelated to the funds' ESG classifications.

We start by examining *aggregate* fund-level net purchases. Two key findings emerge. First, before the crash, aggregate net purchases of stocks increase one-to-one with net flows for all funds, both ESG and conventional. Second, during the crash, the aggregate sensitivity of net purchases to fund flows increases for all fund types, particularly for conventional funds. These findings suggest that we cannot reject the benchmark model of constant share of cash to total assets in the pre-period but that the benchmark model prediction does not hold during the crash.

We then examine *stock-level* net purchases by considering ESG and non-ESG stocks. Here three findings stand out. First, before the crash and for *all* funds, net purchases of non-ESG

stocks increase one-to-one with fund flows, whereas net purchases of ESG stocks increase less than one-to-one with fund flows. Only the trading sensitivity of non-ESG stocks to flows is consistent with the constant-portfolio-share hypothesis.

Second, during the crash, for conventional funds, the sensitivity of net purchases to flows increases for both stock types. In contrast, for ESG funds, trading sensitivities increase only for non-ESG stocks, suggesting that ESG funds choose not to increase net selling of ESG stocks when confronted with outflows during the crash. This finding can be explained by the clientele hypothesis. To test this possibility, we must control for common shocks to expected returns, which can be done using a difference-in-differences approach between ESG and conventional funds. We subsequently find no statistical difference for how trading sensitivities change for ESG funds compared to conventional funds for both ESG stocks and non-ESG stocks.<sup>1</sup> To appreciate the significance of this finding, note that our difference-in-differences analysis controls for changes in expected returns. Thus the differences in trading patterns cannot be attributed to changes in expected returns but can be attributed to a clientele effect. Since we do not find any difference in how trading sensitivities change, other reasons for trading, such as an ESG clientele, do not seem to help explain fund trading during the crash.<sup>2</sup>

These results raise two main questions. First, how can similar ESG and non-ESG stock trading sensitivities across fund types be reconciled with different aggregate fund-level trading

---

<sup>1</sup>To be precise, when we run our tests using the Low Carbon Designation, we find that conventional funds increase their trading sensitivity of ESG stocks more so than low-carbon funds in response to fund flows.

However, when we break down net flows into inflows and outflows, we find no statistically significant difference in the changes in trading sensitivities across stocks. The summary of results in the text reflects our comprehensive assessment of the evidence for the case of low-carbon funds.

<sup>2</sup>The clientele hypothesis is a joint hypothesis that ESG investors are less likely to sell their ESG holdings during the COVID crash and that ESG fund managers cater to these clients. Later, we will discuss evidence suggesting that the composition of investors in ESG funds changed, as predicted, during the crash.

sensitivities for these funds? We argue that the reason is that ESG funds hold a disproportionately larger share of their portfolios in ESG stocks. Since ESG stocks display a lower trading sensitivity than non-ESG stocks, funds with more ESG stocks have lower trading sensitivities at the aggregate level. In summary, the main difference between funds is the proportion of ESG stocks they hold.

The second question raised by our results is what explains the lower trading sensitivity of ESG stocks versus non-ESG stocks for conventional funds that have no ESG clientele. We conjecture that conventional funds treat ESG and non-ESG stocks differently, due to the higher volatility and higher beta of non-ESG stocks (see Luo and Bhattacharya (2009) for volatility and Albuquerque, Koskinen, and Zhang (2019) for beta). One possible hypothesis, which we refer to as the risk hypothesis, is that, following large outflows (inflows), funds adopt a risk-off (risk-on) attitude for idiosyncratic volatility and exposure to market returns and hence have relatively higher net sales (purchases) of non-ESG stocks (for high-frequency risk-on/risk-off investor behavior, see Chari, Dilts Steadman, and Lundblad (2024)). Consistent with this hypothesis, we find that trading sensitivities increase more for non-ESG stocks during the crash than for ESG stocks for both fund types, suggesting fund managers take a risk-off attitude in the presence of large outflows.<sup>3</sup> We, however, do not find any statistical difference in the way trading sensitivities change for ESG and conventional funds. We thus cannot rule out that the same risk-on/risk-off justification also applies to ESG funds.

One overall interpretation of our results is that ESG funds express their sustainability preferences through the portfolio weight allocated to ESG stocks. The clientele hypothesis appears to have limited role in explaining the change in trading sensitivities from pre-crash months to the crash. This evidence relates to the dichotomy of value versus values presented by Starks (2023). She suggests that ESG investors have mixed preferences: they may exhibit nonpecuniary

---

<sup>3</sup>We also find evidence that net purchases of non-ESG stocks decrease with increases in market volatility and find no statistical significant effect for net purchases of ESG stocks.

sustainability preferences, but they are mainly interested in risk-adjusted expected returns. Our results suggest that, during the period of analysis, ESG funds align with their clientele's non-pecuniary values through their tilt toward ESG stock selection. These ESG funds then manifest their preference for financial value through their trading. These results also fit the survey findings of Edmans, Gosling, and Jenter (2024), who emphasize that very few ESG or conventional funds are willing to sacrifice expected returns but that fund mandates affect portfolio selection for ESG funds.

The effects we estimate are not mechanical. Fund managers do not simply pass through the flows they receive. Redoing our analysis with high Morningstar star-rated funds, we do not observe any significant difference in their behavior versus all other funds, nor do we observe a significantly different portfolio share invested in ESG stocks across high and low star-rated funds.

Recent research on ESG investments suggests that an ESG clientele exists in asset management. Bollen (2007) and Renneboog, Ter Horst, and Zhang (2011) show that investors in socially responsible investment funds are less sensitive to fund performance than investors in conventional mutual funds. Hartzmark and Sussman (2019) show that investors respond to new sustainability ratings purchasing funds categorized as low ESG risk, even though there is no difference in fund performance. Rzeknik, Hanley, and Pelizzon (2024) show that investors incorrectly bought stocks when Sustainalytics inverted its ESG ratings, erroneously believing that higher rating meant improved ESG performance. Bauer, Ruof, and Smeets (2021) document that most individual investors in a Dutch pension fund are willing to increase investments based on United Nations' Sustainable Development Goals, even at the expense of financial returns. Baker, Egan, and Sarkar (2024) show that investors in ESG index funds are willing to pay higher fees than for conventional index funds with similar returns. Humphrey, Kogan, Sagi, and Starks (2023) show, in an experiment, that about half of the subjects halve their allocation to stocks associated with negative ES externalities. Giglio, Maggiori, Stroebe, Tan, Utkus, and Xu (2025)

provide survey evidence that investors expect ESG stocks to underperform the market, but about one-fourth of them are willing to invest in ESG stocks due to ethical considerations. Our paper contributes to this literature by showing that ESG funds cater to their ESG clientele through their portfolio composition but not through their trading.

ESG stocks and mutual funds have been shown to have performed better during previous stock market crashes (for stocks, see Lins, Servaes, and Tamayo (2017) and, for funds, see Nofsinger and Varma (2014)). Several papers examine ESG ratings and stock returns during the initial phases of the COVID-19 pandemic. Albuquerque, Koskinen, Yang, and Zhang (2020) show using U.S. data that firms with high E and S scores fared better during the crash. Ding, Levine, Lin, and Xie (2021) provide international evidence that E and S policies have had a positive impact on stock returns. Garel and Petit-Romec (2021) show that only E scores have had a positive effect on stock returns. Our evidence suggests that outflows from conventional funds, which on average hold a vast majority of their portfolio in non-ESG stocks, and the increased net selling sensitivity of non-ESG stocks during the crash by these funds in response to outflows are consistent with the relatively larger stock market decline for non-ESG stocks.

We organize our paper as follows: Section II presents the benchmark trading model and the empirical strategy, and Section III presents the data. Section IV provides the main results, and Section V robustness checks. Section VI concludes.

## **II A model of mutual fund trading and empirical strategy**

### **A A benchmark model**

We frame our empirical analysis using a benchmark model, where mutual funds keep constant proportions of ESG stocks and non-ESG stocks to total net assets following fund flows. That a fund's allocation is optimal, independent of fund flows, is based on two assumptions. First, investor flows are uninformative about future returns to portfolio stocks. Consistent with the

non-informativeness of flows, Ben-David, Li, Rossi, and Song (2022) show that mutual fund flows are explained by performance chasing. Second, no frictions prevent fund managers from building their optimal portfolio allocation prior to flows (see Lou (2012) for a result consistent with this assumption). Following fund flows, deviations from this benchmark may be viewed as discretionary trading that favors one group of stocks versus another.

Assume, for simplicity, that funds have only one ESG stock and one non-ESG stock. Let  $P_G$  be the price of the ESG stock (labelled G for green) and  $Q_G$  the number of shares of that stock held by a mutual fund. Then  $P_G Q_G$  is the total net asset value associated with the mutual fund's portfolio of ESG stocks. Evaluating variables at the end of each period, the percentage change (or growth) in the net asset value of ESG stocks from the end of  $t - 1$  to the end of  $t$  is

$$(1) \quad \widehat{P_G Q_G}_t = \frac{P_{G,t} Q_{G,t} - P_{G,t-1} Q_{G,t-1}}{P_{G,t-1} Q_{G,t-1}}.$$

If the share of ESG stocks in total net assets (TNA) is constant, then

$$(2) \quad \widehat{P_G Q_G}_t = \widehat{TNA}_t.$$

The evolution over time of total net assets is by definition given by

$$(3) \quad TNA_t = (1 + r_t)TNA_{t-1} + NF_t,$$

where  $NF_t$  is the net fund flow during  $t$  and  $r_t$  is the fund's return during  $t$ . Subtracting  $TNA_{t-1}$  from both sides, dividing both sides by  $TNA_{t-1}$ , and denoting  $FF_t = \frac{NF_t}{TNA_{t-1}}$ , we get



$$(4) \quad \widehat{TNA}_t = r_t + FF_t.$$

This equation is the accounting identity that TNA changes due to fund performance and flows. Use equation (2) to replace  $\widehat{TNA}_t$  with  $\widehat{P_G Q_{Gt}}$ ,

$$(5) \quad \widehat{P_G Q_{Gt}} = r_t + FF_t.$$

This equation demonstrates how to rebalance ESG stocks to keep a constant portfolio share in TNA. First, suppose fund flows are zero. Then ESG stocks must grow at the rate of return of TNA; if the return on ESG stocks exceeds that of TNA in period  $t$ , some rebalancing sales must happen to keep the growth of ESG stocks at par with that of TNA. Second, fund flows should not change the portfolio weights, which is accomplished by having the dollar value of ESG stocks grow one-for-one with  $FF_t$ .

Repeating the same steps for non-ESG stocks, which we label with the subscript B (for brown stocks), we obtain a similar equation for the percentage change in value holdings of non-ESG stocks,

$$(6) \quad \widehat{P_B Q_{Bt}} = r_t + FF_t.$$

## B Empirical strategy

We now detail how to go from equations (5) and (6) to an estimatable equation. First, note that the left-hand side of equation (5), the growth in the share of ESG stocks, is the sum of two components, net purchases of ESG stocks and changes in the price of ESG stocks. When there is more than one ESG stock in the portfolio, this last term is the weighted average of the price changes, with weights given by the beginning-of-period value weight of each stock. To see

this, add and subtract  $P_{G,t}Q_{G,t-1}$  to the numerator of the growth in the share of the ESG stocks. Collecting terms, we get

$$(7) \quad \widehat{P_G Q_{Gt}} = \frac{P_{G,t}(Q_{G,t} - Q_{G,t-1})}{P_{G,t-1}Q_{G,t-1}} + \frac{P_{G,t} - P_{G,t-1}}{P_{G,t-1}}.$$

The second term on the right-hand side of equation (7) –the change in price of the ESG stocks—leads to a mechanical change in asset allocation. For this reason, we subtract this term from both sides of equation (5). What remains on the left-hand side of equation (5) is fund  $i$ 's net purchases of ESG stocks,  $\text{NET\_PURCHASES}_{G,i,t}$ . The right-hand side of the modified equation (5) will then have the fund's return,  $r_t$ , the fund's ESG stock portfolio return, and fund flows. To proxy for the unobserved fund ESG-portfolio return, we use the return on a broad ESG index, the S&P 500 ESG index.<sup>4</sup> We modify equation (6) accordingly to obtain an equation for net purchases of non-ESG stocks,  $\text{NET\_PURCHASES}_{B,i,t}$ . The right-hand side of the modified equation (6) contains the unobserved fund non-ESG stock portfolio return, which we again proxy with return on a broad ESG index.<sup>5</sup>

---

<sup>4</sup>This raises the question whether the measurement error introduced by using the ESG index return adds a bias to the estimation of the sensitivity of net purchases to fund flows in our regressions below. For measurement noise to matter, it would have to be correlated with fund flows. That is, fund flows must be correlated with the difference between the unobserved return on a fund's ESG stock portfolio and the return on the S&P 500 ESG index. This is incompatible with our modeling assumption that fund flows are uninformative.

<sup>5</sup>There is no non-ESG index in the market that we can use to proxy for a fund's unobserved return on its non-ESG stock portfolio. Fortunately, we can use the same broad ESG index for non-ESG stocks as well. To see this, note that the return on the market index is a weighted average of the returns on its components,

$r_{Mkt} = w_{ESG}r_{ESG} + (1 - w_{ESG})r_{NESG}$ . Thus, the non-ESG index return

$r_{NESG} = [r_{Mkt} - w_{ESG}r_{ESG}]/(1 - w_{ESG})$ . Assuming fixed weights, by including the return on the S&P 500

index and the return on a broad ESG index in the equation for non-ESG stocks, we capture the mechanical effect

We stack the modified equations (5) and (6) in a single vector and add a regression residual. Further, like Cella, Ellul, and Giannetti (2013), we are interested in how fund managers respond to flows in normal times versus volatile periods. Thus, we include in the regression interactions of fund flows with the dummy  $Crash_t$  that identifies the crash period (defined by February and March of 2020). We also want to distinguish how net purchases respond to flows across funds. We do so by introducing interactions of fund flows with the dummy  $ESG_{it}$ , which classifies a fund as ESG (versus conventional). We let coefficients attached to the independent variables vary for net purchases of ESG stocks versus net purchases of non-ESG stocks. The model to estimate is

$$(8) \quad \begin{aligned} NET\_PURCHASES_{j,i,t} = & \mu_t + \phi_{ji} + \beta_j X_{j,i,t} + \gamma_{j,1} FF_{i,t} + \gamma_{j,2} FF_{i,t} Crash_t ESG_{it} \\ & + \gamma_{j,3} FF_{i,t} Crash_t + \gamma_{j,4} Crash_t ESG_{it} + \gamma_{j,5} ESG_{it} + \gamma_{j,6} FF_{i,t} ESG_{it} + \epsilon_{j,i,t}. \end{aligned}$$

The unit of observation is stock-portfolio  $j$  ( $=G,B$ ), fund  $i$ , and month  $t$ . We estimate the model at the stock-portfolio level by assigning individual stocks into the portfolio of ESG stocks and the portfolio of non-ESG stocks. We run the regressions at the portfolio level instead of the stock level because the benchmark of constant portfolio shares in response to flows is less noisy at this more aggregated level.

The choice of control variables to include in  $X_{j,i,t}$  is influenced by Cella et al. (2013). We include fund-level controls (lagged fund return,<sup>6</sup> lagged fund size, and lagged fund liquidity or

---

of changes in prices on the share of non-ESG stocks; the coefficient associated with fund flows in equation (6) that we focus on is unaffected.

<sup>6</sup>Recall that the model suggests the use of contemporaneous fund return in the regression. We use the lagged fund return in the regression for two reasons. First, the contemporaneous fund return is partly explained by fund flows. Having the contemporaneous fund return in the regression would not allow us to identify the sensitivity of net purchases to fund flows. Second, net purchases during the month also affect the month's return, and including the contemporaneous return would result in an endogenous regressor and possibly biased estimated coefficients.

cash holdings<sup>7</sup>); aggregate controls (contemporaneous market return and volatility); and stock controls aggregated to the fund's portfolios of ESG and non-ESG stocks (firm liquidity and firm leverage, Ramelli and Wagner (2020), and the firm's churn ratio as a proxy for the horizon of the firms' investors, all dated at the beginning of the sample). The stock controls may help identify fund managers' preferences for certain firm characteristics, either because they help predict returns or because they may be associated with lower transaction costs (Lou (2012)).

Lastly, we include stock-portfolio times fund fixed effects,  $\phi_{ji}$ , and month fixed effects,  $\mu_t$ . Month fixed effects subsume the effect of the standalone *Crash* dummy and that of the return to the broad ESG index referred to above.<sup>8</sup> Month fixed effects do not subsume the market return and its volatility because the data provider assigns a different benchmark index to each fund. We estimate robust standard errors, clustered by fund. Clustering at the fund level includes observations for net purchases of ESG and non-ESG stocks.

