Mutual Fund Trading and ESG Clientele During the COVID-19 Stock Market Crash*

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January, 2023

Abstract

This paper studies trading behavior of actively managed equity mutual funds comparing Environmental, Social and Governance (ESG) and conventional funds during a market collapse. Using monthly holdings data and the COVID-19 market crash as a quasi-natural experiment, we find that ESG funds maintained a stable share of their portfolio in ESG stocks in response to fund flows during the crash. In contrast, conventional funds, who experienced outflows the most, increased their net sales to flows for ESG and non-ESG stocks. Results are consistent with ESG funds catering to their clientele in market downturns, contributing to market stability for ESG stocks.

Keywords: Environmental and social responsibility, clientele effects, investor horizon, fund flows, stock market crash
JEL Classifications: G01, G12, G23, G32, M14

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*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 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, and the 2022 Financial Markets and Corporate Governance Conference 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 and ESG Stock Resilience During the COVID-19 Stock Market Crash." 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. Emails: rui.albuquerque@bc.edu (Albuquerque), yrjo.koskinen@ucalgary.ca (Koskinen), raffaele.santioni@bancaditalia.it (Santioni).

1. Introduction

Recent research on Environmental, Social, and Governance (ESG) investments suggests that there is an ESG clientele in asset management. This clientele is attracted to portfolios that are focused on stocks with high ESG ratings, appears less concerned by the financial returns the funds deliver, and is willing to pay higher management fees.[1] Perhaps because of their devoted clientele, ESG stocks seem to offer some protection against market downturns (Chemmanur, Gounopoulos, Koutroumpis, and Zhang 2022, Nofsinger and Varma 2014 and Ilhan, Sautner, and Vilkov 2020). This paper uses the stock market crash of 2020 linked to the COVID-19 pandemic as a quasi-natural experiment to investigate if ESG-oriented equity mutual funds cater to their clientele during a market downturn, and if their trading serves as a stabilizing force during the market crash.

The COVID-19 pandemic lead to a sudden, unexpected, and large US stock market decline of close to 30 percent at the low point of the crash. Performance varied significantly across stocks: stocks with high ESG ratings experienced higher returns and lower volatility relative to non-ESG stocks (see e.g., Albuquerque, Koskinen, Yang, and Zhang 2020, and Ding, Levine, Lin, and Xie 2021). Some of this performance differential may be explained by the discrepancy of fund flows into ESG and conventional funds as documented by Pastor and Vorsatz (2020). We are interested in analyzing the *discretionary trading* behavior of fund managers as they respond to fund flows, in the spirit of Alexander, Cici, and Gibson (2006). We design an empirical strategy that uses as benchmark a model of mutual fund trading based on constant portfolio shares similar to Lou (2012). The deviations from this benchmark allow us to characterize the discretionary trading of mutual fund managers and in particular of ESG-fund managers during

[1] Hartzmark and Sussman (2019) show that investors respond to new sustainability ratings with inflows to funds categorized as low ESG risk, even though there is no difference in fund performance. Bauer, Ruof, and Smeets (2021) document that a majority of 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 (2022) show that investors in ESG index funds are willing to pay 20 basis points higher management than for conventional index funds with similar returns.

the crash, and whether the trading behavior of the latter is consistent with a stabilizing effect for ESG stocks controlling for fund flows.

The empirical tests use a difference-in-differences estimation to study the effects of a market downturn on trading that benefits from two features of our data. First, the COVID-19 crash was sudden, unexpected, and unrelated to pre-existing economic conditions, especially to conditions relating to ESG issues. We thus use the December 2019 classifications of mutual funds as ESG-oriented (treated sample) and conventional funds (control sample) and treat these groups as exogenous in our quasi-natural experiment. One of the main advantages of the difference-in-differences estimation is that it controls for unspecified changes in expected returns during the downturn across ESG and conventional funds as well as other crash-induced effects that are unrelated to ESG, such as the fiscal policy response that occurred later in March.Second, our main data source is a proprietary data set from Morningstar with portfolio holdings collected monthly. Monthly data allow us to identify February and March of 2020 as the stock market crash months, as opposed to the first quarter, which would be the case if we were limited to using the publicly available quarterly data, and to use the significant heterogeneity in fund flows through the crisis months to ESG and conventional funds.

Our data consists of 1,699 unique US equity active mutual funds with total net assets of $3.1 trillion, representing about 400,000 stock positions. We do not take a stance on what specific aspects of funds' ESG-orientation are desired by their investor clienteles. Thus, our tests use three alternative classifications for ESG funds: the fund's own prospectus designation, Morningstar's Globe sustainability ratings,[2] and Morningstar's Low-Carbon designation. The second and third classifications are based on fund actions, not intent, as they are assigned by Morningstar using fund portfolio holdings over the previous 12 months. The separate interest on low carbon funds is justified since low carbon funds appear to have their own clientele as

[2] Hartzmark and Sussman (2019) demonstrate the relevance of Globe ratings by showing that flows increased for funds with high Globe ratings and decreased for funds with low Globe ratings after the ratings were introduced in 2016.

shown by Ceccarelli, Ramelli, and Wagner (2021), while remarkably only 17% of the funds in our sample have both a Low-Carbon designation and a high Globe rating.

We start by examining aggregate fund-level net purchases as a function of funds' ESG-orientation, fund size, fund flows, a stock market crash dummy, market return and volatility, and fund flows interacted with a dummy for the crash months and a fund ESG-orientation dummy. We highlight two findings. First, prior to the crash, an increase in net flows was associated with increased net purchases one-to-one for both ESG and conventional funds, consistent with funds keeping a constant share of cash to total assets on average. Second, the sensitivity of net purchases to fund flows increased for both types of funds during the crash, but significantly more so for conventional funds. In other words, ESG funds increased purchases less aggressively from inflows but also, and more importantly given the outflows generally experienced during the crash, increased sales less aggressively from outflows relative to conventional funds during the crash.

Our main analysis looks into the trading patterns across ES and non-ES stocks by fund category since being an ESG fund does not necessarily preclude investments in non-ES stocks. At the firm level we have enough information to be able to exclude the governance aspect in firm ESG. We add stock controls of firm liquidity, firm leverage, and churn ratio to our regressions, aggregated to the funds' portfolios of ES and non-ES stocks. Our main finding is that ESG funds traded ES stocks in response to fund flows in order to keep the ratio of ES stocks to total net assets constant during the crash, while conventional funds significantly increased their trading intensity of ES stocks in response to flows during the crash. In contrast, trading intensities for non-ES stocks increased for both ESG and conventional funds to the same degree. These findings are consistent with both fund types being more opportunistic buyers of non-ES stocks during the crash if they received inflows, but also generating more fire sales of non-ES stocks if the funds encountered outflows. We note that these effects are not mechanistic: Fund managers did not simply pass through the flows they received from investors. Our analysis compares the changes in trading behavior from normal times to the crash across ESG and conventional funds, conditional on fund flows. Thus we are able to capture the funds' discretionary trading decisions.

To get a more complete picture of the effect of mutual fund trading on the market, we note from prior research (Pastor and Vorsatz 2020) that during the crash ESG funds were the ones that experienced relatively less outflows with some ESG funds quickly recovering flows after mid-March, which arguably is a consequence of a clientele effect, whereas conventional funds mostly experienced outflows.[3] Thus, the cumulative effect of our findings and of the evidence on aggregate flows suggests the interpretation that on average ESG funds were loyal toward ES stocks, thus contributing toward resilience for ES stocks, and were opportunistic traders of non-ES stocks. Conventional funds were, however, on average distressed sellers of ES and non-ES stocks, and amplified the market crash.