We also estimate regressions of aggregate net purchases. The regression model is similar:

$$(9) \quad \begin{aligned} NET\_PURCHASES_{i,t} = & \mu_t + \xi_i + \beta X_{i,t} + \kappa_1 FF_{i,t} + \kappa_2 FF_{i,t} Crash_t ESG_{it} \\ & + \kappa_3 FF_{i,t} Crash_t + \kappa_4 Crash_t ESG_{it} + \kappa_5 ESG_{it} + \kappa_6 FF_{i,t} ESG_{it} + \epsilon_{i,t}. \end{aligned}$$

The unit of observation is fund  $i$  and month  $t$ . We include month fixed effects,  $\mu_t$ , and fund fixed effects,  $\xi_i$ . The vector of control variables  $X_{i,t}$  includes all controls described for model (8), except the stock-portfolio level controls.

The equations above contrast the behavior of ESG versus conventional funds. For example, for ESG stocks, the regression model (8) considers a version of equation (5) for ESG and

---

<sup>7</sup>Pre-crash liquidity levels may have helped funds respond differently to the crisis (Chernenko and Sunderam (2016)), while at the same time, they proxy for frictions that may keep managers from choosing their optimal portfolios (Lou (2012)).

<sup>8</sup>In an earlier version of the paper, we used quarter fixed effects and could estimate the separate effects from the *Crash* dummy and the S&P 500 ESG index return. The main qualitative results were the same.

conventional funds jointly but allows for possibly different sensitivities across funds in the response to flows. Effectively, observations from conventional funds become a control sample that accounts for unobserved changes in market conditions that affect expected returns to all funds, such as changes in expectations of growth in the economy or risk tolerance that occur during the crash. This is important, even when flows are uninformative, as assumed in the benchmark model, because flows can be contemporaneous to changes in expected returns that change the desired allocation to a fund. To see the formal argument, suppose fund managers for both ESG and conventional funds increase by  $\alpha\%$  the weight on ESG stocks in TNA, due to expected return changes during the crash. Thus,  $\widehat{P_G Q_{Gt}} = \widehat{TNA_t} + \alpha$ . These changes in asset allocation due to shared assumptions about expected returns are absorbed by the month fixed effect. Note too that the unexpected nature of the crash and the fact that it is not driven by economic conditions (or any aspect specific to ESG) allow us to use the pre-crash ESG status of funds when defining treated and control samples. Thus, our exercise is a quasi-natural experiment of changes to net purchases by mutual funds in the presence of significant unexpected outflows during the crash.

## C Hypotheses statements

We start with hypotheses directly linked to the benchmark model. To simplify the writing, we refer to the sensitivity of net purchases to fund flows as the trading sensitivity.

The constant-portfolio share hypothesis states that the shares of ESG stocks and of non-ESG stocks in TNA are constant. This leads to two tests. First, the sum of the portfolio shares is constant (see Lou (2012)), which results in the test that the sensitivity of *aggregate* net purchases to fund flows equals 1 (or that the ratio of cash balances to total net asset value is constant following fund flows). In testing this first hypothesis, we estimate the regression equation (9). The second test arising from the constant-portfolio share hypothesis states that ESG and conventional funds display a trading sensitivity of 1 for ESG and non-ESG stocks. For example, for the pre-crash

period, this is tested with  $\gamma_{j,1} = 1$  for conventional funds and  $\gamma_{j,1} + \gamma_{j,6} = 1$  for ESG funds, for  $j = G, B$ . This tests and those that result from the remaining hypotheses use the regression equation (8).

The third and fourth hypotheses address changes in net purchases during the crash period. The third hypothesis notes that the benchmark model does not distinguish across ESG and conventional funds also during the crash and delivers the test that  $\gamma_{G,2} = 0$  for ESG stocks and that  $\gamma_{B,2} = 0$  for non-ESG stocks. Alternatively, finding that  $\gamma_{G,2} < 0$  implies that, during the crash, ESG funds tilt their portfolios to ESG stocks more than conventional funds in the presence of outflows (or that ESG funds tilt their portfolios toward non-ESG stocks more than conventional funds in the presence of inflows).

What is the economic rationale for the alternative of  $\gamma_{G,2} < 0$ ? The benchmark model doesn't make any behavioral assumptions that could lead to predictions when the constant-portfolio share hypothesis is violated. The interest, however, in studying ESG and conventional funds arises from the different clienteles of these funds. Arguably ESG funds have a clientele that cares for the stock returns of portfolio companies, as traditional investors do, but also for their nonpecuniary ESG performance. Suppose that, in times of poor market performance, traditional investors exit ESG funds at faster rate than ESG investors, leading to an increase in the share of ESG investors holding these funds. ESG investors prefer holding ESG stocks and consequentially hold more of their wealth in ESG stocks than traditional investors. In addition, if the ESG fund caters to changes in its investors' preferences by increasing the weight of ESG stocks in its portfolio, then the end allocation comprises a larger share of ESG stocks in the fund's portfolio. Thus, following the outflows accompanying the market downturn, ESG funds display relatively lower net sales of ESG stocks than of non-ESG stocks. With inflows, a symmetric mechanism applies. We refer to this hypothesis as the ESG clientele hypothesis.

There is evidence consistent with the assumptions underlying the clientele hypothesis, some of which is already cited in the introduction. First, ESG investors tend to be more long term

(Starks, Venkat, and Zhu (2023)) and respond less to fund performance (Renneboog et al. (2011) and Bollen (2007) show that investors' redemption decisions in ESG funds display a lower sensitivity to fund performance.) Second, there is evidence that households tilt their portfolios less to ESG stocks than other investors (Pastor, Stambaugh, and Taylor (2023)), and that, during the COVID crash, ESG funds experienced a sharper decline in retail flows unrelated to fund performance (Döttling and Kim (2024)).

The fourth hypothesis considers the possibility that ESG and conventional funds display a lower sensitivity of net purchases for their ESG stock portfolios than they do to their non-ESG stock portfolios (before or during the crash). For example, before the crash, the sensitivity of net purchases of ESG stocks in response to fund flows differs from that of non-ESG stocks by  $\gamma_{G,1} + \gamma_{G,6} - \gamma_{B,1} - \gamma_{B,6}$  for ESG funds, and by  $\gamma_{G,1} - \gamma_{B,1}$  for conventional funds. The null hypothesis of no difference in sensitivities is obtained from the benchmark model, where, for example,  $\gamma_{G,1} + \gamma_{G,6} = \gamma_{B,1} + \gamma_{B,6} = 1$ . An alternative hypothesis for ESG funds that  $\gamma_{G,1} + \gamma_{G,6} - \gamma_{B,1} - \gamma_{B,6} < 0$  is obtained from the above hypothesis on the dynamics of the ESG clientele during market booms and busts. In contrast, we conjecture that conventional funds treat ESG and non-ESG stocks differentially due to the higher idiosyncratic volatility and the higher beta of non-ESG stocks (Luo and Bhattacharya (2009) and Albuquerque et al. (2019)). One possible hypothesis, which we refer to as the risk hypothesis, is that, with large outflows, conventional funds develop a risk-off attitude and become net sellers of stocks with high idiosyncratic volatility and beta; whereas, with large inflows, they turn to a risk-on attitude and become net buyers of stocks with high idiosyncratic volatility and beta. This behavior gives rise to the alternative hypothesis,  $\gamma_{G,1} - \gamma_{B,1} < 0$ .

### III Data

Our sample spans from January 2019 to March 2020. Following Pastor and Vorsatz (2020), and others, we let February and March 2020 be the COVID-19 crash months. Pastor and Vorsatz (2020) note that the S&P 500 index dropped 34% from February 19 to March 23, 2020, and observe that fund flows had decreased for most fund types since approximately the beginning of the third week of February. Thus, the period from January 2019 to January 2020 is the pre-crash or normal period, and the months of February and March of 2020 constitute the crash period. The dummy variable *Crash* identifies the crash period.

Our main data source for mutual fund holdings is Morningstar historical holdings, a proprietary dataset that provides monthly portfolio holdings collected from mutual funds and exchange-traded funds domiciled in more than 50 countries. The data are collected from open-end funds that invest in equities, fixed income, and other asset classes (e.g., commodities, convertible bonds, and housing properties). The funds report all positions held, such as stocks, bonds, cash, and alternative investments, including derivative positions. We obtain monthly portfolio information for all actively managed U.S. equity mutual funds with disclosed ISIN identifiers available for their portfolio stocks. From the universe of funds in the Morningstar historical holdings dataset, we select those funds for which at least 80% of the portfolio is disclosed.

We merge the data with Morningstar Direct using FundID. After removing funds not domiciled in the U.S., we have 7,548 unique funds representing \$15.3 trillion total net assets (TNA) as of December 2018. We remove index funds using the Morningstar Direct identifier for active versus passive funds, leaving a sample of 7,099 unique funds with \$11.5 trillion TNA. After excluding non-equity fund categories (e.g., allocation, fixed income), we obtain 3,385 unique mutual funds with \$5.6 trillion TNA. We also take out all of the funds that do not have monthly data, resulting in a sample of 1,815 unique actively managed mutual funds with \$2.7 trillion of TNA. We have verified that the samples before and after applying the monthly filter appear



similar. As a final filter, we remove funds for which we cannot compute the churn ratio (which requires at least 25 months of past data). Our final sample has 1,699 unique mutual funds with TNA of \$2.6 trillion as of December 2018. This sample contains a monthly average of just under 27,000 stock positions across all funds.

Due to the granularity of the dataset at fund and ISIN level on quantities and prices, we can compute net purchases for each stock and then aggregate to either fund level, like Cella et al. (2013), or stock-portfolio level. Aggregate net purchases,  $NET\_PURCHASES_{i,t}$ , equals the sum across all stocks held by fund  $i$  of gross purchases minus gross sales during month  $t$  as a percentage of the fund's total net assets at the end of month  $t - 1$ . We include in this calculation all equities, both U.S. and non-U.S., traded by U.S. mutual funds. In the online appendix (Figure OA.1), we verify graphically the parallel trends assumption of similar behavior of net purchases by ESG and conventional funds prior to the crash.

Firm-level ESG metrics are obtained from Sustainalytics ESG Risk Ratings. We identify stocks as ESG stocks if their combined ESG risk score falls in the bottom quartile, where the combined risk score equals the average between the environment, social, and governance risk scores as of December 2018. We reset the ESG stock classification every six months.<sup>9</sup> We compute net purchases of ESG stocks,  $NET\_PURCHASES_{G,i,t}$  ( $NET\_PURCHASES_{B,i,t}$  for non-ESG stocks) in the same fashion that we did for aggregate net purchases, though, as suggested

---

<sup>9</sup>We use Sustainalytics data, despite Sustainalytics's small market share, because it offers one main advantage over all other ratings: the Globe ratings classification uses Morningstar Sustainalytics ratings; if a fund wants to remain with a high Globe rating, then it must follow Morningstar rating guidelines. As an alternative, we obtain firm-level ESG metrics from Refinitiv. We focus on the average of the environment and social scores in 2019 and omit the governance score following Albuquerque et al. (2020). We identify ESG stocks as those with an ES score in the top quartile of the distribution. The results from the analysis using Refinitiv data are in Tables OA.5 and OA.6 in the online appendix and are generally unchanged.

by the model, we use as denominator the dollar value of ESG stocks (non-ESG stocks) in the fund's portfolio.

We collect two indicators of funds' environmental, social, and governance performance from Morningstar Direct. First, we label as ESG funds those with Morningstar Sustainability Globe 5 rating. Second, we define ESG funds as those that receive a Low Carbon Designation from Morningstar. We define conventional funds as the complementary set of funds constructed in reference to each of the above classifications. This means, for example, that we do not exclude Globe 5 funds from the list of conventional funds when the ESG criterion is low-carbon funds. Morningstar's Globe ratings and Low Carbon Designation are updated monthly on the basis of a fund's portfolio holdings over the previous 12 months. This classification relies on the assumption that portfolio holdings reveal the preference of fund managers. (Gantchev, Giannetti, and Li (2024) demonstrate that mutual fund managers are aware of potential benefits to and costs of owning ESG stocks.) We use the ESG fund classification as of December 2018 for the following six months of data and reset this classification every six months. The December 2018 TNA of funds with Globe 5 rating is \$253 billion, and the TNA of funds with the Low Carbon Designation is \$879 billion.

The Low Carbon Designation is especially interesting since we cannot classify funds solely based on their E designation, because Morningstar classifies funds as ESG funds, i.e., including social and governance attributes. By using the Low Carbon Designation, we can focus on one of the most important dimensions for institutional investors in the environment component in ESG, namely the climate risk associated with carbon emissions. As Pastor and Vorsatz (2020) indicate, investors appear to favor environmental funds even more during the crash. Moreover, Garel and Petit-Romec (2021) find that stocks with high emission reduction scores perform better during the crash than other funds. In addition, the findings of Ceccarelli, Ramelli, and Wagner (2023) suggest that investors prefer low-carbon funds, and likewise Anderson and Robinson (2021) show that climate-conscious investors tilt their retirement portfolios toward greener investments.

Of note, only 4.5% of the funds have both a Low Carbon Designation and a Globe 5 rating (untabulated). The pairwise correlation between a Globe 5 rating dummy and a Low Carbon Designation dummy is 0.15 (untabulated).

The main independent variable in our panel regressions is  $FUND\_FLOWS_{i,t}$ , fund flows normalized by lagged TNA (denoted as  $FF_{i,t}$  in the model section for simplicity of notation there). Figures 1 and 2 display box plots of monthly fund flows from January 2019 to March 2020 for both ESG funds (Globe 5 rated and Low Carbon Designation funds, respectively) and conventional funds. The rectangular area in the plots marks the cross-sectional interquartile range of fund flows and the line inside marks the median value of fund flows. Median flows into Globe 5 funds are largely stable prior to the crash, whereas conventional funds show a decrease in median flows up to the crash. Both fund types show a significant decrease in median flows in March 2020, with an increase in the cross sectional dispersion of flows. Changes during the crash appear mostly driven by the intensive margin: the fraction of Globe 5 (conventional) fund-month observations experiencing outflows is 57.4% (69.8%) during the crash, not too different from the value prior to the crash of 54.7% (68%). The plots for low-carbon funds are similar. For them, the intensive margin also appears to dominate: the fraction of low-carbon (conventional) fund-month observations experiencing outflows is 70% (68.2%) during the crash, not too different from the value prior to the crash of 65.3% (67.1%). On average, fund flows to Globe 5 and low-carbon funds during the sample period are 0.0032% and  $-0.08\%$  per month, respectively (see Table 1). These patterns have been shown elsewhere (e.g., Pastor and Vorsatz (2020) for Globe rated funds) and are confirmed here for our sample of funds with available monthly holdings data.

[Insert Figures 1 and 2 here]

Appendix Table A1 defines all the variables. Table 1 provides descriptive statistics for our full sample and for subsamples by ESG fund designation for the main variables. Of note is the higher asset allocation to ESG stocks by ESG funds compared to conventional funds, a fact we return to below. For example, Globe 5 rated funds allocate 49% of their portfolio to ESG stocks,

whereas conventional funds allocated only 33% of their portfolio to ESG stocks (the difference in means is statistically significant at the 1% level).

[Insert Table 1 here]

## IV Results

We first report results for fund-level aggregate net purchases and then report results on net purchases of ESG and non-ESG stocks by fund.

### A Aggregate net purchases

Here we present results regarding the first of the above hypotheses. Table 2 contains the estimates from four different regressions of fund-level `NET_PURCHASES` on `FUND_FLOWS` as well as controls and fixed effects as detailed above. In columns (1) and (2), we label a fund as an ESG fund if it has a Morningstar Globe 5 rating, and in columns (3) and (4), the ESG label is given to Morningstar low-carbon funds. For each ESG fund designation, we report two sets of regressions: with and without contemporaneous market returns and market return volatility and lagged fund returns and liquidity.

[Insert Table 2 here]

Consider first the results shown in column 2 in Table 2 (panels A and B) for Globe 5 funds. Prior to the crash, the estimated coefficient associated with `FUND_FLOWS` for conventional funds is 0.9747, for which we reject the hypothesis that it is 0 at 1% level but cannot reject the hypothesis that it is 1 at the 5% level. The coefficient for ESG funds is marginally smaller (0.0004 smaller). This evidence suggests that, prior to the crash, both types of funds maintain constant shares of stocks versus cash after fund flows, consistent with the benchmark model. This evidence is also consistent with that of Lou (2012).

We then analyze how the crash months change the sensitivity of aggregate net purchases to fund flows. We find that the trading sensitivities of ESG and conventional funds dramatically change, especially conventional funds. In column 2, during the crash, conventional funds increase their net buying of stocks per unit of flow by 0.2887, and Globe 5 funds increase their net buying of stocks per unit of flow by  $0.1920 = 0.2887 - 0.0967$ . The increase to a trading sensitivity above 1 is consistent with an increase in fund cash per unit of outflow, all else equal. The differential change across Globe 5 and conventional funds is  $-0.0967$ , statistically significant at the 5% level. This means that Globe 5 funds are less aggressive net buyers when they experience inflows during the crash but, more importantly, less aggressive net sellers when they face redemptions, relative to conventional funds. The results obtained when we use Morningstar's Low Carbon Designation to classify ESG funds (column 4, panels A and B) are almost identical to those of Globe 5 funds.

Lastly, consider the effect of the control variables. Prior to the crash, larger funds tended to have higher net purchases, controlling for flow. During the crash, this effect is amplified somewhat for conventional funds but not for Globe 5 funds. When we use the Low Carbon Designation, the effect of size on net purchases is amplified during the crash for all fund types. Market returns have no effect on net purchases, but higher volatility of aggregate stock market returns is associated with more net sales at the fund level. Including own-fund and market returns and market volatility as we do in columns 1 and 3, does not change the results.

## **B Net purchases of ESG and non-ESG stocks**

In this subsection, we split fund aggregate net purchases into net purchases of ESG stocks and non-ESG stocks. The results of estimating equation (8) are in Table 3. Consider the coefficients associated with fund flows and, for now focus, on the results on Globe 5 funds in column 1 in panel A and columns 1 and 2 in panel B, leaving the discussion of Low Carbon Designation

funds for last. We first address the trading sensitivities in normal times, then during the crash, and finally the change from normal times to the crash.

[Insert Table 3 here]

Consider first the trading sensitivities during normal times. For conventional funds, the sensitivity of NET\_PURCHASES of ESG stocks to FUND\_FLOWS is 0.8588, whereas the sensitivity of NET\_PURCHASES of non-ESG stocks to FUND\_FLOWS is 1.0302; the difference in sensitivities is 0.1714 with a t-statistic of 6.48. For Globe 5 funds, in normal times, the trading sensitivities of ESG and non-ESG stocks display a similar pattern to those of conventional funds. The sensitivities are 0.8149 and 1.0764, respectively, and their difference has a t-statistic of 3.24. In summary, we cannot reject that the sensitivity of net purchases of non-ESG stocks to flows equals one (at the 5% significance), as predicted by the benchmark model, and we cannot reject that this sensitivity exceeds that for ESG stocks.<sup>10</sup> As discussed above, for ESG funds, this differential pattern could be explained by the clientele hypothesis; whereas for conventional funds, the same pattern can arise from the changing risk attitudes of fund managers, which we call the risk hypothesis. The following tests can help us further understand the role of the clientele hypothesis in explaining the trading patterns of ESG funds.

During the crash, Globe 5 and conventional funds have sensitivities of net purchases of ESG stocks to fund flows of 0.9069 and 0.9869, respectively (each statistically insignificantly different from one at standard levels). For non-ESG stocks, the sensitivities are 1.3287 and 1.2781 for Globe 5 and conventional funds, respectively. For Globe 5 funds the difference in

---

<sup>10</sup>One could ask whether, in the presence of outflows, the ESG-stocks share in ESG and conventional funds is growing during the period. The actual share of ESG stocks in a fund changes for many reasons, one of which is fund flows. In the data, we observe a decrease from the pre-crash period to the crash in the average share of ESG stocks for all funds. Globe 5 funds (conventional) see a decrease of 11 p.p. (6 p.p.). Low-carbon funds (conventional) see a decrease of 7.7 p.p. (6.5 p.p.)

sensitivities is 0.4218 with a t-statistic of 3.64, and for conventional funds, the difference in sensitivities is 0.2912 with a t-statistic of 5.22. Despite the increase in sensitivities during the crash, the evidence remains consistent with the hypothesis that net purchases of ESG stocks display a lower sensitivity to flows relative to non-ESG stocks. Since Globe 5 and conventional funds experience outflows on average, at least in March 2020, these results suggest that both fund types on average are net sellers during the crash, especially of non-ESG stocks.

We now turn to how the trading sensitivities *change* from normal times to the crash, i.e., the difference-in-difference analysis. For non-ESG stocks, both fund types increase their trading sensitivities during the crash. The increase for conventional funds is 0.2480, and for Globe 5 funds is 0.2523, with both changes significant at the 1% level. The difference between the two sensitivities (0.0044) is small and statistically insignificant. To appreciate the finding of an insignificant difference-in-differences coefficient estimate, note that the benchmark model suggests that, by using conventional funds as the control group, the analysis controls for changes in expected returns. That is, after controlling for possible changes in expected returns during the crash, there is no statistically significant difference in the way that Globe 5 and conventional funds change the sensitivity of net purchases of non-ESG stocks to fund flows. For ESG stocks, the change in sensitivity of net purchases to flows for globe 5 funds is small (0.0920) and insignificant, but the change in sensitivity of net purchases to flows for conventional funds is larger (0.1281) and significant at the 1% level. The difference-in-differences coefficient equals  $-0.0361$  and is statistically insignificant. The large trading sensitivities during the crash months constitute a rejection of the constant-portfolio-share hypothesis. However, because the difference-in-differences coefficient estimates for ESG stocks and non-ESG stocks are not statistically significantly different from zero, the evidence for Globe 5 funds is inconsistent with the clientele hypothesis.

The evidence for low-carbon funds resembles that for Globe 5 funds during normal times and the crash. The difference-in-differences coefficient estimate for non-ESG stocks is not statistically

significantly different from zero, but it is significant for ESG stocks. This evidence regarding ESG stocks is consistent with the clientele hypothesis, with low-carbon funds increasing the weight on ESG stocks following outflows during the crash.<sup>11</sup>

Overall, our findings suggest that conventional and ESG funds have significantly higher trading sensitivity for non-ESG stocks and change their trading sensitivities for all stocks in the same way going into the crash.

We can now relate the findings from this section to those from section A, which reports on fund aggregate net purchases. ESG stocks display lower trading sensitivities to fund flows than do non-ESG stocks, and since ESG funds have greater allocations of ESG stocks (see Table 1), ESG funds have lower trading sensitivities to fund flows at the aggregate level. The marked differences we find across ESG and conventional funds are not due to their stock-level trading sensitivities in response to fund flows. Instead, they are due to their share allocation between ESG versus non-ESG stocks.

With respect to the control variables, we emphasize the the effect of market return volatility. Market volatility decreases net purchases for non-ESG stocks but not for ESG stocks. This evidence is consistent with the joint assumptions linked to the risk hypothesis that non-ESG stocks have higher volatility (as discussed in the literature cited above) and that, in volatile times, fund managers develop a risk-off attitude and become net sellers of stocks with higher volatility. (This hypothesis is formulated at the end of subsection II.C.)

Some of our results may be influenced by the fact that our analysis reuses a natural experiment that others have already used. Heath, Ringgenberg, Samadi, and Werner (2023) show that this concern may result in an overestimation of t-statistics. In our case, the finding that changes in

---

<sup>11</sup>Preempting the results from the next subsection, where we separate inflows from outflows, the difference-in-differences estimates are insignificant across low-carbon and conventional funds for ESG stocks as well.



trading sensitivities of stock portfolios by ESG and conventional funds during the crash do not differ statistically are therefore unlikely to change.

## **C Analysis of inflows and outflows**

In Table 4, we present results for aggregate net purchases (equation (9)) after separating fund flows into inflows (i.e., positive FUND\_FLOWS) and outflows (i.e., the symmetric of negative FUND\_FLOWS) for each fund type. This analysis is especially relevant since most funds experience outflows through the period, rather than a mix of inflows and outflows. The table shows that the aggregate portfolio result that the sensitivity of net purchases to fund flow increases more for conventional funds than to ESG funds during the crash is due to outflows. Conventional funds increase the net selling to outflows from normal times to the crash period more than Globe 5 funds by 0.2920, significant at the 1% level. The difference-in-differences estimate is 0.1578 for low-carbon funds, significant at the 10% level.

[Insert Table 4 here]

In Table 5, we present results for net purchases of ESG and non-ESG stocks (equation (8)), again separating fund flows into inflows and outflows for each type. The main results are i) trading sensitivities for non-ESG stocks are close to 1 for inflows and -1 for outflows for conventional funds before the crash months, consistent with the constant-portfolio share hypothesis; ii) trading sensitivities following inflows or outflows are higher (in absolute value) for non-ESG stocks than for ESG stocks across all fund types, consistent with the risk hypothesis; and iii) the difference in changes in trading sensitivities from normal times to the crash period between ESG and conventional funds is statistically insignificantly different from zero. Thus, we conclude that ESG and conventional funds trade similarly in response to fund inflows and outflows. This is inconsistent with the ESG clientele hypothesis.

[Insert Table 5 here]

## V Robustness checks

### A Morningstar star rated funds

We conduct a placebo test by redoing the analysis with high star-rated funds. High star-rated funds, which we define as having four or five Morningstar stars, receive net inflows of 0.07% on average (box plot of net flows is in Figure 3) just as Globe 5 funds do. Because of the net inflows, high star-rated funds are arguably less constrained in their trading than low-carbon funds and similar to Globe 5 rated funds in that respect. To isolate our analysis from an ESG effect, we exclude Globe 5 funds, low-carbon funds, and funds that identify themselves as ESG on their prospectuses. Like conventional funds, low star-rated funds (with three or fewer stars) experience significant outflows on average (Pastor and Vorsatz (2020)). However, importantly, the portfolio weight that star-rated funds allocate to ESG stocks is much more in line with that of conventional funds. High star funds have a 29.6% weight on ESG stocks and low star funds have a 31.7% allocation to ESG stocks.

[Insert Figure 3 here]

Table 6 contains a summary of the results. Columns 1 and 2 of Table 6 replicate the estimations in Table 2 for aggregate net purchases, and columns 3 and 4 replicate the estimations conducted in Table 3 with the breakdown between net purchases of ESG and non-ESG stocks. In columns 1 and 2, we find that the change in sensitivity of aggregate net purchases of high star-funds from normal times to the crash period is not statistically different from that of low star-rated funds (differences-in-difference coefficient of 0.1114, insignificant at usual levels in column 2). This contrasts with evidence for ESG funds that responded more conservatively than conventional funds when the crash occurred.

[Insert Table 6 here]

Turning to columns 3 and 4, we find that high and low star funds both display a lower trading sensitivity for ESG stocks compared to the trading sensitivity for non-ESG stocks, just as we found for ESG and conventional funds. This finding suggests that funds generally treat their non-ESG portfolio differently, consistent with the risk hypothesis of changing fund manager attitudes toward risk. Finally, the differences-in-difference coefficients also display no statistical significance, as shown in the last row of panel B, just as it was the case in Table 3.<sup>12</sup>

The documented similarity in aggregate net purchases across high and low star funds can be attributed to the funds' portfolio shares. High star funds allocate a similar percentage of their portfolio to ESG stocks as low star funds and thus have similar sensitivities of aggregate net purchases to flows. In contrast, ESG funds have larger shares of ESG stocks in their portfolios than conventional funds and thus have lower sensitivities of aggregate net purchases to flows.

## **B Fund investment horizon**

One of our main findings is that the sensitivity of net purchases for ESG stocks is lower than that for non-ESG stocks, for both conventional and ESG funds. Because we cannot reject the possibility that ESG and conventional funds have equal changes in trading sensitivities, we find no support in favor of the clientele hypothesis concerning funds' trading. Above, we argued, in line with the risk hypothesis, that changes in fund managers' risk attitudes explain the lower sensitivity of net purchases to ESG stocks versus that for non-ESG stocks.

Here we consider yet another possibility<sup>13</sup> that it is the investors' horizon that gives rise to our result. This hypothesis is motivated by two pieces of evidence: Cella et al. (2013) show

---

<sup>12</sup>Table OA.1 in the Online Appendix presents the breakdown between inflows and outflows. These results are quite similar to those obtained in the main analysis, meaning that the differences in trading sensitivities across high and low star-rated funds in response to inflows and outflows are not qualitatively different from those of ESG versus conventional funds.

<sup>13</sup>We also conduct our analysis excluding oil and gas firms. Oil prices declined sharply in the first half of 2020,

that, during market turmoil, long-term institutional investors trade their holdings less than other investors, and long-term investors tend to prefer ESG stocks (Starks et al. (2023)).

Following Cella et al. (2013), we proxy the trading horizon of institutional investors by their churn ratio, a portfolio turnover measure formalized by Gaspar, Massa, and Matos (2005), and denote it by FUND\_CHURN ratio to distinguish it from the stock-level FIRM\_CHURN ratio variable. A high FUND\_CHURN indicates a short trading horizon by the fund's investors. Table 1 shows that the average FUND\_CHURN for all mutual funds in our sample is 0.1124. The FUND\_CHURN is lower for all ESG funds (0.0905 for Globe 5 funds and 0.1028 for low-carbon funds). Hence conventional funds have on average shorter trading horizons, consistent with Starks et al. (2023).

Table OA.4 in the online appendix presents the results for net purchases of ESG stocks and non-ESG stocks. Before the crash, conventional funds and low-carbon funds generally display no sensitivity of net purchases to fund investor horizon. During the crash, all funds with historically shorter horizons sold relatively more of both ESG and non-ESG stocks and, importantly, with no significant difference across ESG and conventional funds. Otherwise, the main findings regarding the sensitivity of net purchases to fund flows are unchanged: for all funds, the trading sensitivities for non-ESG stocks are higher than for ESG stocks, and the difference-in-differences coefficient estimates all differ insignificantly from zero (again with the exception of low-carbon funds for ESG stocks, though this effect disappears when flows are split between inflows and outflows).

---

so outflows from those firms could relate to the oil price change and not to low ESG ratings. Results remain qualitatively the same.

## VI Conclusion

This paper uses the exogenous stock market crash of February and March of 2020 as a quasi-natural experiment to study changes in trading across ESG and conventional mutual funds when most funds experience significant outflows. We develop an empirical model to study trading that is unrelated to changes in expected returns: we aim to capture trading that is motivated by an ESG clientele effect, driven partly by nonpecuniary preferences. We find that ESG and conventional funds trade similarly: the trading sensitivities are lower for the ESG stock portfolio than for the non-ESG stock portfolio for both fund types. While the evidence in this respect for ESG funds is consistent with a clientele hypothesis, this hypothesis does not explain why we find a similar pattern for conventional funds. In addition, the clientele hypothesis also does not explain why we cannot reject that the change in trading sensitivities during the crash for ESG funds equals those of conventional funds.

In contrast to these stock-portfolio-level results, we find that, during the crash, aggregate net purchases of ESG funds are less sensitive to flows than aggregate net purchases of conventional funds. We argue that the similarities in trading sensitivities at the stock-portfolio level are consistent with the differences in trading sensitivities at the aggregate level because ESG funds have a higher portfolio weight on the less actively traded ESG stocks. Thus ESG funds differ from conventional funds in their portfolio allocation decisions, while their trading in response to flows is remarkably similar. The ESG clientele effect thus manifests primarily through fund holdings.

Our results may be viewed as illuminating why ESG funds performed relatively well during the crash: They had a larger allocation to less risky ESG stocks when the crash occurred. It would be interesting to examine these issues and mechanisms using European actively managed equity mutual fund data, since ESG investing is more prevalent in Europe, and actively managed funds are more dominant there than in the U.S. We leave that for further study.