The loyalty of ESG funds toward ES stocks in downturns that we identify may have several origins, which we are unable to determine in this paper. It is possible that the funds themselves have a preference for ES stocks just like some fund investors have. In addition, the evidence in Bollen (2007) and Renneboog, Ter Horst, and Zhang (2008) can be used to argue that in a market crash fund managers sell stocks in anticipation of future outflows, and especially non-ES stocks, but less so if they cater to an ESG clientele that is less likely to sell their holdings in ESG funds. An alternative explanation that does not rely on a clientele effect is that firm-level ES is a proxy for other pre-determined characteristics that fund managers may have cared for during the crisis. These other firm characteristics may have been perceived by fund managers as being associated with a smaller exposure to fire sales in a down market (Ramelli and Wagner 2020). For this reason, we include in our regressions firm-level cash, leverage, and a proxy for firm investor horizon. Second, it is possible that the resilience of ES stocks during the crash resulted from the role of fund investment horizon. Starks, Venkat, and Zhu (2020) find that

[3] Institutional investors are responsible for the inflows to ESG funds, since retail investor inflows to ESG funds declined sharply (Döttling and Kim 2022).

investors with longer trading horizons prefer ES stocks. As Cella, Ellul, and Giannetti (2013) have shown, during market turmoil periods, long-term institutional investors sell shares to a lesser extent than short-term investors. We test if the resiliency of ES stocks is associated with greater long-term investor ownership in a horse race with the ESG-orientation of funds. We find that investor horizon has no significant impact on our main results. Third, high Star-rated funds can serve as a placebo test since they experienced relatively fewer outflows during the crash, like the high Globe-rated funds and Low-Carbon designated funds, and unlike low Star-rated funds and non-ESG funds. In this additional test, we show that there is no significant difference in how the trading intensities changed during the crash across high and low Star-rated funds.

The rest of the paper is structured as follows. The next section discusses related literature. Section 3 describes the empirical strategy and data used. Section 4 reports the main results. Section 5 examines alternative hypotheses and robustness checks. Section 6 concludes.

2. Related literature

This paper provides evidence consistent with ESG mutual funds catering to their clientele's preferences to provide stability to ESG stocks in market downturns. There is evidence of investor clienteles for specific asset classes or investing styles. Evidence for ESG preferences by individual investors has been documented by Bauer et al. (2021) using data on pension funds that grant their members a real vote on ESG policies. Huang, Karolyi, and Kwan (2021) show that when investors pay more attention to ESG issues they are less likely to sell and more likely to buy stocks with high ESG ratings. Humphrey, Kogan, Sagi, and Starks (2021) show in an experiment that about half of the subjects demonstrate a significant preference for responsible investing by halving their allocation to stocks associated with negative ES externalities. Zhang (2021) shows that mutual funds and other investment managers required to file the SEC 13f form are less prone to sell overpriced stocks with high ESG scores. Rzeznik, Hanley, and Pelizzon (2021) show that investors incorrectly bought stocks when Sustainalytics inverted their ESG ratings, erroneously believing that higher rating meant improved ESG performance.[4] Other investor clienteles in mutual funds have been identified in value versus growth mutual funds (Blackburn, Goetzmann, and Ukhov 2009), dividends (Harris, Hartzmark, and Solomon 2015), and direct-sold versus broker-sold funds (Del Guercio and Reuter 2014). Our results contribute to the study of investment clienteles by analyzing how trading by fund managers caters to their clientele during a stock market crash.

There is a large literature that studies the potential for destabilizing trading behavior of institutional investors. Choe, Kho, and Stulz (1999) find evidence of herding behavior by foreign investors in Korea before the 1997 East Asian crisis, but not so during the crisis itself. Cella et al. (2013) find evidence consistent with short-term investors amplifying market-wide negative movements. Lakonishok, Shleifer, and Vishny (1992) and Wermers (1999) show that there is some evidence of herding in small stocks. Glossner, Matos, Ramelli, and Wagner (2021) show that stock price performance during the COVID-19 was more negative for firms with institutional investors facing outflows. The authors conclude that institutional investors amplified the crash by engaging in fire sales. Arguably that conclusion should apply to institutional investors in the degree that they experienced outflows. Our work shows that ESG actively managed equity funds, who experienced relatively more inflows than conventional funds, acted in a way that stabilized the market for ES stocks and attenuated the effects of the crash for non-ES stocks.The average trading behavior of conventional funds toward ES and non-ES stocks is, however, consistent with positive feedback trading and an amplification of the market crash.

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 recent papers examine ESG ratings and stock returns during the initial phases of the COVID-19 pandemic. Albuquerque et al. (2020) show using U.S. data that firms with high E and S scores fared better during the crash. Ding, Levine, Lin, and Xie

[4] For other references see Hartzmark and Sussman 2019, Gantchev, Giannetti, and Li 2021, Bollen 2007, and Renneboog et al. 2008.

(2021) provide international evidence that E and S polices had positive impact on stock returns. Garel and Petit-Romec (2021) show that only E scores had a positive effect on stock returns. Bae, El Ghoul, Gong, and Guedhami (2021) and Demers, Hendrikse, Joos, and Lev (2021), however, find no evidence that ES ratings affected stock returns. One reason for the discrepancy in results in these two last papers is their use of market-based measures of firm size as a control variable, which tend to absorb the effect of other variables. In addition, control variables are more important when using cross-sectional regressions as in Bae et al. (2021) and Demers et al. (2021), but not when conducting difference-in-differences regressions with daily data as Albuquerque et al. (2020) do for their main analysis.

3. Empirical strategy and data

3.1. A benchmark model of mutual fund trading

We frame our empirical analysis using a benchmark model where mutual funds keep constant proportions of ES stocks and non-ES stocks to total net assets following fund flows. This is a natural benchmark that assumes that a fund's allocation is optimal independently of fund flows.[5] Deviations from this benchmark can detect discretionary trading that favored one group of stocks versus another.

Let P_G be the price of the ES stock (labelled 'G' for green) and Q_G the number of shares of that stock held by a mutual fund (and for simplicity assume only one stock exists of the ES variety), then $P_G Q_G$ is the total net asset value associated with the mutual fund's portfolio of ES stocks. The percentage change (or growth) in the net asset value of ES stocks over two consecutive periods is

$$\widehat{P_G Q_G}_{t+1} = \frac{P_{G,t+1} Q_{G,t+1} - P_{G,t} Q_{G,t}}{P_{G,t} Q_{G,t}}. \tag{1}$$

[5] Ultimately, it assumes that investor flows are largely uninformative about future returns to either group of stocks (see Lou 2012 for a result consistent with this assumption), and there are no frictions that would keep fund managers from building their unconstrained optimal portfolio allocation prior to the flows.

In the benchmark setting where the share of ES stocks in total net assets (TNA) is constant,

$$\widehat{P_G Q_G}_{t+1} = \widehat{TNA}_{t+1}. \tag{2}$$

The evolution over time of total net assets is given by

$$TNA_{t+1} = (1 + r_{t+1})TNA_t + NF_{t+1}, \tag{3}$$

where NF_{t+1} is the net fund flow from t to t+1 and r_{t+1} is the fund's return performance from t to t+1. Subtract TNA_t from both sides, divide both sides by TNA_t, and denote $FF_t = \frac{NF_t}{TNA_{t-1}}$, to get

$$\widehat{TNA}_{t+1} = r_{t+1} + FF_{t+1}. \tag{4}$$

This equation simply states the accounting identity that TNA changes due to fund performance or fund flows.

Use equation (2) to replace $\widehat{TNA}_{t+1}$ with $\widehat{P_G Q_G}_{t+1}$,

$$\widehat{P_G Q_G}_{t+1} \quad = \quad r_{t+1} + FF_{t+1}. \tag{5}$$

Because TNA changes with fund performance and with fund flows, in order to keep a constant proportion of ES stocks to TNA, dollar holdings of ES stocks must also change in the same way with fund performance and fund flows.