## References

- Albuquerque, R.; Y. Koskinen; S. Yang; and C. Zhang. “Resiliency of environmental and social stocks: An analysis of the exogenous COVID-19 market crash.” *Review of Corporate Finance Studies*, 9 (2020), 593–621. ISSN 2046-9128. 10.1093/rcfs/cfaa011.
- Albuquerque, R.; Y. Koskinen; and C. Zhang. “Corporate social responsibility and firm risk: Theory and empirical evidence.” *Management Science*, 65 (2019), 4451–4469.
- Anderson, A., and D. T. Robinson. “Climate fears and the demand for green investment.” Swedish House of Finance Research Paper.
- Baker, M.; M. L. Egan; and S. K. Sarkar. “How do investors value ESG?” (2024).
- Bauer, R.; T. Ruof; and P. Smeets. “Get real! Individuals prefer more sustainable investments.” *Review of Financial Studies*, 34 (2021), 3976–4043. 10.1093/rfs/hhab037.
- Ben-David, I.; J. Li; A. Rossi; and Y. Song. “What do mutual fund investors really care about?” *Review of Financial Studies*, 35 (2022), 1723–1774. ISSN 0893-9454. 10.1093/rfs/hhab081.
- Bollen, N. P. B. “Mutual fund attributes and investor behavior.” *Journal of Financial and Quantitative Analysis*, 42 (2007), 683–708. ISSN 00221090, 17566916.
- Ceccarelli, M.; S. Ramelli; and A. F. Wagner. “Low carbon mutual funds.” *Review of Finance*, 28 (2023), 45–74.
- Cella, C.; A. Ellul; and M. Giannetti. “Investors’ horizons and the amplification of market shocks.” *Review of Financial Studies*, 26 (2013), 1607–1648. ISSN 0893-9454. 10.1093/rfs/hht023.
- Chari, A.; K. Dilts Steadman; and C. Lundblad. “Risk-on/risk-off: Measuring shifts in investor

- sentiment.” (2024). KC FED Working Paper No. 24-12.
- Chernenko, S., and A. Sunderam. “Liquidity transformation in asset management: Evidence from the cash holdings of mutual funds.” (2016). 10.3386/w22391.
- Ding, W.; R. Levine; C. Lin; and W. Xie. “Corporate immunity to the COVID-19 pandemic.” *Journal of Financial Economics*, 141 (2021), 802–830.
- Döttling, R., and S. Kim. “Sustainability preferences under stress: Evidence from COVID-19.” *Journal of Financial and Quantitative Analysis*, 59 (2024), 435–473. 10.1017/S0022109022001296.
- Edmans, A.; T. Gosling; and D. Jenter. “Sustainable investing: Evidence from the field.” (2024).
- Gantchev, N.; M. Giannetti; and R. Li. “Sustainability or performance? Ratings and fund managers’ incentives.” *Journal of Financial Economics*, 155 (2024), 103831.
- Garel, A., and A. Petit-Romec. “Investor rewards to environmental responsibility in the COVID-19 crisis.” *Journal of Corporate Finance*, 68 (2021), 101948.
- Gaspar, J.-M.; M. Massa; and P. Matos. “Shareholder investment horizons and the market for corporate control.” *Journal of Financial Economics*, 76 (2005), 135–165.
- Giglio, S.; M. Maggiori; J. Stroebe; Z. Tan; S. Utkus; and X. Xu. “Four facts about ESG beliefs and investor portfolios.” *Journal of Financial Economics*, 164.
- Hartzmark, S. M., and A. B. Sussman. “Do investors value sustainability? A natural experiment examining ranking and fund flows.” *The Journal of Finance*, 74 (2019), 2789–2837. <https://doi.org/10.1111/jofi.12841>.
- Heath, D.; M. C. Ringgenberg; M. Samadi; and I. M. Werner. “Reusing Natural Experiments.” *The Journal of Finance*, 78 (2023), 2329–2364. <https://doi.org/10.1111/jofi.13250>.

- Humphrey, J.; S. Kogan; J. Sagi; and L. Starks. “The asymmetry in responsible investing preferences.” (2023). 10.3386/w29288.
- Lins, K. V.; H. Servaes; and A. Tamayo. “Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis.” *The Journal of Finance*, 72 (2017), 1785–1821.
- Lou, D. “A flow-based explanation for return predictability.” *Review of Financial Studies*, 25 (2012), 3457–3489. ISSN 0893-9454. 10.1093/rfs/hhs103.
- Luo, X., and C. Bhattacharya. “The Debate over Doing Good: Corporate Social Performance, Strategic Marketing Levers, and Firm-Idiosyncratic Risk.” *Journal of Marketing*, 73 (2009), 198–213. 10.1509/jmkg.73.6.198.
- Nofsinger, J., and A. Varma. “Socially responsible funds and market crises.” *Journal of Banking and Finance*, 48 (2014), 180–193. ISSN 0378-4266. <https://doi.org/10.1016/j.jbankfin.2013.12.016>.
- Pastor, L.; R. F. Stambaugh; and L. A. Taylor. “Sustainable investing in equilibrium.” *Journal of Financial Economics*, 142 (2021), 550–571.
- Pastor, L.; R. F. Stambaugh; and L. A. Taylor. “Green tilts.” *SSRN Electronic Journal*.
- Pastor, L., and M. B. Vorsatz. “Mutual fund performance and flows during the COVID-19 crisis.” *Review of Asset Pricing Studies*, 10 (2020), 791–833.
- Pedersen, L. H.; S. Fitzgibbons; and L. Pomorski. “Responsible investing: The ESG-efficient frontier.” *Journal of Financial Economics*, 142 (2021), 572–597.
- Ramelli, S., and A. F. Wagner. “Feverish stock price reactions to COVID-19.” *Review of Corporate Finance Studies*, 9 (2020), 622–655. ISSN 2046-9128. 10.1093/rcfs/cfaa012.



Renneboog, L.; J. Ter Horst; and C. Zhang. “Is ethical money financially smart? Nonfinancial attributes and money flows of socially responsible investment funds.” *Journal of Financial Intermediation*, 20 (2011), 562–588.

Rzeznik, A.; K. W. Hanley; and L. Pelizzon. “Investor reliance on ESG ratings and stock price performance.” SAFE Working Paper No. 310.

Starks, L. T. “Presidential Address: Sustainable Finance and ESG Issues—Value versus Values.” *The Journal of Finance*, 78 (2023), 1837–1872. <https://doi.org/10.1111/jofi.13255>.

Starks, L. T.; P. Venkat; and Q. Zhu. “Corporate ESG profiles and investor horizons.” SSRN Electronic Journal.

FIGURE 1

**FUND.FLOWS** when ESG funds are funds with Morningstar Globe 5 sustainability rating. This figure presents box plots of monthly flows divided by lagged TNA from January 2019 to March 2020 for funds that receive Morningstar Globe 5 rating (ESG funds) and all others (conventional funds). The rectangular area marks the interquartile range and the line inside marks the median value. Outside values of fund flows are not plotted.

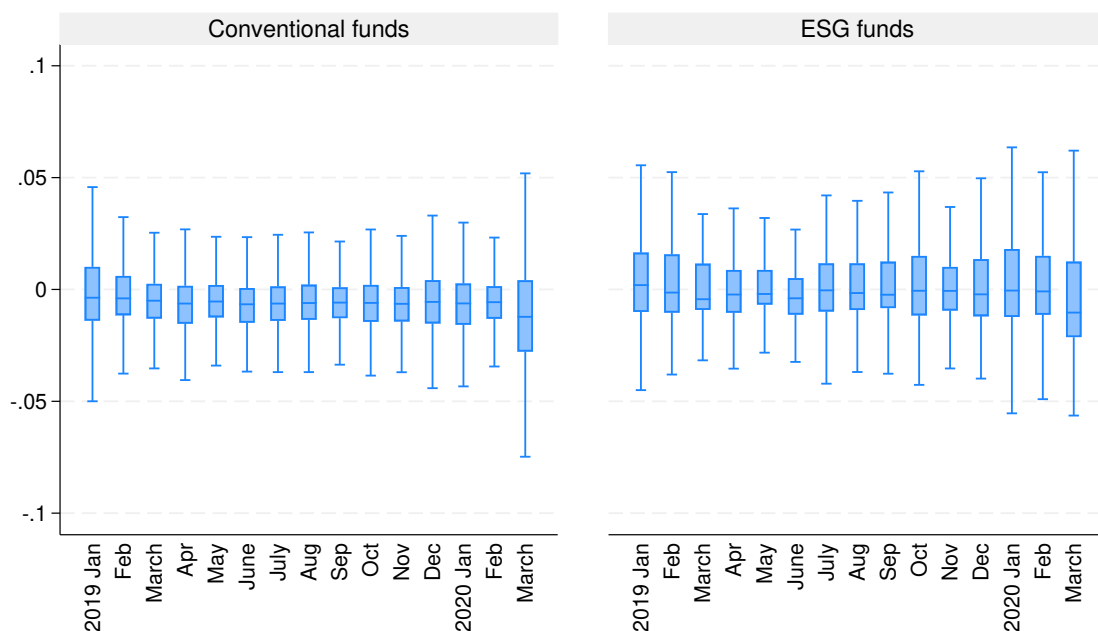


FIGURE 2

**FUND\_FLOWS** when ESG funds are funds with Morningstar Low Carbon Designation. This figure presents box plots of monthly flows divided by lagged TNA from January 2019 to March 2020 for funds that receive a Low Carbon Designation by Morningstar (ESG funds) and all others (conventional funds). The rectangular area marks the interquartile range and the line inside marks the median value. Outside values of fund flows are not plotted.

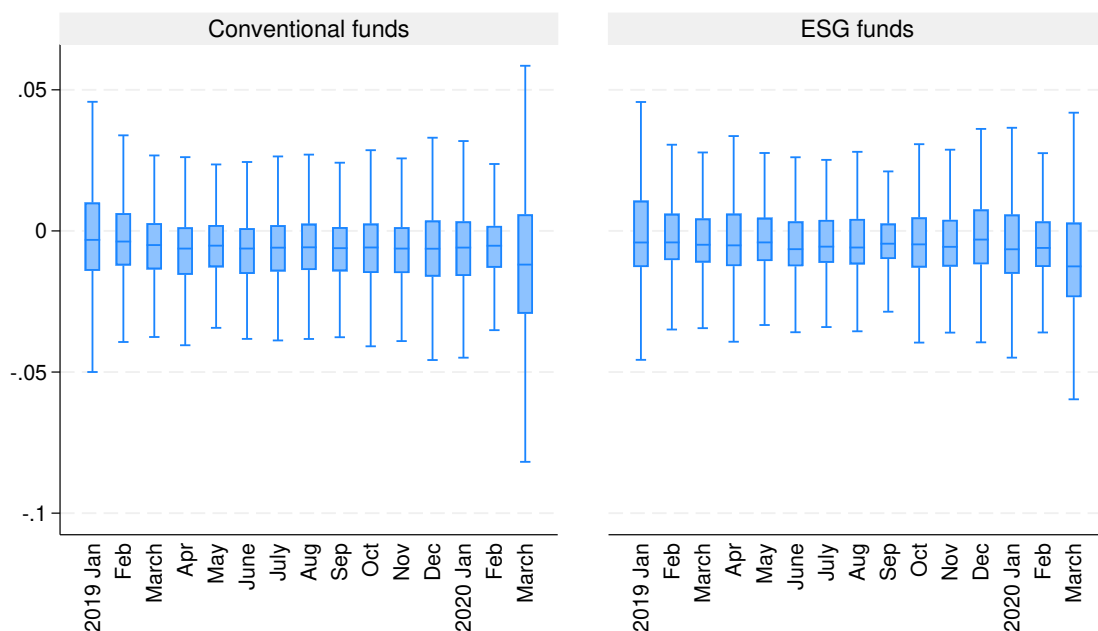


FIGURE 3

**FUND\_FLOWS** across different star rating classifications. This figure presents box plots of monthly flows divided by lagged TNA from January 2019 to March 2020 for funds that receive 4 or 5 Morningstar star ratings (high star funds) and all others (low star funds). We exclude those funds that satisfy one of the following conditions: (i) are identified as ESG in their prospectuses, (ii) receive Morningstar Globe 5 rating, (iii) receive a Low Carbon Designation from Morningstar. The rectangular area marks the interquartile range and the line inside marks the median value. Outside values of fund flows are not plotted.

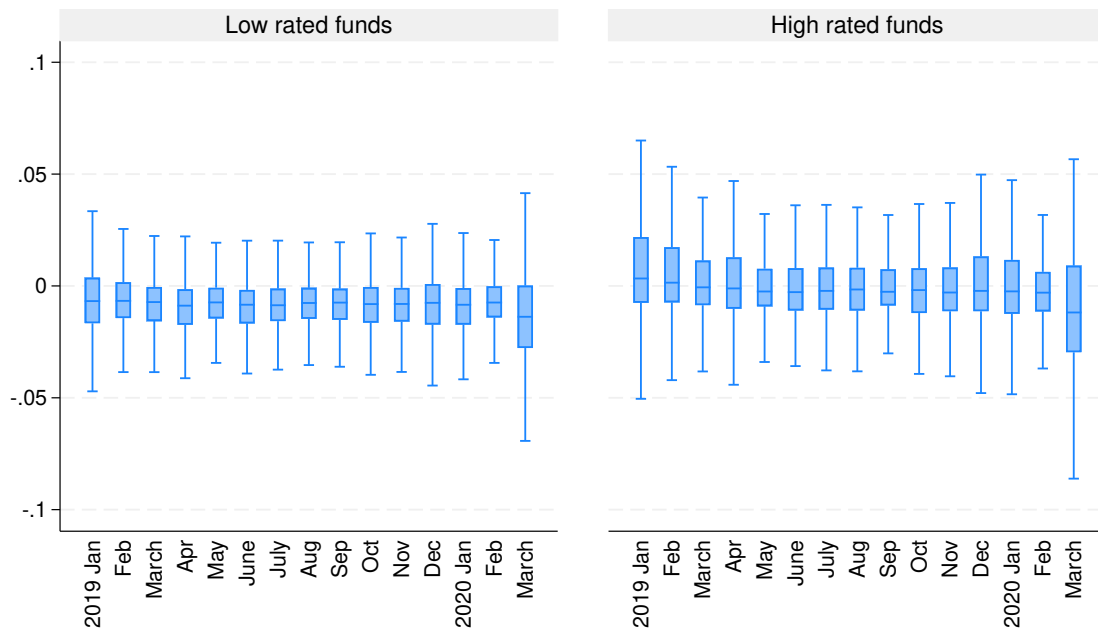


TABLE 1  
Summary Statistics

The table shows descriptive statistics for the variables used in the analysis. The sample includes all U.S. actively managed equity funds with monthly holdings data available from Morningstar historical holdings from January 2019 through March 2020. SD is the sample standard deviation, P05 is the 5th percentile, and P95 is the 95th percentile. Appendix Table A1 provides a description of the variables and units of measurement.

	N	Mean	SD	min	P05	Median	P95	max
<b>All Mutual Funds</b>								
NET_PURCHASES	23,738	-0.0046	0.0425	-0.6791	-0.059	-0.005	0.0531	0.3466
NET_PURCHASES ESG stocks	20,971	-0.0028	0.0624	-0.3202	-0.0965	-0.0005	0.096	0.3752
NET_PURCHASES non-ESG stocks	22,117	-0.0049	0.0526	-0.3186	-0.0827	-0.0049	0.0733	0.378
FUND_CHURN ratio	23,738	0.1124	0.0752	0.0043	0.0384	0.0961	0.2324	1.1704
FUND_FLOWS	23,738	-0.0035	0.0341	-0.2935	-0.0454	-0.0056	0.046	0.3304
FUND_SIZE	23,738	19.6632	2.0067	13.2611	16.2205	19.8301	22.7987	25.5394
FUND_RETURN	23,278	0.0053	0.0526	-0.2224	-0.0911	0.015	0.0828	0.2243
FUND_LIQUIDITY	22,776	0.002	0.2566	-25.6354	-0.0003	0	0.0403	0.2698
MARKET_RETURN	23,738	0.0022	0.0544	-0.1949	-0.1235	0.0194	0.0756	0.1079
MARKET_RETURN_VOLATILITY	23,738	0.0082	0.0096	0.0029	0.0031	0.0049	0.0306	0.0515
Share ESG Stocks	23,190	0.3477	0.1992	0	0.0186	0.3455	0.6674	0.9173
Share non-ESG Stocks	23,738	0.6603	0.2037	0.0827	0.3341	0.6608	0.9934	1
<b>ESG (5 Globes)</b>								
NET_PURCHASES	2,266	0.0027	0.0421	-0.3281	-0.0515	-0.0007	0.0655	0.2325
NET_PURCHASES ESG stocks	2,039	0.002	0.057	-0.2843	-0.0813	0	0.095	0.336
NET_PURCHASES non-ESG stocks	2,104	0.0043	0.0633	-0.3073	-0.0906	0.0023	0.1073	0.3664
FUND_CHURN ratio	2,266	0.0905	0.0557	0.0133	0.0252	0.0777	0.1996	0.4929
FUND_FLOWS	2,266	0.0032	0.0363	-0.266	-0.0369	-0.0019	0.0627	0.2363

(continued)

FUND_SIZE	2,266	19.6167	2.0047	13.3349	16.4645	19.4256	22.9019	24.174
FUND_RETURN	2,204	0.0073	0.0479	-0.1383	-0.0849	0.0175	0.0747	0.2046
FUND_LIQUIDITY	2,204	0.0083	0.0239	-0.0895	0	0	0.0528	0.2698
MARKET_RETURN	2,266	0.0027	0.0536	-0.1448	-0.1235	0.0194	0.0756	0.0801
MARKET_RETURN_VOLATILITY	2,266	0.008	0.0093	0.0029	0.0032	0.0049	0.0306	0.0493
Share ESG Stocks	2,226	0.4875	0.1954	0	0.0765	0.5179	0.7555	0.9007
Share non-ESG Stocks	2,266	0.5211	0.2041	0.0993	0.245	0.4905	0.9358	1
Share ESG Stocks (conventional funds)	20,496	0.3342	0.193	0	0.0177	0.3324	0.6431	0.9173
Share non-ESG Stocks (conventional funds)	20,927	0.6727	0.1968	0.0827	0.3587	0.674	0.9921	1
<b>ESG (Low Carbon Designation )</b>								
NET_PURCHASES	6,338	-0.0018	0.04	-0.6408	-0.0516	-0.0049	0.0593	0.2918
NET_PURCHASES ESG stocks	5,818	-0.0018	0.0572	-0.317	-0.0866	-0.001	0.0881	0.3752
NET_PURCHASES non-ESG stocks	5,878	-0.0025	0.0532	-0.3073	-0.0784	-0.0042	0.081	0.3767
FUND_CHURN ratio	6,338	0.1028	0.0577	0.0133	0.0378	0.09	0.1959	0.5917
FUND_FLOWS	6,338	-0.0008	0.0347	-0.266	-0.0395	-0.0053	0.0543	0.2618
FUND_SIZE	6,338	19.9483	1.9624	13.3349	16.5367	20.0052	22.9798	25.5394
FUND_RETURN	6,239	0.0092	0.0491	-0.1766	-0.0822	0.0191	0.0802	0.1467
FUND_LIQUIDITY	6,113	0.0042	0.1754	-13.6355	-0.0002	0	0.0375	0.2698
MARKET_RETURN	6,338	0.0011	0.0558	-0.1949	-0.1235	0.0194	0.0756	0.1079
MARKET_RETURN_VOLATILITY	6,338	0.0085	0.0101	0.0029	0.0031	0.0051	0.0389	0.0515
Share ESG Stocks	6,283	0.4224	0.1533	0	0.1286	0.4229	0.6684	0.9007
Share non-ESG Stocks	6,338	0.5812	0.1576	0.0993	0.3318	0.5787	0.8811	1
Share ESG Stocks (conventional funds)	16,871	0.3197	0.2067	0	0.0121	0.3	0.6664	0.9173
Share non-ESG Stocks (conventional funds)	17,364	0.6893	0.2106	0.0827	0.3363	0.7079	1	1