Repeating the same steps for non-ES stocks, which we label with the subscript 'B' (for brown stocks),[6] we obtain a similar equation for the percentage change in value holdings of

[6] A fund's TNA would include cash besides the fund's portfolio of ES and of non-ES stocks. If the shares of ES stocks and of non-ES stocks in TNA are constant, so is the share of cash in TNA.

non-ES stocks,

$$\widehat{P_B Q_B}_{t+1} = r_{t+1} + FF_{i,t+1}. \tag{6}$$

To turn equations (5) and (6) into a model that can be estimated, we make the following assumptions. First, we replace $r_{t+1} = E_t[r_{t+1}] + \epsilon_{t+1}$, where ϵ_{t+1} has the property that $E_t[\epsilon_{t+1}] = 0$. We further replace expected returns by their determinants, which include the fund's lagged performance and the market's performance and volatility. Likewise, assuming fund flows follow a process close to a random walk, we replace FF_{t+1} by lagged net flows, FF_t, and allow in addition fund performance to also affect flows while leaving the unexplained portion of fund flows in the error term of the regression. We add several control variables, described below, to account for possible deviations from the benchmark of constant shares that are unrelated to how the fund's trading responds to flows or to performance.

Second, note that $\widehat{P_G Q_G}$ is the sum of two components, the change in net asset value of ES stocks due to changes in the price of ES stocks and Net Purchases of ES stocks. Since we are interested in active trading decisions by mutual fund managers to buy or sell certain stocks, we subtract the first component (i.e., the return on ES stocks) from both sides of equation (5) (and likewise for non-ES stocks). Thus, the left hand side of equation (5) becomes Net Purchases of ES stocks, and in the right hand side of the same equation we replace the return on TNA by the return on non-ES stocks (in effect we keep both the fund's total return and the return on a ES portfolio as right-hand-side variables). Intuitively, if during period t non-ES stocks performed well, to keep a constant share of ES stocks in the fund's portfolio more of the ES stocks should be purchased.

Third, for each fund, we aggregate individual stocks to either the portfolio of ES stocks or the portfolio of non-ES stocks. We run the regressions at this portfolio level instead of running the regressions at the stock level. This choice is motivated by the assumption that the benchmark of constant portfolio shares in response to flows is less noisy at this more aggregated level than at the stock level. Combining these assumptions, the empirical approach is to estimate

$$\begin{aligned} NetPurch_{j,i,t+1} &= \beta_j X_{j,i,t} + \gamma_{j,1} FF_{i,t} + \gamma_{j,2} FF_{i,t} Crash_t ESG_i + \gamma_{j,3} FF_{i,t} Crash_t \\ &+ \gamma_{j,4} Crash_t ESG_i + \gamma_{j,5} Crash_t + \gamma_{j,6} ESG_i + \gamma_{j,7} FF_{i,t} ESG_i + \epsilon_{j,i,t+1}, \quad (7) \end{aligned}$$

where the unit of observation is stock-portfolio j in fund i and month t, for $j = G, B$. To estimate how trading changes from normal times to the crash for different fund types, we include in equation 7 interactions of Fund Flows with a dummy that classifies the fund as ESG (vs conventional), denoted ESG_i, and also with a dummy that identifies the crash period (defined in the main analysis with the months of February and March), denoted $Crash_t$. The control variables identified by $X_{j,i,t}$, include the fund's lagged return performance and performance of a ES benchmark, lagged fund size, and contemporaneous market return and volatility. We also control for lagged fund liquidity (cash holdings) since it may have helped funds respond differently to the crisis (Chernenko and Sunderam 2016), besides proxying for frictions that may keep managers from ex-ante choosing their optimal portfolios in normal times (Lou 2012).[7] $X_{j,i,t}$ also includes lagged stock-portfolio controls. Fund managers may have a preference for certain firm characteristics, either because they help predict returns, or they may make the firm less likely to experience fire sales in downturns, or they may be associated with lower costs of transacting the firm's stock (Lou 2012). These additional controls are firm liquidity and firm leverage (Ramelli and Wagner 2020), and firm churn ratio (a proxy for the horizon of the firms' investors and for the liquidity of the stocks), aggregated to the fund's portfolios of ES and non-ES stocks. We include stock-portfolio times fund fixed effects and quarter fixed effects. The estimation uses the Stata command *reghdfe* (see Correia 2017).

The null hypothesis of constant proportions in response to fund flows states that the sen-

[7]Later we will include also lagged fund-level churn ratio, as a proxy for fund investment horizon. The churn ratio may also proxy for trading frictions in portfolio formation at the fund level.

sitivity of Net Purchases to Fund Flows equals 1. For example, outside the crash period, this sensitivity is given by $\gamma_{j,1}$ for conventional funds and by $\gamma_{j,1}+\gamma_{j,7}$ for ESG funds, where $j = G, B$. One important sensitivity in our study is that of ESG funds' Net Purchases of ES-stocks to Fund Flows during the crash, $\gamma_{G,1} + \gamma_{G,2} + \gamma_{G,3} + \gamma_{G,7}$. If the estimated sensitivity is larger than one, then the fund manager is actively increasing the proportion of the corresponding asset class if flows are positive and actively decreasing the proportion of the same asset class if flows are negative. In contrast, if the estimated sensitivity is smaller than one, then the fund manager is actively decreasing the proportion of the corresponding asset class if flows are positive and actively increasing the proportion if flows are negative. To reject the null that the sensitivity is one is equivalent to reject the hypothesis that the fund manager is actively maintaining a constant proportion of ES stocks to TNA.

The difference-in-differences approach allows us to separate the effect of net flows across ESG and conventional funds, before and after the crash, which we can measure with the parameters $\gamma_{j,2}$, for $j = G, B$. The identification relies on two features linked to the crash that make it a quasi-natural experiment to study the effects of an ESG clientele during a market crash. First, the unexpected nature of the crash gives a clear break in the sample. Later we will verify the parallel trends assumption in the variable Net Purchases. Second, the crash was not driven by economic conditions (or any aspect specific to ESG), but rather a virus pandemic. This allows us to consider ESG funds as a treated sample and conventional funds as a control sample. The sample of conventional funds allows us to control for unobserved changes in market conditions that affect everyone such as changes in aggregate discount rates and risk tolerance or expectations of growth in the aggregate economy. We are therefore able to control for unobserved changes in expected returns to both asset class. A finding that $\gamma_{G,2} < 0$ implies that during the crash, conventional funds tilted their portfolios toward ES stocks more than ESG funds in the presence of inflows, and also that conventional funds tilted their portfolio away from ES stocks more than ESG funds in the presence of outflows. Thus, $\gamma_{G,2} < 0$ suggests a more stable trading strategy during the crash for ESG funds regarding their ES portfolio in general and specifically in the presence of outflows.

We also run regressions with fund-level, aggregate net purchases as the dependent variable. In these regressions, we exclude the firm-level control variables, and include only fund and quarter fixed effects. In this empirical model, which resembles the model in Cella et al. (2013), the null hypothesis that the sensitivity of Net Purchases to Fund Flows equals one is a statement that the ratio of cash balances to total stock value remains constant over time for the average fund (see Lou 2012).[8]

Following the benchmark model of stable portfolio shares in the presence of fund flows, the paper's main null hypothesis is that ESG funds displayed the same trading intensity for ES stocks relative to Fund Flows, compared to conventional funds from pre-crash to the crash (i.e., $H0 : \gamma_{G,2} = 0$). A rejection of this hypothesis, specifically in favor of an alternative where $\gamma_{G,2} < 0$, is interpreted as an indication that ESG funds displayed greater resilience toward ES stocks than conventional funds during the crash, especially in the presence of fund outflows. To motivate how this resilience connects with the clientele hypothesis, consider the decision of a fund manager experiencing sudden outflows and having to liquidate some of her portfolio while watching the crash unfold. The fund manager will likely sell stock to meet current redemptions, but also to cover expected future withdrawals and thus avoid selling later at even lower prices. With an ESG clientele with demonstrated lower sensitivity to fund performance (Renneboog et al. 2008, Bollen 2007, and Zhang 2021), ESG funds may end up being less aggressive sellers in general, and of ES stocks in particular as these are the distinctive assets that their investors appreciate. In addition, this clientele effect may support a self-fulfilling equilibrium where fund managers display herding in non-ES stocks (see Wermers 1999 for evidence of mutual fund herd behavior). In this equilibrium, fund managers expect that non-ES stocks will fall in value

[8] Cella et al. (2013) control for fund investor horizon in their tests; we leave the inclusion of this variable and the treatment of fund investor horizon for later in the paper so as to keep the presentation of the tables more manageable.

faster and postponing their sales will result in larger losses in case of continuing redemptions going forward. The ESG fund manager would then prefer to sell the non-ES stocks in the portfolio generating a likely price drop, and validating the expectations that prices of non-ES stocks would fall faster. Alternatively, the fund manager may choose to sell the ES stocks in her portfolio so as to keep the current realized losses at a minimum. We turn to data to inform us on the net contribution of these effects.

3.2. Data sources and sample

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.[9] The only other paper we know that makes use of the same dataset is Maggiori, Neiman, and Schreger (2020). 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, also including derivative positions. We obtain monthly portfolio information from December 2019 to June 2020 for all actively managed U.S. equity mutual funds with disclosed ISIN identifiers available for their portfolio stocks. We focus on 2020 data to be comparable with other papers on the COVID crisis, but later do a robustness analysis that includes 2019 data. From Morningstar Direct, we obtain information on the characteristics of the U.S. mutual funds in our sample, such as the Morningstar global category classification, net fund flows, and total net assets.

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 then merge the data with Morningstar Direct using FundID to identify the legal domicile. We remove all funds not domiciled in the U.S. We have 6,989 unique funds representing $29.2 trillion total net assets. We then

[9]Across the world, funds report to Morningstar typically on a monthly basis and, when not, then almost always quarterly. Morningstar uses these data to update their Star ratings.

remove index funds using the Morningstar Direct identifier for active versus passive funds, leaving us a sample of 6,630 unique funds with \$20.4 trillion TNA. After excluding non-equity fund categories (e.g., allocation, fixed income), we obtain 3,176 unique mutual funds with \$6.9 trillion TNA. This sample contains all funds with available quarterly data. We take out all of the funds that do not have monthly data, resulting in a sample of 1,717 unique actively managed mutual funds with \$3.1 trillion of TNA. 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 \$3.1 trillion as of December 2019. This sample contains a monthly average of just under 400,000 stock portfolio positions.

Due to the granularity of our dataset at fund and ISIN level on quantities and prices, we are able to compute net purchases for each stock and then aggregate to fund level as in Cella et al. (2013). $NetPurchases_{t,i}$ 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 dollar holdings 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, we verify graphically the parallel trends assumption of similar behavior of net purchases by ESG funds and non-ESG funds prior to the crash months.

We collect several indicators of funds' environmental, social, and governance performance from Morningstar Direct. First, we denote as ESG funds those that report being ESG funds in their prospectus. Second, we label as ESG funds those with 4 or 5 Morningstar Sustainability Globe ratings as of January 2020. As a third definition, ESG funds are those that receive a Low-Carbon Designation from Morningstar as of January 2020. There are two main differences between using the fund's prospectus information versus the Globe ratings or Low-Carbon designation. Prospectus information is dated and requires truthful revelation to be credible, both of which may be a concern because Gibson, Glossner, Krueger, Matos, and Steffen (2022) report that U.S.-domiciled institutions that publicly commit to ESG policies appear to engage in greenwashing. Morningstar's Globe ratings and Low-Carbon designation are instead updated monthly on the basis of the fund's actual portfolio holdings over the previous 12 months. The assumption that portfolio holdings reveal the preference of fund managers is consistent with Gantchev et al. (2021) who demonstrate that mutual fund managers are aware of potential benefits of owning ESG stocks. In our sample, in January of 2020, TNA of funds that identify as ESG in their prospectus is \$64 billion, TNA of funds with 4 or 5 Globe ratings is \$894 billion, and TNA of funds with Low-Carbon designation is \$988 billion. Despite similar TNA values, only 17% of the funds have both a Low-Carbon Designation and a high Globe rating, and 54% of the funds have both a Low-Carbon Designation and a low Globe rating (untabulated). The pairwise correlation between a Globe rating dummy and a Low-Carbon designation dummy is 0.32, between a Globe rating dummy and a prospectus dummy is 0.24, and between a Low-Carbon designation dummy and a prospectus dummy is 0.16 (untabulated).

The Low-Carbon Designation is especially interesting since we are not able classify funds solely based on their ES designation, because Morningstar classifies funds as ESG funds, i.e., including 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 appeared to favor environmental funds even more during the crash. Moreover, Garel and Petit-Romec (2021) find that stocks with high emission reduction scores performed particularly well during the crash. In addition, the findings in Ceccarelli, Ramelli, and Wagner (2021) suggest that investors have a preference for low-carbon funds, and likewise Anderson and Robinson (2021) show that environmentally concerned investors tilt their retirement portfolios toward more sustainable investments.

The main independent variable in our panel regressions is $FundFlows_{i,t}$, fund flows normalized by lagged TNA. Fund Flows are truncated at the bottom and top 1% of the monthly distribution. Figures 1-3 display average cumulative Fund Flows from January 2020 to June 2020 for both ESG funds (under the prospectus designation, 4 or 5 Globe ratings, and the low-carbon designation, respectively) and non-ESG, or conventional funds. ESG funds generally experienced a modest decrease in flows in February and March, except for ESG-prospectus funds who saw continued inflows all through June of 2020. High Globe rated funds and Low-Carbon designation funds recovered partially in April. In contrast, non-ESG funds experienced a pronounced decline in net flows through the whole period, independently of the ESG definition used, especially starting in March. These patterns have been shown elsewhere (e.g., Pastor and Vorsatz 2020 for Globe rated funds) and are confirmed here for our reduced sample of funds with available monthly holdings data. Understanding the consequences of the heterogeneousbehavior of flows for ESG funds and for conventional flows is one of the objectives of this study. The exogenous crash that occurred in February and March, 2020, is an ideal event where we can test for the clientele hypothesis, and for which we benefit from the higher monthly frequency data on portfolio holdings.

Figures 1-3 here

Firm-level ESG metrics are obtained from Thomson Reuters' Refinitiv. We focus on the average of the environment and social scores in 2019, denoted by ES, and omit the governance score following Albuquerque et al. (2020). We identify ES stocks if their ES score is in the top quartile of the distribution. We compute net purchases of ES stocks (non-ES stocks) in the same fashion that we did for aggregate net purchases, though as suggested by the model, we use as denominator the dollar value of ES stocks (non-ES stocks) in the fund's portfolio. One noteworthy aspect regarding Refinitiv ES scores is that they are calculated relative to an industry benchmark. It is therefore not expected that a single industry should drive the results in our paper. For example, the oil and gas industry is typically thought to have low environmental performance, but the firms in that industry need not have low E scores because of the relative scoring. Nonetheless, in a robustness analysis available in the online appendix, we omit the oil and gas industry. We do so mostly because oil prices experienced a sharp decline in the first half of 2020, so outflows from the industry could be related to the oil price change and not with it scoring low on ES. We obtain similar results to our main analysis.

Appendix Table A1 provides detailed definitions of the variables of interest and control variables. Table 1 provides descriptive statistics for our full sample and for subsamples by ESG fund designation for the main variables. Note that there are many more funds classified as ESG based on Globe ratings than there are based on prospectus declarations, an indication that more funds have converted to become ESG funds.

Table 1 here

4. Results

We first report results for fund-level, aggregate net purchases and then report on net purchases of ES and non-ES stocks for ESG and conventional funds.