TABLE 2  
**Determinants of Aggregate Net Purchases**

The table reports regressions for NET\_PURCHASES at the fund level (Panel A) and  $t$ -tests on linear combinations of parameters (Panel B). The dependent variable in Panel A is NET\_PURCHASES, total dollar purchases less total dollar sales made by fund  $i$  during month  $t$  as a percentage of the total dollar holdings of fund  $i$  at the end of month  $t - 1$ . The sample is composed of all U.S. actively managed equity funds. The sample period is from January 2019 to March 2020. The variable *Crash* takes the value of one in February and March of 2020. The pre-determined *ESG* variable takes the value of one if the fund receives Globe 5 rating (columns 1 and 2) or Low Carbon Designation (columns 3 and 4) from Morningstar and is reset every 6 months. *FUND\_FLOWS* is the monthly change in net assets under management less the returns in month  $t$  divided by net assets under management at the end of month  $t-1$ . All control variables are defined in the Appendix (see Table A1). All models are estimated by ordinary least squares. Standard errors are White-corrected for heteroskedasticity and clustered at the fund level. Month and fund fixed effects included.  $p$ -values are in parentheses. \* indicates significance at 1% (\*\*\*), 5% (\*\*), 10% (\*).

Panel A: Coefficient estimates

VARIABLES	ESG (Globe 5)		ESG (Low Carbon)	
	(1)	(2)	(3)	(4)
Crash × ESG	0.0441** (0.020)	0.0465** (0.020)	0.0220 (0.016)	0.0170 (0.016)
Crash × FUND_FLOWS	0.3022*** (0.026)	0.2887*** (0.025)	0.3283*** (0.028)	0.3049*** (0.025)
Crash × FUND_FLOWS × ESG	-0.0990** (0.047)	-0.0967** (0.049)	-0.1351** (0.054)	-0.1219** (0.054)
Crash × Lagged FUND_SIZE	0.0024*** (0.000)	0.0024*** (0.000)	0.0026*** (0.000)	0.0026*** (0.000)
Crash × Lagged FUND_SIZE × ESG	-0.0022** (0.001)	-0.0024** (0.001)	-0.0010 (0.001)	-0.0008 (0.001)
FUND_FLOWS	0.9681*** (0.012)	0.9747*** (0.012)	0.9850*** (0.012)	0.9865*** (0.013)
FUND_FLOWS × ESG	0.0099 (0.026)	-0.0004 (0.028)	-0.0403 (0.025)	-0.0284 (0.025)
Lagged FUND_SIZE	0.0043*** (0.001)	0.0045*** (0.001)	0.0049*** (0.002)	0.0054*** (0.002)

	(continued)			
Lagged FUND_SIZE × ESG	0.0005	0.0006	0.0001	0.0002
	(0.001)	(0.001)	(0.000)	(0.000)
Lagged FUND_RETURN		-0.0213***		-0.0204***
		(0.006)		(0.006)
Crash × Lagged FUND_RETURN		0.0359		0.0217
		(0.025)		(0.025)
MARKET_RETURN		0.0302		0.0246
		(0.019)		(0.019)
MARKET_RETURN_VOLATILITY		-0.4702***		-0.5726***
		(0.120)		(0.133)
Lagged FUND_LIQUIDITY		-0.0007		-0.0007**
		(0.001)		(0.000)



(continued)				
Crash × Lagged FUND_LIQUIDITY		0.1224		0.0998***
		(0.076)		(0.025)
ESG	-0.0103	-0.0142	-0.0016	-0.0039
	(0.012)	(0.012)	(0.007)	(0.007)
Observations	23,193	21,861	23,702	22,338
R-squared	0.777	0.783	0.757	0.767

Panel B: *t*-tests on linear combinations of parameters

<b>Sensitivity of net purchases by conventional funds to:</b>				
FUND_FLOWS/non-Crash	0.9681***	0.9747***	0.9850***	0.9865***
FUND_FLOWS/Crash	1.2703***	1.2634***	1.3133***	1.2914***
<b>Sensitivity of net purchases by ESG funds to:</b>				
FUND_FLOWS/non-Crash	0.9780***	0.9742***	0.9447***	0.9580***
FUND_FLOWS/Crash	1.1812***	1.1663***	1.1379***	1.1410***
<b>Difference in sensitivities across periods (Crash - non-Crash):</b>				
conventional funds/FUND_FLOWS	0.3022***	0.2887***	0.3283***	0.3049***
ESG funds/FUND_FLOWS	0.2031***	0.1920***	0.1932***	0.1830***
<b>Difference in sensitivities across funds (ESG - conventional):</b>				
FUND_FLOWS/non-Crash	0.0099	-0.0004	-0.0403	-0.0284
FUND_FLOWS/Crash	-0.0891**	-0.0971**	-0.1754***	-0.1504***
<b>Diff-in-Diff (ESG - conventional and Crash - non-Crash):</b>				
ESG - conventional/FUND_FLOWS	-0.0990**	-0.0967**	-0.1351**	-0.1219**

TABLE 3

**Determinants of Net Purchases of ESG and non-ESG Stocks**

The table reports regressions for NET\_PURCHASES at the stock-portfolio level (Panel A) and *t*-test on linear combinations of parameters (Panel B). The dependent variables in Panel A are NET\_PURCHASES of *ESG Stocks* and *non-ESG Stocks*. The sample is composed of all U.S. actively managed equity funds. The sample period is from January 2019 to March 2020. The variable *Crash* takes the value of one in February and March 2020. The pre-determined *ESG* variable takes the value of one if the fund receives Globe 5 rating (column 1) or Low Carbon Designation (column 2) from Morningstar and is reset every 6 months. An *ESG Stock* is a pre-determined variable that takes a value of one if the stock receives an ESG Risk Score from Sustainalytics below the bottom quartile of the distribution and zero otherwise, and is reset every 6 months. *FUND\_FLOWS* is the monthly change in net assets under management less the returns in month *t* divided by net assets under management at the end of month *t-1*. All control variables are defined in the Appendix (see Table A1). All models are estimated by ordinary least squares. Standard errors are White-corrected for heteroskedasticity and clustered at the fund level. Month and stock-portfolio times fund fixed effects included. *p*-values are in parentheses. \* indicates significance at 1% (\*\*\*), 5% (\*\*), 10% (\*).

## Panel A: Coefficient estimates

VARIABLES	ESG (Globe 5)		ESG (Low Carbon)	
	(1)		(2)	
	non-ESG Stocks	ESG Stocks	non-ESG Stocks	ESG Stocks
Crash × ESG	0.0230 (0.032)	0.0919** (0.041)	0.0240 (0.019)	0.0039 (0.031)
Crash × FUND_FLOWS	0.2480*** (0.034)	0.1281*** (0.049)	0.2278*** (0.037)	0.1847*** (0.052)
Crash × FUND_FLOWS × ESG	0.0044 (0.089)	-0.0361 (0.097)	0.0476 (0.070)	-0.1942** (0.092)
Crash × Lagged FUND_SIZE	0.0014*** (0.000)	0.0018** (0.001)	0.0016*** (0.001)	0.0012 (0.001)
Crash × Lagged FUND_SIZE × ESG	-0.0013 (0.002)	-0.0042** (0.002)	-0.0012 (0.001)	-0.0003 (0.002)
FUND_FLOWS	1.0302*** (0.016)	0.8588*** (0.021)	1.0555*** (0.017)	0.8313*** (0.026)
FUND_FLOWS × ESG	0.0681 (0.052)	-0.0515 (0.053)	-0.0458 (0.035)	0.0659* (0.040)
Lagged FUND_SIZE	0.0030* (0.003)	0.0050* (0.003)	0.0028 (0.003)	0.0050* (0.003)

	(continued)			
	(0.002)	(0.003)	(0.002)	(0.003)
Lagged FUND.SIZE × ESG	0.0012	-0.0005	-0.0004	0.0000
	(0.001)	(0.001)	(0.001)	(0.001)
Lagged FUND.RETURN	-0.0035	-0.0046	-0.0017	-0.0027
	(0.013)	(0.017)	(0.013)	(0.017)
Crash × Lagged FUND.RETURN	-0.0148	0.0663	-0.0170	0.0661
	(0.037)	(0.063)	(0.038)	(0.066)
MARKET.RETURN	-0.0027	0.0759*	-0.0041	0.0747*
	(0.040)	(0.045)	(0.040)	(0.044)
MARKET.RETURN.VOLATILITY	-1.1593***	-0.4700**	-1.1451***	-0.4644**
	(0.180)	(0.207)	(0.177)	(0.207)
Lagged FUND.LIQUIDITY	-0.0034***	0.0015*	-0.0036***	0.0014
	(0.000)	(0.001)	(0.001)	(0.001)
Crash × Lagged FUND.LIQUIDITY	-0.0614	0.1377*	-0.0609	0.1258*
	(0.059)	(0.072)	(0.059)	(0.068)
FIRM.CHURN Ratio	0.3132***	0.0636	0.3022***	0.0649
	(0.077)	(0.120)	(0.077)	(0.118)
Crash × FIRM.CHURN Ratio	-0.1947***	-0.1173	-0.1683***	-0.1287
	(0.067)	(0.100)	(0.064)	(0.102)
FIRM.LEVERAGE	0.0631***	0.0082	0.0647***	0.0105
	(0.019)	(0.019)	(0.019)	(0.019)
Crash × FIRM.LEVERAGE	-0.0000	-0.0205	-0.0026	-0.0213
	(0.016)	(0.020)	(0.015)	(0.020)
FIRM.LIQUIDITY	0.0787***	-0.0640**	0.0830***	-0.0658**
	(0.022)	(0.027)	(0.022)	(0.027)
Crash × FIRM.LIQUIDITY	0.0177	0.0136	0.0176	0.0183
	(0.019)	(0.019)	(0.018)	(0.021)
ESG	-0.0218	0.0075	0.0094	-0.0030
	(0.020)	(0.021)	(0.016)	(0.021)

(continued)

Observations	39,871	40,190
R-squared	0.415	0.413

Panel B: *t*-tests on linear combinations of parameters

	non-ESG Stocks	ESG Stocks	non-ESG Stocks	ESG Stocks
	(1)	(2)	(3)	(4)
<b>Sensitivity of net purchases by conventional funds to:</b>				
FUND_FLOWS/non-Crash	1.0302***	0.8588***	1.0555***	0.8313***
FUND_FLOWS/Crash	1.2781***	0.9869***	1.2833***	1.0159***
<b>Sensitivity of net purchases by ESG funds to:</b>				
FUND_FLOWS/non-Crash	1.0764***	0.8149***	1.0192***	0.8942***
FUND_FLOWS/Crash	1.3287***	0.9069***	1.2946***	0.8846***
<b>Difference in sensitivities across periods (Crash - non-Crash):</b>				
conventional funds/FUND_FLOWS	0.2480***	0.1281***	0.2278***	0.1847***
ESG funds/FUND_FLOWS	0.2523***	0.0920	0.2754***	-0.0096
<b>Difference in sensitivities across funds (ESG - conventional):</b>				
FUND_FLOWS/non-Crash	0.0462	-0.0439	-0.0364	0.0629
FUND_FLOWS/Crash	0.0506	-0.0800	0.0112	-0.1313
<b>Diff-in-Diff (ESG - conventional and Crash - non-Crash):</b>				
ESG - conventional/FUND_FLOWS	0.0044	-0.0361	0.0476	-0.1942**

TABLE 4

**Determinants of Aggregate Net Purchases with Inflows and Outflows**

The table reports regressions for NET\_PURCHASES at the fund level (Panel A) and  $t$ -tests on linear combinations of parameters (Panel B). The dependent variable in Panel A is NET\_PURCHASES, total dollar purchases less total dollar sales made by fund  $i$  during month  $t$  as a percentage of the total dollar holdings of fund  $i$  at the end of month  $t - 1$ . The sample is composed of all U.S. actively managed equity funds. The sample period is from January 2019 to March 2020. The variable *Crash* takes the value of one in February and March 2020. The pre-determined ESG variable takes the value of one if the fund receives Globe 5 rating (columns 1 and 2) or Low Carbon Designation (columns 3 and 4) from Morningstar and is reset every 6 months. *Inflows* equal the positive of *FUND\_FLOWS* and *Outflows* equal the symmetric of *FUND\_FLOWS* if negative. *FUND\_FLOWS* is the monthly change in net assets under management less the returns in month  $t$  divided by net assets under management at the end of month  $t-1$ . All control variables are defined in the Appendix (see Table A1). All models are estimated by ordinary least squares. Standard errors are White-corrected for heteroskedasticity and clustered at the fund level. Month and fund fixed effects included.  $p$ -values are in parentheses. \* indicates significance at 1% (\*\*\*), 5% (\*\*), 10% (\*).

## Panel A: Coefficient estimates

VARIABLES	ESG (Globe 5)		ESG (Low Carbon)	
	(1)	(2)	(3)	(4)
Crash $\times$ ESG	0.0363*	0.0387*	0.0176	0.0141
	(0.021)	(0.021)	(0.015)	(0.016)
Crash $\times$ Inflows	0.2514***	0.2516***	0.2779***	0.2795***
	(0.038)	(0.038)	(0.033)	(0.033)
Crash $\times$ Inflows $\times$ ESG	0.0228	0.0231	-0.0699	-0.0832
	(0.075)	(0.076)	(0.078)	(0.078)
Crash $\times$ Outflows	-0.3539***	-0.3291***	-0.3735***	-0.3294***
	(0.042)	(0.039)	(0.049)	(0.044)
Crash $\times$ Outflows $\times$ ESG	0.2719***	0.2920***	0.1912**	0.1578*
	(0.084)	(0.095)	(0.079)	(0.081)
Crash $\times$ Lagged FUND_SIZE	0.0023***	0.0023***	0.0025***	0.0026***
	(0.000)	(0.000)	(0.000)	(0.000)
Crash $\times$ Lagged FUND_SIZE $\times$ ESG	-0.0020**	-0.0022**	-0.0009	-0.0007
	(0.001)	(0.001)	(0.001)	(0.001)
Inflows	0.9862***	0.9907***	0.9942***	0.9924***
	(0.015)	(0.016)	(0.017)	(0.018)

	(continued)			
Inflows × ESG	-0.0454 (0.040)	-0.0552 (0.042)	-0.0295 (0.028)	-0.0158 (0.028)
Outflows	-0.9429*** (0.020)	-0.9520*** (0.021)	-0.9725*** (0.020)	-0.9787*** (0.021)
Outflows × ESG	-0.0983*** (0.028)	-0.0911*** (0.031)	0.0625 (0.047)	0.0548 (0.051)
Lagged FUND_SIZE	0.0043*** (0.001)	0.0045*** (0.001)	0.0048*** (0.002)	0.0054*** (0.002)
Lagged FUND_SIZE × ESG	0.0004 (0.001)	0.0005 (0.001)	0.0001 (0.000)	0.0003 (0.000)
Lagged FUND_RETURN		-0.0214*** (0.006)		-0.0202*** (0.006)
Crash × Lagged FUND_RETURN		0.0352 (0.026)		0.0217 (0.025)
MARKET_RETURN		0.0302 (0.019)		0.0242 (0.019)
MARKET_RETURN_VOLATILITY		-0.4743*** (0.120)		-0.5727*** (0.133)
Lagged FUND_LIQUIDITY		-0.0007 (0.001)		-0.0007** (0.000)
Crash × Lagged FUND_LIQUIDITY		0.1225 (0.076)		0.0994*** (0.025)
ESG	-0.0068 (0.011)	-0.0107 (0.012)	-0.0023 (0.006)	-0.0046 (0.007)
Observations	23,193	21,861	23,702	22,338
R-squared	0.777	0.784	0.757	0.767