4.1. Fund-level net purchases

Table 2 contains the results from six different regressions of fund-level Net Purchases on Fund Flows, as well as controls and fixed effects detailed above. In columns (1) and (2) we use the fund's prospectus to identify a fund as an ESG fund. In columns (3) and (4) we label a fund as an ESG fund if the fund has 4 or 5 Morningstar Globe ratings, and in columns (5) and (6) the ESG label is given to to Morningstar Low-Carbon Designated funds. For each ESG fund designation, we report two sets of regressions: with and without fund and market returns, ESG index returns, market return volatility, and fund liquidity. The reason for considering results without these performance variables is that they could subsume the Crash dummy, since in our short sample the crash period coincides with the larger negative returns and higher volatility months of the sample. We report robust standard errors, clustered by fund.

Table 2 here

Consider the effect of the control variables first. Note that the results are similar across specifications. The results show that all funds sold more stocks (or bought less) during the crash than they did on average during the sample period, with ESG funds selling significantly less as shown by the interaction term Crash x ESG, all else equal. Outside of the crash, fund size has no statistically significant effect for trading, after controlling for fund liquidity, with no statistically significant difference between ESG and conventional funds (with the exception of large Low-Carbon funds that decreased net purchases during the sample relative to conventional funds). However, during the crash, larger conventional funds increased their net purchases by more than comparable ESG funds. Surprisingly, outside of the crash funds sold more after higher past performance, but purchased more stock if they had more liquid assets. Market returns had no effect on net purchases but higher volatility of aggregate stock market returns was associated with more net sales at the fund level.

We next turn to the effect of Fund Flows on the behavior of ESG and conventional funds. Recall that under the null hypothesis of the empirical model presented above, a coefficient of 1 means that the fund keeps a constant proportion of stock holdings to TNA (including cash) with every dollar of fund flow. Consider first the results shown in column 6 in Table 2 (panels A and B) for Low-Carbon funds. Outside of the crash months, the estimated coefficient associated with Fund Flows for conventional funds is 0.9760, for which we reject the hypothesis that it is 0 at 1% level and cannot reject the hypothesis that it is 1 at the 1% level. The coefficient for ESG funds is marginally smaller (0.0044 smaller). This evidence suggests that the empirical model constructed above provides a good characterization of how funds change their stock holdings to TNA ratio in response to fund flows, outside of the crash. This is evidence is consistent with that in Lou (2012).

The crash months see a dramatic change in the trading intensities of ESG and conventional funds, especially for the latter. In column 6, Conventional funds increased their buying of stocks per unit of inflow by 0.3503 relative to normal times, and Low-Carbon funds increased their buying of stocks per unit of inflow by 0.2170 relative to normal times.[10] The differential change

[10]The significant increase in trading intensity especially for conventional funds is consistent with a decline in

is -0.1333 and is statistically significant at the 1% level. This means that ESG funds were less aggressive buyers when they experienced inflows during the crash, but, more importantly, also less aggressive sellers when they faced redemptions, relative to conventional funds. We interpret this evidence as suggestive of a greater resilience of ESG funds, especially when combined with the evidence in Figures 1-3 (and in Pastor and Vorsatz 2020) showing that ESG funds experienced relatively less outflows than conventional funds during the crash, and even obtained inflows on average at least in April.

The results obtained when we use Morningstar's Globe ratings to classify ESG funds (see column 4, panels A and B) are almost identical to those of Low-Carbon funds. Results differ significantly, however, for ESG funds based on their prospectus designations (see column 2, panels A and B). The evidence shows that during normal times ESG-prospectus funds were buying stock less than 1-to-1 of fund inflows, but conventional funds kept their stocks holdings to TNA constant. In addition, during the crash months ESG-prospectus funds trading intensities increased so much that they became equal to those of conventional funds (both fund types increased their stock holdings relative to TNA significantly). This difference in behavior for ESG-prospectus funds, and other differences we note below, may be indicative of greenwashing. They may also arise due to having only a small number of funds in our sample that explicitly identify as ESG funds in their prospectuses.

4.2. Net purchases of ES and non-ES stocks

In this subsection, we separate net purchases of ES stocks from net purchases of non-ES stocks for each fund in order to estimate equation 7. The results are in Table 3. In the two columns labelled (1), we use the fund's own prospectus designation, in the next two columns, labelled (2), ESG funds have 4 or 5 Morningstar Globe ratings, and in the final two columns, labelled (3), we label as ESG funds all those with a Low-Carbon Designation. For each ESG/non-ESG fund designation, we report results for Net Purchases of non-ES stocks and Net Purchases

fund cash and equivalents on average all through 2020 per unit of inflow.

of ES stocks. The regressions include fund fixed effects and quarter times stock-portfolio fixed effects, as well as the stock-portfolio controls listed above. We report robust standard errors clustered by fund.

Table 3 here

The results across columns 1 through 3 are similar with regard to the control variables. Starting with the fund-level controls, the Crash dummy on its own does not capture any additional trading in either ES-stocks and non-ES stocks. The effect of fund size is close to symmetric between ES stocks and non-ES stocks (positive for ES stocks and negative for non-ES stocks; a pattern that may explain the aggregate results documented above) and does not change significantly for ESG funds. As with aggregate Net Purchases, funds sold more ES and non-ES stocks after high past performance during normal times. Market volatility decreases Net Purchases for non-ES stocks, but not for ES stocks.

We turn now to the stock-level controls. Portfolios whose stocks have high leverage experienced increased sales during the crash but only for non-ES stocks. These findings are consistent with Ramelli and Wagner (2020) who show that stocks with higher leverage experienced larger price declines and with Albuquerque et al. (2020) who show that stocks with higher ES ratings experienced smaller price declines during the crash, even after controlling for firm leverage. In contrast, outside of the crash, portfolios whose stocks have lower liquid assets are associated with increased Net Purchases, but only for ES stocks.

Next consider the estimated coefficients associated with Fund Flows, and for now focus on columns 5 and 6 in panels A and B. For conventional funds, during normal times, the sensitivity of Net Purchases of ES stocks to Fund Flows is 0.7209, which is statistically smaller than 1, whereas the sensitivity of Net Purchases of non-ES stocks to Fund Flows is 1.0533, which is not statistically larger than 1. The trading intensities of Low-Carbon funds during normal times are similar, with the exception that Low-Carbon funds bought more ES stock per unit of inflow (a difference of 0.1558, significant at 1% level). During the crash, though, Low-Carbon funds kept their share of ES stocks constant (sensitivity of 0.9342, insignificantly different from 1), whereas conventional funds increased the sensitivity of Net Purchases of ES stocks to Fund Flows significantly to 1.1514. The difference-in-differences coefficient is −0.3730, representing the additional sensitivity for conventional funds during the crash. Both fund types increased their trading intensities for non-ES stocks during the crash: the increase for conventional funds is 0.2947 and for Low-Carbon funds 0.4066, both significant at 1% level (the difference of 0.1118 is not statistically significant). Since conventional funds mostly experienced outflows, these results suggest that conventional funds were on average selling both ES and non-ES stocks. For non-ES stocks, the trading intensities of both Low-Carbon and conventional funds increased by about the same amount resulting in no difference in behavior from prior the crash to the crash period across the fund types. Overall, these results support the hypothesis that ESG funds demonstrated stability towards ES stocks during the crash, but they also increased significantly Net Purchases for non-ES stocks when they experienced inflows, which for Low-Carbon funds happened in April and May. Thus, the evidence supports the view that ESG funds provided support for ES stocks during the crash.

The results above are confirmed when we split fund flows into inflows (i.e., positive Fund Flows) and outflows (i.e., the symmetric of negative Fund Flows) for each fund type (see Table OA.2 in the online appendix). For Low-Carbon funds, their trading intensities stay the same for ES stocks during the crash compared to normal times for both inflows and outflows. Conventional funds bought more ES stocks during the crash when they encountered inflows (an increase of 0.5724, significant at 1% level), but they also, more importantly, sold more ES-stocks when the funds experienced outflows (an increase of 0.3001, significant at 1% level). For non-ES stocks, both Low-Carbon and conventional funds bought more during the crash when the funds experienced inflows (0.3962 and 0.2066, respectively, both significant at 1% level). Likewise, both fund types sold more non-ES stocks during the crash when the funds had outflows (−0.3592 and −0.3921, respectively, both significant at 1% level).