(continued)

Panel B: <i>t</i> -tests on linear combinations of parameters				
<b>Sensitivity of net purchases by conventional funds to:</b>				
Inflows/non-Crash	0.9862***	0.9907***	0.9942***	0.9924***
Inflows/Crash	1.2376***	1.2423***	1.2722***	1.2719***
Outflows/non-Crash	-0.9429***	-0.9520***	-0.9725***	-0.9787***
Outflows/Crash	-1.2967***	-1.2811***	-1.3460***	-1.3081***
<b>Sensitivity of net purchases by ESG funds to:</b>				
Inflows/non-Crash	0.9408***	0.9355***	0.9647***	0.9766***
Inflows/Crash	1.2150***	1.2102***	1.1728***	1.1729***
Outflows/non-Crash	-1.0412***	-1.0431***	-0.9100***	-0.9239***
Outflows/Crash	-1.1231***	-1.0802***	-1.0923***	-1.0955***
<b>Difference in sensitivities across periods (Crash - non-Crash):</b>				
conventional funds/Inflows	0.2514***	0.2516***	0.2779***	0.2795***
ESG funds/Inflows	0.2743***	0.2747***	0.2080***	0.1963***
conventional funds/Outflows	-0.3539***	-0.3291***	-0.3735***	-0.3294***
ESG funds/Outflows	-0.0819	-0.0371	-0.1823***	-0.1716**
<b>Difference in sensitivities across funds (ESG - conventional):</b>				
Inflows/non-Crash	-0.0454	-0.0552	-0.0295	-0.0158
Inflows/Crash	-0.0226	-0.0321	-0.0994	-0.0990
Outflows/non-Crash	-0.0983***	-0.0911***	0.0625	0.0548
Outflows/Crash	0.1736**	0.2009**	0.2538***	0.2126***
<b>Diff-in-Diff (ESG - conventional and Crash - non-Crash):</b>				
ESG - conventional funds/Inflows	0.0228	0.0231	-0.0699	-0.0832
ESG - conventional funds/Outflows	0.2719***	0.2920***	0.1912**	0.1578*

TABLE 5

**Determinants of Net Purchases of ESG and non-ESG Stocks with Inflows and Outflows**

The table reports regressions for NET\_PURCHASES at the stock-portfolio level (Panel A) and  $t$ -test on linear combinations of parameters (Panel B). The dependent variables in Panel A are NET\_PURCHASES of *ESG Stocks* and *non-ESG Stocks*. The sample is composed of all U.S. actively managed equity funds. The sample period is from January 2019 to March 2020. The variable *Crash* takes the value of one in February and March 2020. The pre-determined *ESG* variable takes the value of one if the fund receives Globe 5 rating (column 1) or Low Carbon Designation (column 2) from Morningstar and is reset every 6 months. An *ESG Stock* is a pre-determined variable that takes a value of one if the stock receives an ESG Risk Score from Sustainalytics below the bottom quartile of the distribution and zero otherwise, and is reset every 6 months. *Inflows* equal the positive of *FUND\_FLOWS* and *Outflows* equal the symmetric of *FUND\_FLOWS* if negative. *FUND\_FLOWS* is the monthly change in net assets under management less the returns in month  $t$  divided by net assets under management at the end of month  $t-1$ . All control variables are defined in Table A1 of the paper. All models are estimated by ordinary least squares. Standard errors are White-corrected for heteroskedasticity and clustered at the fund level. Month and stock-portfolio times fund fixed effects included.  $p$ -values are in parentheses. \* indicates significance at 1% (\*\*), 5% (\*), 10% (\*).

## Panel A: Coefficient estimates

VARIABLES	ESG (Globe 5)		ESG (Low Carbon)	
	(1)		(2)	
	non-ESG Stocks	ESG Stocks	non-ESG Stocks	ESG Stocks
Crash $\times$ ESG	0.0172 (0.034)	0.0804* (0.042)	0.0186 (0.020)	0.0029 (0.031)
Crash $\times$ Inflows	0.2420*** (0.060)	0.0773 (0.080)	0.2154*** (0.064)	0.1574** (0.078)
Crash $\times$ Inflows $\times$ ESG	0.0749 (0.124)	0.1376 (0.129)	0.1080 (0.107)	-0.1718 (0.140)
Crash $\times$ Outflows	-0.2541*** (0.049)	-0.1846** (0.074)	-0.2394*** (0.052)	-0.2156*** (0.082)
Crash $\times$ Outflows $\times$ ESG	0.1257 (0.181)	0.3353 (0.212)	0.0362 (0.112)	0.2147 (0.153)
Crash $\times$ Lagged FUND_SIZE	0.0014*** (0.000)	0.0017** (0.001)	0.0016*** (0.001)	0.0012 (0.001)
Crash $\times$ Lagged FUND_SIZE $\times$ ESG	-0.0012 (0.002)	-0.0039* (0.002)	-0.0010 (0.001)	-0.0002 (0.002)
Inflows	1.0303***	0.8871***	1.0492***	0.8543***



	(continued)			
	(0.022)	(0.031)	(0.026)	(0.040)
Inflows × ESG	0.0062	-0.1074	-0.0310	0.0592
	(0.067)	(0.069)	(0.045)	(0.053)
Outflows	-1.0291***	-0.8206***	-1.0626***	-0.8042***
	(0.025)	(0.034)	(0.024)	(0.037)
Outflows × ESG	-0.1718**	-0.0359	0.0645	-0.0656
	(0.078)	(0.071)	(0.065)	(0.069)
Lagged FUND.SIZE	0.0031*	0.0051*	0.0026	0.0051*
	(0.002)	(0.003)	(0.002)	(0.003)
Lagged FUND.SIZE × ESG	0.0011	-0.0006	-0.0004	0.0000
	(0.001)	(0.001)	(0.001)	(0.001)
Lagged FUND.RETURN	-0.0034	-0.0046	-0.0014	-0.0026
	(0.013)	(0.017)	(0.013)	(0.017)
Crash × Lagged FUND.RETURN	-0.0148	0.0675	-0.0162	0.0663
	(0.037)	(0.064)	(0.039)	(0.066)
MARKET.RETURN	-0.0019	0.0769*	-0.0043	0.0745*
	(0.040)	(0.045)	(0.040)	(0.045)
MARKET.RETURN.VOLATILITY	-1.1622***	-0.4706**	-1.1421***	-0.4625**
	(0.180)	(0.207)	(0.178)	(0.208)
Lagged FUND.LIQUIDITY	-0.0034***	0.0015*	-0.0036***	0.0014
	(0.000)	(0.001)	(0.001)	(0.001)
Crash × Lagged FUND.LIQUIDITY	-0.0614	0.1377*	-0.0613	0.1258*
	(0.059)	(0.072)	(0.059)	(0.068)
FIRM.CHURN Ratio	0.3123***	0.0619	0.3016***	0.0629
	(0.077)	(0.119)	(0.077)	(0.117)
Crash × FIRM.CHURN Ratio	-0.1961***	-0.1159	-0.1676***	-0.1280
	(0.066)	(0.101)	(0.063)	(0.103)
FIRM.LEVERAGE	0.0631***	0.0079	0.0652***	0.0106
	(0.019)	(0.019)	(0.019)	(0.019)
Crash × FIRM.LEVERAGE	0.0004	-0.0205	-0.0022	-0.0213

	(continued)			
	(0.016)	(0.020)	(0.015)	(0.020)
FIRM.LIQUIDITY	0.0789***	-0.0635**	0.0835***	-0.0656**
	(0.022)	(0.027)	(0.022)	(0.027)
Crash × FIRM.LIQUIDITY	0.0177	0.0127	0.0177	0.0182
	(0.019)	(0.020)	(0.018)	(0.021)
ESG	-0.0183	0.0109	0.0088	-0.0031
	(0.020)	(0.021)	(0.016)	(0.021)
Observations	39,871		40,190	
R-squared	0.415		0.413	

(continued)

Panel B: <i>t</i> -tests on linear combinations of parameters				
	non-ESG Stocks	ESG Stocks	non-ESG Stocks	ESG Stocks
	(1)	(2)	(3)	(4)
<b>Sensitivity of net purchases by conventional funds to:</b>				
Inflows/non-Crash	1.0303***	0.8871***	1.0492***	0.8543***
Inflows/Crash	1.2723***	0.9644***	1.2645***	1.0116***
Outflows/non-Crash	-1.0291***	-0.8206***	-1.0626***	-0.8042***
Outflows/Crash	-1.2832***	-1.0051***	-1.3020***	-1.0199***
<b>Sensitivity of net purchases by ESG funds to:</b>				
Inflows/non-Crash	1.0364***	0.7796***	1.0182***	0.9135***
Inflows/Crash	1.3533***	0.9946***	1.3416***	0.8991***
Outflows/non-Crash	-1.2009***	-0.8564***	-0.9981***	-0.8699***
Outflows/Crash	-1.3293***	-0.7057***	-1.2014***	-0.8708***
<b>Difference in sensitivities across periods (Crash - non-Crash):</b>				
conventional funds/Inflows	0.2420***	0.0773	0.2154***	0.1574**
ESG funds/Inflows	0.3169***	0.2149**	0.3234***	-0.0144
conventional funds/Outflows	-0.2541***	-0.1846**	-0.2394***	-0.2156***
ESG funds/Outflows	-0.1284	0.1507	-0.2032**	-0.0009
<b>Difference in sensitivities across funds (ESG - conventional):</b>				
Inflows/non-Crash	0.0062	-0.1074	-0.0310	0.0592
Inflows/Crash	0.0810	0.0302	0.0770	-0.1125
Outflows/non-Crash	-0.1718**	-0.0359	0.0645	-0.0656
Outflows/Crash	-0.0461	0.2994	0.1006	0.1491
<b>Diff-in-Diff (ESG - conventional and Crash - non-Crash):</b>				
ESG - conventional funds/Inflows	0.0749	0.1376	0.1080	-0.1718
ESG - conventional funds/Outflows	0.1257	0.3353	0.0362	0.2147

TABLE 6  
**Determinants of Net Purchases by Star Rated Funds**

The table reports regressions for NET\_PURCHASES (Panel A) and  $t$ -test on linear combinations of parameters (Panel B). In columns (1) and (2), the dependent variable is aggregate NET\_PURCHASES, in column (3) it is NET\_PURCHASES of *non-ESG Stocks*, and in column (4) it is NET\_PURCHASES of *ESG Stocks*. The sample is composed of all U.S. actively managed equity funds. The sample period is from January 2019 to March 2020. The variable *Crash* takes the value of one in February and March 2020. The pre-determined *High Rated Funds* variable takes the value of one if the fund receives star rating of 4 or 5 stars from Morningstar and is reset every 6 months. An *ESG Stock* is a pre-determined variable that takes a value of one if the stock receives an ESG Risk Score from Sustainalytics below the bottom quartile of the distribution and zero otherwise, and is reset every 6 months. *FUND\_FLOWS* is the monthly change in net assets under management less the returns in month  $t$  divided by net assets under management at the end of month  $t-1$ . All variables are defined in the Appendix (see Table A1). All models are estimated by ordinary least squares. Standard errors are White-corrected for heteroskedasticity and clustered at the fund level. Columns 1 and 2 use month and fund fixed effects, and columns 3 and 4 use month and stock-portfolio times fund fixed effects.  $p$ -values are in parentheses. \* indicates significance at 1% (\*\*\*), 5% (\*\*), 10% (\*).

Panel A: Coefficient estimates

VARIABLES	Star ratings			
	(1)	(2)	(3)	(4)
			non-ESG Stocks	ESG Stocks
Crash $\times$ High Rated Funds	-0.0069 (0.025)	-0.0053 (0.024)	-0.0465 (0.033)	0.0379 (0.043)
Crash $\times$ FUND_FLOWS	0.3089*** (0.031)	0.3081*** (0.031)	0.2769*** (0.039)	0.1281* (0.075)
Crash $\times$ FUND_FLOWS $\times$ High Rated Funds	0.1271 (0.082)	0.0641 (0.070)	-0.0779 (0.109)	0.1961 (0.122)
Crash $\times$ Lagged FUND_SIZE	0.0032*** (0.001)	0.0031*** (0.001)	0.0010 (0.001)	0.0019 (0.001)
Crash $\times$ Lagged FUND_SIZE $\times$ High Rated Funds	0.0001 (0.001)	-0.0000 (0.001)	0.0021 (0.002)	-0.0016 (0.002)
FUND_FLOWS	0.9957*** (0.015)	1.0023*** (0.015)	1.0629*** (0.021)	0.8687*** (0.033)
FUND_FLOWS $\times$ High Rated Funds	-0.0343 (0.029)	-0.0413 (0.030)	-0.0448 (0.039)	-0.0809 (0.061)
Lagged FUND_SIZE	0.0088* (0.001)	0.0103** (0.001)	0.0027 (0.001)	0.0036 (0.001)

(continued)

	(0.005)	(0.005)	(0.003)	(0.004)
Lagged FUND_SIZE × High Rated Funds	-0.0102**	-0.0110*	-0.0004	0.0025
	(0.005)	(0.006)	(0.001)	(0.002)
Lagged FUND_RETURN		-0.0208***	-0.0031	-0.0029
		(0.008)	(0.015)	(0.021)
Crash × Lagged FUND_RETURN		0.0212	0.0204	0.0710
		(0.031)	(0.046)	(0.086)
MARKET_RETURN		0.0131	-0.0119	0.1191**
		(0.025)	(0.048)	(0.059)
MARKET_RETURN_VOLATILITY		-0.6391***	-1.3502***	-0.8563***
		(0.198)	(0.222)	(0.264)
Lagged FUND_LIQUIDITY		-0.0009***	-0.0039***	0.0007
		(0.000)	(0.000)	(0.001)
Crash × Lagged FUND_LIQUIDITY		0.0796**	-0.1507***	0.0767
		(0.034)	(0.057)	(0.053)
FIRM_CHURN Ratio			0.3693***	0.1853
			(0.110)	(0.139)
Crash × FIRM_CHURN Ratio			-0.2118***	-0.2497**
			(0.074)	(0.113)
FIRM_LEVERAGE			0.0333	-0.0064
			(0.025)	(0.023)
Crash × FIRM_LEVERAGE			0.0098	-0.0157
			(0.019)	(0.024)
FIRM_LIQUIDITY			0.0237	-0.1105***
			(0.028)	(0.040)
Crash × FIRM_LIQUIDITY			0.0062	0.0620**
			(0.024)	(0.029)
Observations	14,783	14,115		25,439
R-squared	0.746	0.758		0.390

(continued)

Panel B: <i>t</i> -tests on linear combinations of parameters				
			non-ESG Stocks	ESG Stocks
	(1)	(2)	(3)	(4)
<b>Sensitivity of net purchases by Low Rated funds to:</b>				
FUND_FLOWS/non-Crash	0.9957***	1.0092***	1.0629***	0.8687***
FUND_FLOWS/Crash	1.3047***	1.3307***	1.3397***	0.9968***
<b>Sensitivity of net purchases by High Rated funds to:</b>				
FUND_FLOWS/non-Crash	0.9614***	0.9631***	1.0181***	0.7877***
FUND_FLOWS/Crash	1.3974***	1.3960***	1.2170***	1.1120***
<b>Difference in sensitivities across periods (Crash - non-Crash):</b>				
Low rated funds/FUND_FLOWS	0.3089***	0.3215***	0.2769***	0.1281*
High rated funds/FUND_FLOWS	0.4360***	0.4329***	0.1990*	0.3242***
<b>Difference in sensitivities across funds (High Rated - Low Rated):</b>				
FUND_FLOWS/non-Crash	-0.0343	-0.0461	-0.0448	-0.0809
FUND_FLOWS/Crash	0.0928	0.0653	-0.1227	0.1152
<b>Diff-in-Diff (High Rated - Low Rated and Crash - non-Crash):</b>				
High Rated - Low Rated funds/FUND_FLOWS	0.1271	0.1114	-0.0779	0.1961