As with the results in Table 2, the results do not change in any material way if instead we classify ESG funds using Globe ratings (columns 3 and 4). Again, differences arise when the funds prospectus designation is used (columns 1 and 2). ESG-prospectus funds changed their trading intensities of ES stocks during the crash in the same direction and magnitude as conventional funds, with the difference-in-differences coefficient estimate equal to 0.1762 that we cannot reject to be equal to zero. In addition, ESG-prospectus funds bought more non-ES stocks per unit of Fund Flows during the crash compared to conventional funds (the difference-in-difference coefficient is 0.3487, significant at 10% level), increasing their share of non-ES stocks in their portfolios as these funds largely experienced inflows during the sample period.

5. Alternative hypotheses and robustness checks

5.1. Morningstar Star funds

We next investigate the possibility that ESG funds behaved differently, because these funds encountered less outflows or even inflows during the crash. We do this by comparing the trading behavior of Star-rated funds with that of ESG funds, since funds with high Star-ratings experienced less outflows on average during the crash - five Star funds even received small amount of inflows. Similarly to non-ESG funds, funds with low Star-ratings experienced significant outflows on average (see Pastor and Vorsatz 2020).

Table 4 contains the results. Columns 1 and 2 are a replica of the estimations in Table 2 and the two columns under the label 3 replicate the estimations conducted in Table 3.

Table 4 here

Considering columns (1) and (2), we observe significant changes in trading intensities during the crash in response to fund flows for low-rated funds, but no statistically significant changes for high-rated funds. Focusing on the critical difference-in-differences parameter, we find no significant difference across low-rated and high-rated Starfunds. When comparing trading intensities for non-ES and ES stocks (columns 3 and 4), the increases are of the same magnitude during the crash: the difference in the change in trading intensities across funds is 0.0019 for non-ES stocks and −0.0276 for ES stocks, none of which are significantly different from zero. Thus there are no differences in trading behavior across low- and high-Star funds during the crash compared to normal times for aggregate fund purchases, as well as for ES and non-ES stocks. This provides a clear contrast to ESG- and conventional fund behavior differences during the crash: ESG funds exhibited stable trading behavior towards ES stocks, whereas conventional funds increased their trading intensities for ES stocks, with a statistically significant difference between the two fund types.

5.2. *Fund investment horizon*

Investor horizon is another mechanism for fund loyalty towards ES stocks. The basic hypothesis is motivated by the work of Cella et al. (2013), who show that during market turmoil periods, long-term institutional investors trade their holdings less than other investors. As long-term investors tend to have a preference for ES stocks (Starks et al. 2020), it appears reasonable to hypothesize that investor loyalty toward ES stocks is tied to investors' trading horizon.

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 from the stock-level *Churn Ratio* variable.[11] A high Fund Churn Ratio indicates a short trading horizon by the fund's investors. Table 1 shows that the average Fund Churn Ratio for all mutual funds in our sample is 0.1119. The Fund Churn Ratio for ESG funds is lower (0.083 for prospectus definition, 0.1027 for high Globe ratings, and 0.1018 for Low-Carbon Designation). Hence, conventional funds have on average shorter trading horizons, consistent with Starks, Venkat, and Zhu (2020).

[11] For each mutual fund, we compute the churn ratio every month. The trading horizon is then measured by the average churn ratio over the last 36 months (a minimum of 25 months is required). See Appendix A for a complete definition of fund churn ratio. By averaging across different stocks held by a mutual fund, the churn ratio removes idiosyncratic firm-level shocks that may affect investors' holding periods. At the same time, by averaging over a long time period, we mitigate the effect of investor-specific shocks that may generate deviations in the investor's holding period from its preferred horizon.

For brevity, we present in Table 5 the results for Net Purchases of ES stocks and of non-ES stocks, and omit the results for aggregate Net Purchases. Fund investor horizon appears to matter most for Low-Carbon designation funds (column 3). In particular, during the sample period, conventional funds with longer-term investors (lower churn ratio) sold more ES stocks. Low-Carbon funds behaved the opposite way: they sold more non-ES stocks and bought more ES stocks.This behavior did not significantly change during the crash period. To see the effect that adding Fund Churn Ratio has on our main variable of interest, Fund Flows, we again focus on the difference-in-differences coefficient, which can be read from the triple interaction Crash dummy x Fund Flows x ESG dummy. Again, the results show that trading intensities of ESG and conventional funds changed dramatically and in a similar way during the crash for non-ES stocks, but for ES stocks the change in trading intensity during the crash for ESG funds was significantly smaller than that for conventional funds.

5.3. Sample with longer time series

We redo the main analysis extending the sample period by 12 months, back to January 2019. We conduct this analysis in order to potentially better control for any prior trends for funds that were classified as ESG and non-ESG in the main sample period. The longer sample also allows us to benchmark our results to the corresponding months of 2019. The shorter time series of the first half of 2020 constitute our main focus, in order to be compatible with other papers on COVID-19 that share the goal of better isolating the crisis. The longer data set from January 2019 through June 2020 (where we use December 2018 to calculate the first net sales observations) leads to more than triple the number of fund-month observations from about 16,000 in Table 3 to around 53,000 in the new results. The Morningstar data that we have lacks the historical values of the firm-level variables that we use to construct several stock-level controls and so the regressions we present omit these controls.

We proceed with some re-definitions. ESG funds are classified in the following way: prospectus definitions are unchanged; Globe rating and Low-Carbon Designation definitions are fixed in windows of six months; that is, we use the December 2018 values of these variables to classify funds from January 2019 through June 2019, then use the June 2019 value to classify funds from July 2019 through December 2019, and so on. Note that because the fund-ESG classification changes when we use the extended time series, we include a fund-ESG dummy in the regressions where we also employ fund fixed effects. Firms are classified as ES firms based on last available observation before January 2019, which is then kept fixed for the full sample.

The results from this robustness are virtually the same as in the main analysis and a table with these results can be found in the online appendix. Again focusing on the difference-in-differences coefficient associated with the triple interaction Crash dummy x Fund Flows x ESG dummy, the results show that ESG funds and conventional funds significantly increased Net Purchases of non-ES stocks per unit of Fund Flow during the crash, but that only conventional funds increased Net Purchases of ES stocks per unit of Fund Flow during the crash. Recalling that conventional funds experienced outflows the most, these results suggest that conventional funds sold on average non-ES stocks and ES stocks during the crash. In contrast, because ESG funds encountered less outflows and even saw a rebound in flows in April, they show stability towards ES stocks and some buying of non-ES stocks at least in April (and also May for low-carbon funds).

5.4. Defining Crash dummy using only March

The COVID-19 stock market crash started at the end of February and continued all through the third week of March. An alternative definition of the Crash dummy is to assign only the value of 1 to the month of March. As Figures 1-2 show the outflows from conventional funds are more pronounced in March, but also that ESG funds experienced outflows, especially the Low-Carbon funds, who actually at that point have encountered even more outflows than conventional funds (see Figure3). A Table with the results can be found in the online appendix. The results show that if anything there is a slightly bigger change in trading intensities for conventional funds for both ES and non-ES stocks, and for ESG funds for non-ES stocks. However, ESG funds display no change in trading intensity from pre-crash to crash for ES stocks.

6. Conclusion

This paper provides evidence that U.S. actively managed equity mutual funds with an ESG focus catered to their clientele's preferences to provide stability for ESG stocks in the 2020 market downturn. In this paper, we use the exogenous stock market crash of February and March of 2020 as a quasi-natural experiment to study changes in the trading behavior of ESG funds and of conventional funds during a significant market downturn. Not to take a stance on a definition of ESG, we classify all funds as either ESG or non-ESG funds according to their prospectuses, Morningstar Globe ratings, and Morningstar Low-Carbon designation. Overall, the results are supportive of the joint hypothesis that there is an investor ESG-clientele and that ESG fund managers catered to their investor clientele by displaying remarkable stability in the trading behavior of ES stocks during the crash. These results also shed light on why ESG funds performed relatively well during the crash: they kept their ES stock portfolio share constant, while at the same time selling more of their underperforming non-ES stocks, or when receiving inflows, opportunistically buying non-ES stocks.

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 than they are in the U.S. We leave that for further study.

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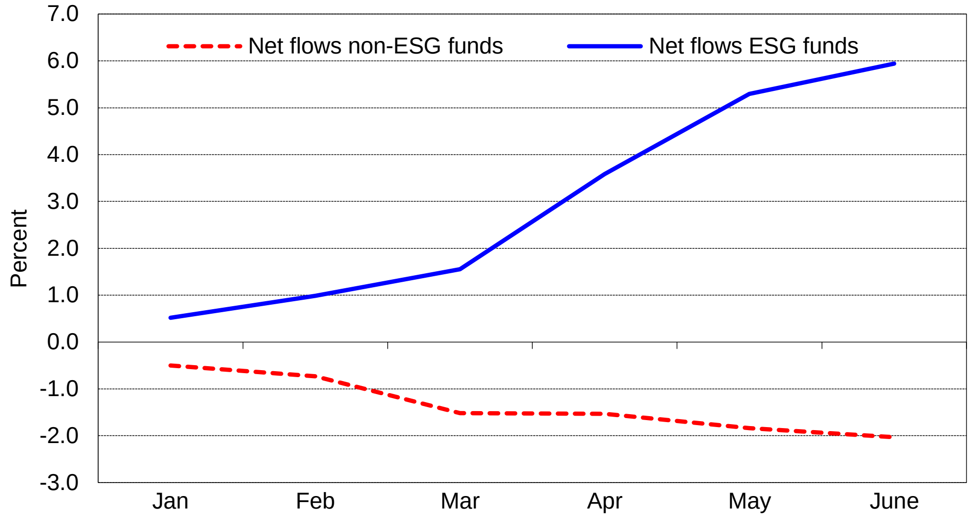

Figure 1: Net fund flows and sustainability rating. This figure plots aggregate cumulative net fund flows normalized by total net assets from January 1 to June 30, 2020 using monthly data, for two fund categories, whether or not they identify as ESG in their prospectus.

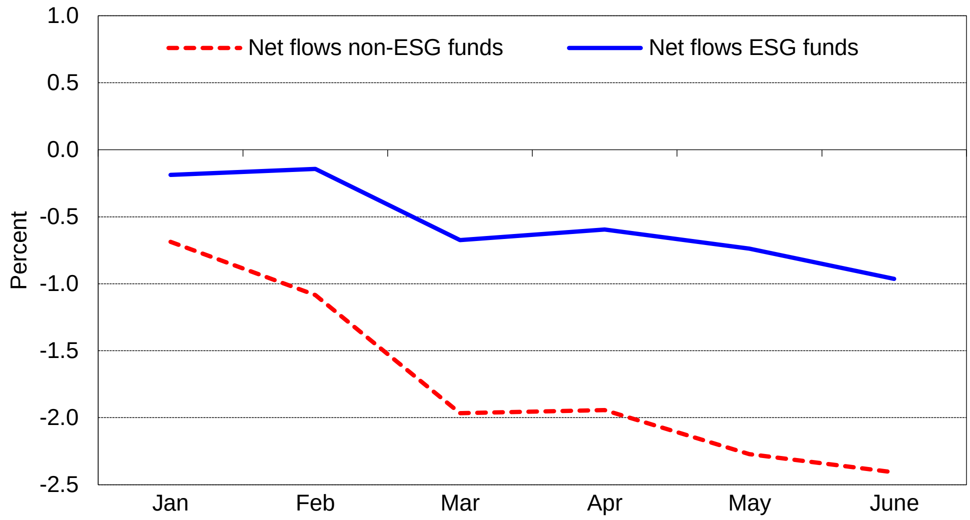

Figure 2: Net fund flows and sustainability rating. This figure plots aggregate cumulative net fund flows normalized by total net assets from January 1 to June 30, 2020 using monthly data, for two fund categories, those that receive by Morningstar 4 or 5 Globe sustainability ratings (ESG funds) and those with less than 4 Globe ratings (non-ESG, or conventional funds).

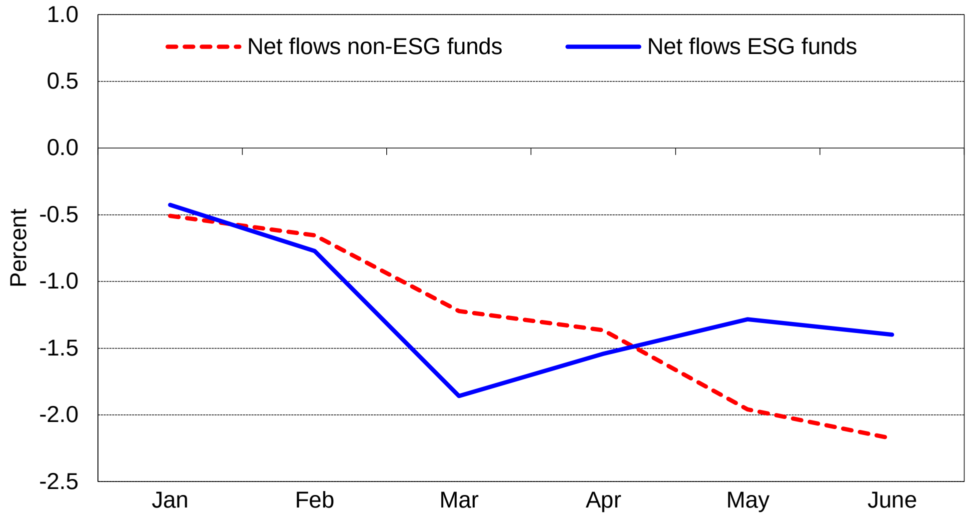

Figure 3: Net fund flows and sustainability rating. This figure plots aggregate cumulative net fund flows normalized by total net assets from January 1 to June 30, 2020 using monthly data, for two fund categories, those that receive a Low-Carbon designation by Morningstar (ESG funds) and those without it (non-ESG, or conventional funds).

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 in the period from December 2019 through June 2020. Appendix Table A1 provides a description of the variables and units of measurement.

	N	Mean	SD	P05	Median	P95
All Mutual Funds						
Net Purchases	9,332	-0.0101	0.0576	-0.0878	-0.0071	0.063
Fund Churn Ratio	9,332	0.1119	0.0731	0.0384	0.0969	0.2287
Fund Flow	9,332	-0.0067	0.0435	-0.0648	-0.0068	0.0572
Fund size	9,332	19.5988	2.0046	16.1973	19.7073	22.822
Fund Return	9,157	-0.0078	0.0995	-0.1883	0.0149	0.1381
Fund Liquidity	8,969	0.0044	0.0524	-0.0004	0	0.0439
Market Return	9,332	-0.0072	0.081	-0.1448	-0.0004	0.1282
Market Return Volatility	9,332	0.0172	0.0125	0.0049	0.0127	0.0493
ESG (prospectus)						
Net Purchases	375	0.0049	0.0507	-0.0635	0.0017	0.0808
Fund Churn Ratio	375	0.083	0.0446	0.021	0.0762	0.1556
Fund Flow	375	0.0071	0.0451	-0.0444	0.0004	0.0816
Fund size	375	19.1078	1.8125	16.3579	19.1656	22.1605
Fund Return	363	-0.0033	0.0837	-0.1537	0.0172	0.1195
Fund Liquidity	356	0.0104	0.0282	0	0	0.0816
ESG (4 and 5 Globes)						
Net Purchases	3,047	-0.0055	0.053	-0.0782	-0.0055	0.0741
Fund Churn Ratio	3,047	0.1027	0.0607	0.0376	0.0903	0.2071
Fund Flow	3,047	-0.0026	0.0444	-0.059	-0.0053	0.0707
Fund size	3,047	19.4982	1.9588	16.3623	19.4791	22.7167
Fund Return	2,998	-0.0033	0.0908	-0.163	0.0155	0.1344
Fund Liquidity	2,952	0.0072	0.0219	0	0	0.0453
ESG (Low-Carbon Designation)						
Net Purchases	2,566	-0.0045	0.0482	-0.0638	-0.0055	0.0655
Fund Churn Ratio	2,566	0.1018	0.0557	0.0394	0.0896	0.1948
Fund Flow	2,566	-0.0021	0.0404	-0.0463	-0.0058	0.0626
Fund size	2,566	19.9152	1.9722	16.4693	19.9577	22.9915
Fund Return	2,528	0.0078	0.0863	-0.1346	0.0217	0.1447
Fund Liquidity	2,468	0.0065	0.0176	-0.0002	0	0.0379