## Appendix

TABLE A1

**Variable Definitions.**

Crash	A dummy variable that takes a value of one during February and March 2020 and zero otherwise.
ESG (using Globe 5 Rating)	A dummy variable that takes a value of one if the fund receives a Sustainability rating of 5 Globes and zero otherwise. We reset the dummy every 6 months: the December 2018 Globe rating classification applies to values of the dummy variable from January to June of 2019, the June 2019 classification to July–December 2019, and the December 2019 classification to January–March 2020. Morningstar assigns Sustainability Ratings by ranking all scored funds within a Morningstar Global Category by their Historical Sustainability Scores. The ranked funds are then divided into five groups, based on a normal distribution, and each receives a rating from “High” to “Low.” Percent Rank Rating Depiction (Top 10%) High – 5 globes; (Next 22.5%) Above Average – 4 globes; (Next 35%) Average – 3 globes; (Next 22.5%) Below Average - 2 globes; (Bottom 10%) Low - 1 globe. (Source: Morningstar Direct)
ESG (using Low Carbon Designation)	A dummy variable that takes a value of one if the fund has a Low Carbon Designation and zero otherwise. We reset the dummy every 6 months: the December 2018 Low Carbon Designation applies to values of the dummy variable from January to June of 2019, the June 2019 designation to July–December 2019, and the December 2019 designation to January–March 2020. Based on Morningstar Portfolio Carbon Risk Score and The Morningstar Portfolio Fossil Fuel Involvement. To receive the designation, a fund must have a 12-month average Portfolio Carbon Risk Score below 10 and a 12-month average Fossil Fuel Involvement of less than 7% of assets. (Source: Morningstar Direct)

(continued)

---

ESG Stocks	A dummy variable that takes a value of one if the stock receives an ESG Risk Score (Sustainalytics) below the bottom quartile of the distribution and zero otherwise. We reset the dummy every 6 months: the December 2018 classification applies to values of the dummy from January to June of 2019, the June 2019 classification to July 2019–December 2019, and the December 2019 classification to January 2020–March 2020. The ESG Risk Score is the average between the Environment, the Social, and the Governance risk scores as of December 2019. If a stock does not receive a score from Sustainalytics, the dummy is set to zero. (Source: Morningstar Direct)
FIRM_CHURN ratio	The weighted average of the churn ratios of firm $j$ 's investors where the weights are the number of shares held by investor $i$ in firm $j$ and the firm $j$ 's total shares outstanding in month $t$ . (Source: Morningstar historical holdings and Direct)
FIRM_LEVERAGE	For each fund $i$ , FIRM_LEVERAGE is the weighted average of the book value of firm debt divided by book value of total assets, where the weights are given by the market value of fund $i$ 's holdings in each firm at end of month $t$ . The December 2018 firm leverage is applied to the period from January to December 2019, while the December 2019 firm leverage is applied to the period from January to March 2020. (Source: Morningstar Direct)
FIRM_LIQUIDITY	For each fund $i$ , FIRM_LIQUIDITY is the weighted average of firm cash divided by the book value of total assets, where the weights are given by the market value of fund $i$ 's holdings in each firm at the end of month $t$ . The December 2018 firm liquidity is applied to the period from January to December 2019, while the December 2019 firm liquidity is applied to the period from January to March 2020. (Source: Morningstar Direct)

---



(continued)

FUND_CHURN ratio	This variable measures how frequently institutional investors trade the stocks in their portfolios and is constructed as in Gaspar, Massa, and Matos (2005). For each mutual fund, we compute the churn ratio every month and then take the average churn ratio over months $t$ through $t - 35$ (a minimum of 25 months is required). Averaging over a long time period mitigates the effect of investor-specific shocks that may generate deviations in the investor's holding period from its preferred horizon. (Source: Morningstar historical holdings)
FUND_FLOWS	The monthly change in net assets under management less the returns in month $t$ divided by net assets under management in month $t - 1$ . (Source: Morningstar Direct)
Inflows	Equal to FUND_FLOWS if positive
Outflows	Equal to the symmetric value of FUND_FLOWS if negative
FUND_LIQUIDITY	End-of-month $t$ fund Cash (i.e., currency and coins, negotiable checks, and balances in bank accounts) divided by fund total net assets under management in month $t - 1$ . (Source: Morningstar Direct)
FUND_RETURN	The return of the fund during month $t$ as provided by Morningstar. (Source: Morningstar Direct)
FUND_SIZE	End-of-month $t$ total net asset value of the fund in log of USD millions. (Source: Morningstar Direct)
MARKET_RETURN	The return of the reference index as defined in the prospectus or provided by Morningstar during month $t$ . (Source: Morningstar Direct)

(continued)

---

MARKET_RETURN_VOLATILITY	The standard deviation of the reference index daily returns during month $t$ . (Source: Morningstar Direct)
NET_PURCHASES	Gross dollar purchases minus gross dollar sales made by mutual fund $i$ during month $t$ as a percentage of the total dollar holdings of the same fund at the end of month $t - 1$ . (Source: Morningstar historical holdings)
Share ESG Stocks	The proportion of a fund's portfolio allocated to <i>ESG stocks</i> (Sustainalytics), expressed as a percentage of its total net assets. (Source: Morningstar Direct)
Share non-ESG Stocks	The proportion of a fund's portfolio not allocated to <i>ESG stocks</i> (Sustainalytics), expressed as a percentage of its total net assets. (Source: Morningstar Direct)
STAR_RATING	A dummy variable that takes a value of one if the fund receives a star rating of 4 and 5 stars and zero otherwise. We reset the dummy every 6 months: the December 2018 star rating applies to values of the dummy from January to June 2019, the June 2019 star rating to July–December 2019, and the December 2019 star rating to January–March 2020. To determine a fund's star rating for a given time period (three, five, or 10 years), the fund's risk-adjusted return is plotted on a bell curve: if the fund scores in the top 10% of its category, it receives 5 stars (Highest); if it falls in the next 22.5% it receives 4 stars (Above Average); a place in the middle 35% earns 3 stars (Average); those lower still, in the next 22.5%, receive 2 stars (Below Average); and the bottom 10% get only 1 star (Lowest). The Overall Morningstar Rating is a weighted average of the available three-, five-, and 10-year ratings. (Source: Morningstar Direct)

---

## **Online Appendix**

### **List of tables**

Figure OA1 Fund Net Purchases and Sustainability rating

Table OA1 re-estimates Table 6 considering fund inflows and outflows

Table OA2 re-estimates Table 3 while excluding stocks operating in the oil and gas industry

Table OA.3 re-estimates Table 3 considering only March as the crash month

Table OA.4 re-estimates Table 3 considering the fund investment horizon

FIGURE OA.1

**Fund Net Purchases and sustainability rating. This figure plots aggregate fund Net Purchases from January 2019 to June 2020 using monthly net purchases for two fund categories, those that receive by Morningstar Globe 5 sustainability ratings (ESG funds) and those with less than Globe 5 ratings (conventional funds).**

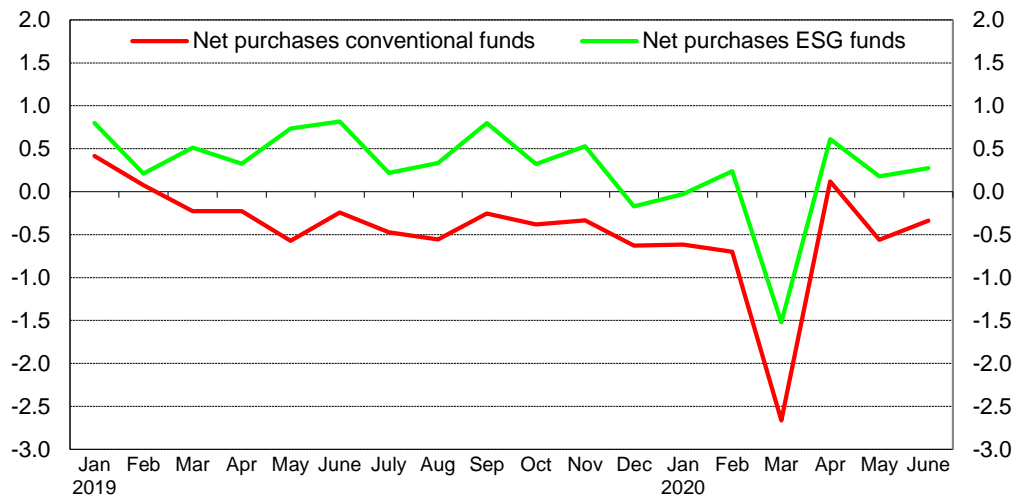


TABLE OA.1

# **Determinants of Net Purchases of ESG and non-ESG Stocks by Star Rated Funds with Inflows and Outflows**

The table reports regressions for NET\_PURCHASES at the stock-portfolio level (Panel A) and *t*-test on linear combinations of parameters (Panel B). The dependent variables are NET\_PURCHASES of *non-ESG Stocks* (column 1) and NET\_PURCHASES of *ESG Stocks* (column 2). The sample is composed of all U.S. actively managed equity funds. The sample period is from January 2019 to March 2020. The variable *Crash* takes the value of one in February and March 2020. The pre-determined *High Rated Funds* variable takes the value of one if the fund receives star rating of 4 or 5 stars from Morningstar and is reset every 6 months. An *ESG Stock* is a pre-determined variable that takes a value of one if the stock receives an ESG Risk Score from Sustainalytics below the bottom quartile of the distribution and zero otherwise, and is reset every 6 months. *Inflows* equal the positive of *FUND\_FLOWS* and *Outflows* equal the symmetric of *FUND\_FLOWS* if negative. *FUND\_FLOWS* is the monthly change in net assets under management less the returns in month *t* divided by net assets under management at the end of month *t-1*. All variables are defined in the Appendix (see Table A1). All models are estimated by ordinary least squares. Standard errors are White-corrected for heteroskedasticity and clustered at the fund level. *p*-values are in parentheses. \* indicates significance at 1% (\*\*\*), 5% (\*\*), 10% (\*).

Panel A: Coefficient estimates

VARIABLES	Star ratings	
	(1)	
	non-ESG Stocks	ESG Stocks
Crash × High Rated Funds	-0.0400 (0.030)	0.0361 (0.043)
Crash × Inflows	0.3118*** (0.061)	0.0519 (0.142)
Crash × Inflows × High Rated Funds	-0.1682 (0.214)	0.2637 (0.205)
Crash × Outflows	-0.2496*** (0.061)	-0.1903* (0.103)
Crash × Outflows × High Rated Funds	-0.0301 (0.121)	-0.1258 (0.173)
Crash × Lagged FUND.SIZE	0.0010 (0.001)	0.0018 (0.001)
Crash × Lagged FUND.SIZE × High Rated Funds	0.0019 (0.001)	-0.0016 (0.002)
Inflows	1.0206*** (0.036)	0.9566*** (0.049)
Inflows × High Rated Funds	0.0311 (0.059)	-0.1909** (0.094)
Outflows	-1.0972*** (0.027)	-0.7953*** (0.049)
Outflows × High Rated Funds	0.1362** (0.063)	-0.0288 (0.087)
Lagged FUND.SIZE	0.0026 (0.003)	0.0037 (0.004)
Lagged FUND.SIZE × High Rated Funds	-0.0001 (0.001)	0.0023 (0.002)
Lagged FUND.RETURN	-0.0028 (0.015)	-0.0032 (0.021)
Crash × Lagged FUND.RETURN	0.0198 (0.047)	0.0696 (0.086)

		(continued)
MARKET_RETURN	-0.0122 (0.048)	0.1199** (0.059)
MARKET_RETURN_VOLATILITY	-1.3467*** (0.223)	-0.8619*** (0.265)
Lagged FUND_LIQUIDITY	-0.0040*** (0.000)	0.0007 (0.001)
Crash × Lagged FUND_LIQUIDITY	-0.1506*** (0.058)	0.0772 (0.053)
FIRM_CHURN Ratio	0.3700*** (0.110)	0.1805 (0.138)
Crash × FIRM_CHURN Ratio	-0.2114*** (0.074)	-0.2508** (0.114)
FIRM_LEVERAGE	0.0333 (0.025)	-0.0054 (0.023)
Crash × FIRM_LEVERAGE	0.0104 (0.019)	-0.0163 (0.024)
FIRM_LIQUIDITY	0.0233 (0.027)	-0.1090*** (0.040)
Crash × FIRM_LIQUIDITY	0.0065 (0.024)	0.0613** (0.029)
High Rated Funds	0.0015 (0.025)	-0.0477 (0.037)
Observations		25,439
R-squared		0.522

(continued)

Panel B: <i>t</i> -tests on linear combinations of parameters		
	non-ESG Stocks	ESG Stocks
	(1)	(2)
<b>Sensitivity of net purchases by Low Rated funds to:</b>		
Inflows/non-Crash	1.0206***	0.9566***
Inflows/Crash	1.3325***	1.0085***
Outflows/non-Crash	-1.0972***	-0.7953***
Outflows/Crash	-1.3468***	-0.9856***
<b>Sensitivity of net purchases by High Rated funds to:</b>		
Inflows/non-Crash	1.0517***	0.7657***
Inflows/Crash	1.1954***	1.0813***
Outflows/non-Crash	-0.9609***	-0.8241***
Outflows/Crash	-1.2407***	-1.1401***
<b>Difference in sensitivities across periods (Crash - non-Crash):</b>		
Low Rated funds/Inflows	0.3118***	0.0519
High Rated funds/Inflows	0.1437	0.3156**
Low Rated funds/Outflows	-0.2496***	-0.1903*
High Rated funds/Outflows	-0.2797***	-0.3161**
<b>Difference in sensitivities across funds (High Rated - Low Rated):</b>		
Inflows/non-Crash	0.0311	-0.1909**
Inflows/Crash	-0.1370	0.0728
Outflows/non-Crash	0.1362**	-0.0288
Outflows/Crash	0.1061	-0.1546
<b>Diff-in-Diff (High Rated - Low Rated and Crash - non-Crash):</b>		
High Rated - Low Rated funds/Inflows	-0.1682	0.2637
High Rated - Low Rated funds/Outflows	-0.0301	-0.1258

TABLE OA.2

**Determinants of Net Purchases of ESG and non-ESG Stocks, Excluding Oil and Gas****Industry**

The table reports regressions for NET\_PURCHASES at the stock-portfolio level (Panel A) and *t*-test on linear combinations of parameters (Panel B). The dependent variables in Panel A are NET\_PURCHASES of *ESG Stocks* (column 1) and *non-ESG Stocks* (column 2). The sample is composed of all U.S. actively managed equity funds. The sample period is from January 2019 to March 2020 and it excludes firms operating in the Oil and Gas industry. The variable *Crash* takes the value of one in February and March 2020. The pre-determined *ESG* variable takes the value of one if the fund receives Globe 5 rating (column 1) or Low Carbon Designation (column 2) from Morningstar and is reset every 6 months. An *ESG Stock* is a pre-determined variable that takes a value of one if the stock receives an ESG Risk Score from Sustainalytics below the bottom quartile of the distribution and zero otherwise, and is reset every 6 months. *FUND\_FLOWS* is the monthly change in net assets under management less the returns in month *t* divided by net assets under management at the end of month *t-1*. All control variables are defined in Table A1 of the paper. All models are estimated by ordinary least squares. Standard errors are White-corrected for heteroskedasticity and clustered at the fund level. Month and stock-portfolio times fund fixed effects included. *p*-values are in parentheses. \* indicates significance at 1% (\*\*\*), 5% (\*\*), 10% (\*).

Panel A: Coefficient estimates

VARIABLES	ESG (Globe 5)		ESG (Low Carbon)	
	(1)		(2)	
	non-ESG Stocks	ESG Stocks	non-ESG Stocks	ESG Stocks
Crash × ESG	0.0121 (0.034)	0.1008** (0.040)	0.0179 (0.020)	0.0067 (0.031)
Crash × FUND_FLOWS	0.2460*** (0.035)	0.1373*** (0.047)	0.2259*** (0.037)	0.2046*** (0.050)
Crash × FUND_FLOWS × ESG	0.0300 (0.088)	-0.0172 (0.103)	0.0588 (0.070)	-0.2182** (0.091)
Crash × Lagged FUND_SIZE	0.0013*** (0.000)	0.0019** (0.001)	0.0015*** (0.001)	0.0013 (0.001)
Crash × Lagged FUND_SIZE × ESG	-0.0008 (0.002)	-0.0047** (0.002)	-0.0009 (0.001)	-0.0004 (0.002)
FUND_FLOWS	1.0362*** (0.016)	0.8605*** (0.020)	1.0573*** (0.018)	0.8244*** (0.025)
FUND_FLOWS × ESG	0.0194 (0.054)	-0.0897 (0.067)	-0.0475 (0.036)	0.0757* (0.040)
Lagged FUND_SIZE	0.0016 (0.002)	0.0045* (0.003)	0.0015 (0.002)	0.0047* (0.003)
Lagged FUND_SIZE × ESG	0.0012 (0.001)	0.0006 (0.001)	-0.0007 (0.001)	0.0003 (0.001)
Lagged FUND_RETURN	-0.0068 (0.014)	-0.0078 (0.017)	-0.0053 (0.013)	-0.0068 (0.017)
Crash × Lagged FUND_RETURN	-0.0064 (0.039)	0.0850 (0.064)	-0.0063 (0.041)	0.0837 (0.067)
MARKET_RETURN	0.0036 (0.040)	0.0796* (0.044)	0.0017 (0.040)	0.0780* (0.044)
MARKET_RETURN_VOLATILITY	-1.0755*** (0.179)	-0.4403** (0.208)	-1.0599*** (0.176)	-0.4405** (0.208)
Lagged FUND_LIQUIDITY	-0.0034*** (0.000)	0.0015* (0.001)	-0.0035*** (0.001)	0.0014 (0.001)
Crash × Lagged FUND_LIQUIDITY	-0.0533 (0.059)	0.1318* (0.070)	-0.0529 (0.058)	0.1195* (0.066)
FIRM_CHURN Ratio	0.3468*** (0.076)	0.0547 (0.119)	0.3353*** (0.075)	0.0649 (0.116)



(continued)

Crash × FIRM_CHURN Ratio	-0.1980*** (0.066)	-0.0881 (0.097)	-0.1738*** (0.063)	-0.1000 (0.098)
FIRM_LEVERAGE	0.0657*** (0.020)	0.0024 (0.018)	0.0675*** (0.020)	0.0044 (0.018)
Crash × FIRM_LEVERAGE	0.0109 (0.017)	-0.0097 (0.018)	0.0080 (0.017)	-0.0108 (0.018)
FIRM_LIQUIDITY	0.0755*** (0.022)	-0.0648** (0.027)	0.0800*** (0.022)	-0.0669** (0.028)
Crash × FIRM_LIQUIDITY	0.0202 (0.019)	0.0093 (0.019)	0.0209 (0.019)	0.0138 (0.021)
ESG	-0.0202 (0.019)	-0.0131 (0.022)	0.0145 (0.015)	-0.0100 (0.022)
Observations	39,838		40,156	
R-squared	0.414		0.413	

Panel B: *t*-tests on linear combinations of parameters

	non-ESG Stocks (1)	ESG Stocks (2)	non-ESG Stocks (3)	ESG Stocks (4)
<b>Sensitivity of net purchases by conventional funds to:</b>				
FUND_FLOWS/non-Crash	1.0362***	0.8605***	1.0573***	0.8244***
FUND_FLOWS/Crash	1.2821***	0.9978***	1.2832***	1.0289***
<b>Sensitivity of net purchases by ESG funds to:</b>				
FUND_FLOWS/non-Crash	1.0354***	0.7577***	1.0243***	0.8900***
FUND_FLOWS/Crash	1.3114***	0.8778***	1.3090***	0.8764***
<b>Difference in sensitivities across periods (Crash - non-Crash):</b>				
conventional funds/FUND_FLOWS	0.2460***	0.1373***	0.2259***	0.2046***
ESG funds/FUND_FLOWS	0.2760***	0.1201	0.2847***	-0.0136
<b>Difference in sensitivities across funds (ESG - conventional):</b>				
FUND_FLOWS/non-Crash	-0.0007	-0.1028	-0.0330	0.0657
FUND_FLOWS/Crash	0.0293	-0.1200	0.0258	-0.1526*
<b>Diff-in-Diff (ESG - conventional and Crash - non-Crash):</b>				
ESG - conventional funds/FUND_FLOWS	0.0300	-0.0172	0.0588	-0.2182**

TABLE OA.3

### Determinants of Net Purchases of ESG and non-ESG Stocks with Only March as the Crash Month

The table reports regressions for NET\_PURCHASES at the stock-portfolio level (Panel A) and *t*-test on linear combinations of parameters (Panel B). The dependent variables in Panel A are NET\_PURCHASES of *ESG Stocks* (column 1) and *non-ESG Stocks* (column 2). The sample is composed of all U.S. actively managed equity funds. The sample period is from January 2019 to March 2020. The variable *Crash* takes the value of one for only March 2020. The pre-determined *ESG* variable takes the value of one if the fund receives Globe 5 rating (column 1) or Low Carbon Designation (column 2) from Morningstar and is reset every 6 months. An *ESG Stock* is a pre-determined variable that takes a value of one if the stock receives an ESG Risk Score from Sustainalytics below the bottom quartile of the distribution and zero otherwise, and is reset every 6 months. *FUND\_FLOWS* is the monthly change in net assets under management less the returns in month *t* divided by net assets under management at the end of month *t-1*. All control variables are defined in Table A1 of the paper. All models are estimated by ordinary least squares. Standard errors are White-corrected for heteroskedasticity and clustered at the fund level. Month and stock-portfolio times fund fixed effects included. *p*-values are in parentheses. \* indicates significance at 1% (\*\*\*), 5% (\*\*), 10% (\*).

Panel A: Coefficient estimates

VARIABLES	ESG (Globe 5)		ESG (Low Carbon)	
	(1)		(2)	
	non-ESG Stocks	ESG Stocks	non-ESG Stocks	ESG Stocks
Crash × ESG	0.0230 (0.032)	0.0919** (0.041)	0.0240 (0.019)	0.0039 (0.031)
Crash × FUND_FLOWS	0.2480*** (0.034)	0.1281*** (0.049)	0.2278*** (0.037)	0.1847*** (0.052)
Crash × FUND_FLOWS × ESG	0.0044 (0.089)	-0.0361 (0.097)	0.0476 (0.070)	-0.1942** (0.092)
Crash × Lagged FUND_SIZE	0.0014*** (0.000)	0.0018** (0.001)	0.0016*** (0.001)	0.0012 (0.001)
Crash × Lagged FUND_SIZE × ESG	-0.0013 (0.002)	-0.0042** (0.002)	-0.0012 (0.001)	-0.0003 (0.002)
FUND_FLOWS	1.0302*** (0.016)	0.8588*** (0.021)	1.0555*** (0.017)	0.8313*** (0.026)
FUND_FLOWS × ESG	0.0681 (0.052)	-0.0515 (0.053)	-0.0458 (0.035)	0.0659* (0.040)
Lagged FUND_SIZE	0.0030* (0.002)	0.0050* (0.003)	0.0028 (0.002)	0.0050* (0.003)
Lagged FUND_SIZE × ESG	0.0012 (0.001)	-0.0005 (0.001)	-0.0004 (0.001)	0.0000 (0.001)
Lagged FUND_RETURN	-0.0035 (0.013)	-0.0046 (0.017)	-0.0017 (0.013)	-0.0027 (0.017)
Crash × Lagged FUND_RETURN	-0.0148 (0.037)	0.0663 (0.063)	-0.0170 (0.038)	0.0661 (0.066)
MARKET_RETURN	-0.0027 (0.040)	0.0759* (0.045)	-0.0041 (0.040)	0.0747* (0.044)
MARKET_RETURN_VOLATILITY	-1.1593*** (0.180)	-0.4700** (0.207)	-1.1451*** (0.177)	-0.4644** (0.207)
Lagged FUND_LIQUIDITY	-0.0034*** (0.000)	0.0015* (0.001)	-0.0036*** (0.001)	0.0014 (0.001)
Crash × Lagged FUND_LIQUIDITY	-0.0614 (0.059)	0.1377* (0.072)	-0.0609 (0.059)	0.1258* (0.068)
FIRM_CHURN Ratio	0.3132*** (0.077)	0.0636 (0.120)	0.3022*** (0.077)	0.0649 (0.118)

	(continued)			
Crash × FIRM_CHURN Ratio	-0.1947*** (0.067)	-0.1173 (0.100)	-0.1683*** (0.064)	-0.1287 (0.102)
FIRM_LEVERAGE	0.0631*** (0.019)	0.0082 (0.019)	0.0647*** (0.019)	0.0105 (0.019)
Crash × FIRM_LEVERAGE	-0.0000 (0.016)	-0.0205 (0.020)	-0.0026 (0.015)	-0.0213 (0.020)
FIRM_LIQUIDITY	0.0787*** (0.022)	-0.0640** (0.027)	0.0830*** (0.022)	-0.0658** (0.027)
Crash × FIRM_LIQUIDITY	0.0177 (0.019)	0.0136 (0.019)	0.0176 (0.018)	0.0183 (0.021)
ESG	-0.0218 (0.020)	0.0075 (0.021)	0.0094 (0.016)	-0.0030 (0.021)
Observations	39,871		40,190	
R-squared	0.415		0.413	

Panel B: *t*-tests on linear combinations of parameters

	non-ESG Stocks (1)	ESG Stocks (2)	non-ESG Stocks (3)	ESG Stocks (4)
<b>Sensitivity of net purchases by conventional funds to:</b>				
FUND_FLOWS/Non-crash	1.0302***	0.8588***	1.0555***	0.8313***
FUND_FLOWS/Crash	1.2781***	0.9869***	1.2833***	1.0159***
<b>Sensitivity of net purchases by ESG funds to:</b>				
FUND_FLOWS/Non-crash	1.0764***	0.8149***	1.0192***	0.8942***
FUND_FLOWS/Crash	1.3287***	0.9069***	1.2946***	0.8846***
<b>Difference in sensitivities across periods (Crash - non-Crash):</b>				
conventional funds/FUND_FLOWS	0.2480***	0.1281***	0.2278***	0.1847***
ESG funds/FUND_FLOWS	0.2523***	0.0920	0.2754***	-0.0096
<b>Difference in sensitivities across funds (ESG - conventional):</b>				
FUND_FLOWS/Non-crash	0.0462	-0.0439	-0.0364	0.0629
FUND_FLOWS/Crash	0.0506	-0.0800	0.0112	-0.1313
<b>Diff-in-Diff (ESG - conventional and Crash - non-Crash):</b>				
ESG - conventional/FUND_FLOWS	0.0044	-0.0361	0.0476	-0.1942**

TABLE OA.4

**Investor Horizon and Net Purchases of ESG and non-ESG Stocks**

The table reports regressions for NET\_PURCHASES at the stock-portfolio level (Panel A) and  $t$ -test on linear combinations of parameters (Panel B). The dependent variables in Panel A are NET\_PURCHASES of *ESG Stocks* (column 1) and *non-ESG Stocks* (column 2). The sample is composed of all U.S. actively managed equity funds. The sample period is from January 2019 to March 2020. The variable *Crash* takes the value of one in February and March 2020. The pre-determined *ESG* variable takes the value of one if the fund receives Globe 5 rating (column 1) or Low Carbon Designation (column 2) from Morningstar and is reset every 6 months. FUND\_CHURN ratio measures how frequently investors trade stocks in their portfolios during the past 36 months. An *ESG Stock* is a pre-determined variable that takes a value of one if the stock receives an ESG Risk Score from Sustainalytics below the bottom quartile of the distribution and zero otherwise, and is reset every 6 months. FUND\_FLOWS is the monthly change in net assets under management less the returns in month  $t$  divided by net assets under management at the end of month  $t-1$ . All control variables are defined in the Appendix (see Table A1). All models are estimated by ordinary least squares. Standard errors are White-corrected for heteroskedasticity and clustered at the fund level. Month and stock-portfolio times fund fixed effects included.  $p$ -values are in parentheses. \* indicates significance at 1% (\*\*\*), 5% (\*\*), 10% (\*).

## Panel A: Coefficient estimates

VARIABLES	ESG (Globe 5)		ESG (Low Carbon)	
	(1)		(2)	
	non-ESG Stocks	ESG Stocks	non-ESG Stocks	ESG Stocks
Crash × ESG	0.0154 (0.034)	0.0773* (0.042)	0.0184 (0.020)	0.0088 (0.031)
Crash × FUND_FLOWS	0.2449*** (0.034)	0.1308*** (0.049)	0.2259*** (0.037)	0.1910*** (0.052)
Crash × FUND_FLOWS × ESG	0.0071 (0.090)	-0.0425 (0.098)	0.0441 (0.070)	-0.2021** (0.092)
Crash × FUND_CHURN Ratio	-0.0428 (0.028)	-0.0536* (0.028)	-0.0393 (0.029)	-0.0556** (0.023)
Crash × FUND_CHURN Ratio × ESG	0.0367 (0.078)	0.0497 (0.084)	0.0256 (0.049)	-0.0118 (0.069)
Crash × Lagged FUND_SIZE	0.0011** (0.000)	0.0014* (0.001)	0.0015*** (0.001)	0.0009 (0.001)
Crash × Lagged FUND_SIZE × ESG	-0.0012 (0.002)	-0.0038* (0.002)	-0.0011 (0.001)	-0.0005 (0.001)
FUND_FLOWS	1.0304*** (0.016)	0.8565*** (0.021)	1.0560*** (0.017)	0.8283*** (0.026)
FUND_FLOWS × ESG	0.0625 (0.052)	-0.0448 (0.053)	-0.0462 (0.036)	0.0678* (0.040)
FUND_CHURN Ratio	-0.0630** (0.031)	0.0239 (0.031)	-0.0594* (0.031)	0.0245 (0.030)
FUND_CHURN Ratio × ESG	0.0531 (0.056)	-0.0503 (0.049)	-0.0342 (0.033)	0.0047 (0.052)
Lagged FUND_SIZE	0.0033* (0.002)	0.0053** (0.003)	0.0031* (0.002)	0.0053** (0.003)
Lagged FUND_SIZE × ESG	0.0014 (0.001)	-0.0008 (0.001)	-0.0004 (0.001)	0.0000 (0.001)
Lagged FUND_RETURN	-0.0032 (0.013)	-0.0049 (0.017)	-0.0016 (0.013)	-0.0030 (0.017)
Crash × Lagged FUND_RETURN	-0.0144 (0.037)	0.0726 (0.064)	-0.0145 (0.038)	0.0765 (0.066)
MARKET_RETURN	-0.0055 (0.040)	0.0736* (0.045)	-0.0068 (0.040)	0.0725 (0.044)
MARKET_RETURN_VOLATILITY	-1.1285*** (0.180)	-0.4302** (0.208)	-1.1100*** (0.178)	-0.4170** (0.208)

(continued)

Lagged FUND_LIQUIDITY	-0.0032*** (0.000)	0.0015 (0.001)	-0.0034*** (0.001)	0.0014 (0.001)
Crash × Lagged FUND_LIQUIDITY	-0.0611 (0.059)	0.1337* (0.075)	-0.0589 (0.059)	0.1254* (0.072)
FIRM_CHURN Ratio	0.3075*** (0.079)	0.0465 (0.121)	0.2981*** (0.079)	0.0455 (0.118)
Crash × FIRM_CHURN Ratio	-0.1502** (0.067)	-0.0829 (0.102)	-0.1228* (0.068)	-0.0946 (0.103)
FIRM_LEVERAGE	0.0613*** (0.019)	0.0079 (0.019)	0.0630*** (0.019)	0.0102 (0.019)
Crash × FIRM_LEVERAGE	-0.0010 (0.015)	-0.0214 (0.020)	-0.0030 (0.015)	-0.0220 (0.020)
FIRM_LIQUIDITY	0.0803*** (0.022)	-0.0620** (0.027)	0.0846*** (0.022)	-0.0637** (0.027)
Crash × FIRM_LIQUIDITY	0.0184 (0.019)	0.0151 (0.020)	0.0185 (0.018)	0.0218 (0.021)
ESG	-0.0313* (0.019)	0.0183 (0.021)	0.0120 (0.016)	-0.0035 (0.022)
Observations	39,868		40,188	
R-squared	0.415		0.413	

Panel B: *t*-tests on linear combinations of parameters

	non-ESG Stocks (1)	ESG Stocks (2)	non-ESG Stocks (3)	ESG Stocks (4)
<b>Sensitivity of net purchases by conventional funds to:</b>				
FUND_FLOWS/non-crash	1.0304***	0.8565***	1.0560***	0.8283***
FUND_FLOWS/Crash	1.2753***	0.9873***	1.2818***	1.0194***
FUND_CHURN Ratio/non-Crash	-0.0630**	0.0239	-0.0594*	0.0245
FUND_CHURN Ratio/Crash	-0.1059**	-0.0296	-0.0988**	-0.0310
<b>Sensitivity of net purchases by ESG funds to:</b>				
FUND_FLOWS/non-Crash	1.0928***	0.8117***	1.0097***	0.8962***
FUND_FLOWS/Crash	1.3448***	0.9000***	1.2798***	0.8851***
FUND_CHURN Ratio/non-Crash	-0.0100	-0.0263	-0.0937**	0.0292
FUND_CHURN Ratio/Crash	-0.0161	-0.0302	-0.1075*	-0.0382
<b>Difference in sensitivities across periods (Crash - non-Crash):</b>				
conventional funds/Fund flows	0.2449***	0.1308***	0.2259***	0.1910***
ESG funds/Fund flows	0.2520***	0.0883	0.2700***	-0.0111
<b>Difference in sensitivities across funds (ESG - conventional):</b>				
FUND_FLOWS/non-Crash	0.0625	-0.0448	-0.0462	0.0678*
FUND_FLOWS/Crash	0.0695	-0.0873	-0.0021	-0.1343
FUND_CHURN Ratio/non-Crash	0.0531	-0.0503	-0.0342	0.0047
FUND_CHURN Ratio/Crash	0.0898	-0.0006	-0.0087	-0.0071
<b>Diff-in-Diff (ESG - conventional and Crash - non-Crash):</b>				
ESG - conventional funds/FUND_FLOWSs	0.0071	-0.0425	0.0441	-0.2021**
ESG - conventional funds/FUND_CHURN Ratio	0.0367	0.0497	0.0256	-0.0118