Table 2: Determinants of mutual fund 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 2020 to June 2020. The variable *Crash* takes the value of one in February and March. All variables are defined in the Appendix (see Table A1). All models are estimated by ordinary least squares and include a constant term, but the coefficient is not reported. Standard errors are White-corrected for heteroskedasticity and clustered at the fund level. Quarter and fund fixed effects included. p–values are in parentheses. * indicates significance at 1% (***), 5% (**), 10% (*).

Panel A: Coefficient estimates

	ESG (prospectus)		ESG (Globe ratings)		ESG (Low Carbon)	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Crash	-0.0643***	-0.0581***	-0.0674***	-0.0627***	-0.0686***	-0.0624***
	(0.009)	(0.010)	(0.009)	(0.010)	(0.011)	(0.011)
Crash × ESG	0.0495**	0.0429*	0.0319**	0.0311**	0.0362**	0.0266*
	(0.022)	(0.022)	(0.015)	(0.015)	(0.015)	(0.015)
Crash × Fund Flow	0.3482***	0.3090***	0.3755***	0.3488***	0.3916***	0.3503***
	(0.030)	(0.028)	(0.040)	(0.039)	(0.037)	(0.035)
Crash × Fund Flow × ESG	0.0536	0.0805	-0.1046**	-0.1047**	-0.1595***	-0.1333***
	(0.090)	(0.101)	(0.051)	(0.050)	(0.048)	(0.048)
Crash × Fund size	0.0030***	0.0028***	0.0032***	0.0031***	0.0033***	0.0031***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Crash × Fund size × ESG	-0.0023**	-0.0020*	-0.0016**	-0.0016**	-0.0018**	-0.0014**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Fund Flow	0.9739***	0.9828***	0.9720***	0.9813***	0.9678***	0.9760***
	(0.022)	(0.021)	(0.028)	(0.028)	(0.026)	(0.026)
Fund Flow × ESG	-0.1072*	-0.1104*	0.0103	0.0099	-0.0037	-0.0044
	(0.058)	(0.062)	(0.037)	(0.037)	(0.032)	(0.033)
Fund size	0.0204***	0.0022	0.0218***	0.0027	0.0275***	0.0102*
	(0.006)	(0.007)	(0.005)	(0.004)	(0.006)	(0.006)
Fund size × ESG	-0.0023	-0.0047	-0.0168	-0.0155	-0.0315*	-0.0334*
	(0.013)	(0.015)	(0.014)	(0.014)	(0.018)	(0.018)
Fund return		-0.0455***		-0.0450***		-0.0477***
		(0.016)		(0.016)		(0.016)
Crash × Fund return		0.0225		0.0166		0.0157
		(0.033)		(0.031)		(0.033)
Market return		-0.0047		0.0056		-0.0078
		(0.024)		(0.025)		(0.024)
Market return volatility		-0.6591***		-0.6587***		-0.6784***
		(0.086)		(0.086)		(0.086)
S&P 500 ESG index return		-0.0406		-0.0519		-0.0465
		(0.032)		(0.033)		(0.034)

(continued)

Fund liquidity		0.1211*		0.2126***		0.1206*
		(0.069)		(0.061)		(0.069)
Crash × Fund liquidity		0.0866***		0.0687		0.0858***
		(0.026)		(0.073)		(0.026)
Observations	9,332	8,801	9,219	8,700	9,330	8,799
R-squared	0.752	0.771	0.771	0.786	0.753	0.772

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

Sensitivity of net purchases by non-ESG funds to:						
Fund Flow/Normal	0.9739***	0.9828***	0.9720***	0.9813***	0.9678***	0.9760***
Fund Flow/Crash	1.3221***	1.2918***	1.3474***	1.3301***	1.3594***	1.3263***
Sensitivity of net purchases by ESG funds to:						
Fund Flow/Normal	0.8666***	0.8724***	0.9823***	0.9912***	0.9641***	0.9716***
Fund Flow/Crash	1.2685***	1.2619***	1.2532***	1.2354***	1.1962***	1.1886***
Diff-in-Diff (Crash - Normal):						
non-ESG funds/Fund Flow	0.3482***	0.3090***	0.3755***	0.3488***	0.3916***	0.3503***
ESG funds/Fund Flow	0.4019***	0.3895***	0.2709***	0.2441***	0.2321***	0.2170***
ESG - non-ESG / Fund Flow	0.0536	0.0805	-0.1046**	-0.1047**	-0.1595***	-0.1333***

Table 3: Determinants of mutual fund Net Purchases of ES and non-ES stocks

The table reports regressions for Net Purchases at the fund level (Panel A) and *t*-test on linear combinations of parameters (Panel B). The dependent variables in Panel A are Net Purchases of ES stocks and of non-ES stocks. The sample is composed of all U.S. actively managed equity funds. The sample period is from January 2020 to June 2020. The variable *Crash* takes the value of one in February and March. All variables are defined in the Appendix (see Table A1). All models are estimated by ordinary least squares and include a constant term, but the coefficient is not reported. Standard errors are White-corrected for heteroskedasticity and clustered at the fund level. Quarter and fund fixed effects included. *p*–values are in parentheses. * indicates significance at 1% (***), 5% (**), 10% (*).

Panel A: Coefficient estimates

	ESG (prospectus)		ESG (Globe ratings)		ESG (Low Carbon)	
VARIABLES	(1)		(2)		(3)	
	non-ES stocks	ES stocks	non-ES stocks	ES stocks	non-ES stocks	ES stocks
Crash	0.0312	-0.0158	0.0013	-0.0020	0.0318	-0.0162
	(0.022)	(0.029)	(0.022)	(0.032)	(0.023)	(0.031)
Crash × ESG	0.1059	-0.0567	0.0519**	-0.0297	0.0185	-0.0030
	(0.072)	(0.051)	(0.025)	(0.033)	(0.025)	(0.030)
Crash × Fund Flow	0.3017***	0.3295***	0.3129***	0.4272***	0.2947***	0.4306***
	(0.041)	(0.054)	(0.052)	(0.071)	(0.048)	(0.066)
Crash × Fund Flow × ESG	0.3487*	-0.1762	0.0245	-0.2813***	0.1118	-0.3730***
	(0.200)	(0.123)	(0.086)	(0.098)	(0.092)	(0.093)
Crash × Fund size	0.0014**	0.0004	0.0022***	-0.0001	0.0014*	0.0005
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Crash × Fund size × ESG	-0.0053	0.0031	-0.0025**	0.0012	-0.0009	-0.0003
	(0.004)	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)
Fund Flow	1.0552***	0.7692***	1.0579***	0.7361***	1.0533***	0.7209***
	(0.021)	(0.038)	(0.026)	(0.048)	(0.026)	(0.047)
Fund Flow × ESG	-0.0216	-0.0682	-0.0109	0.1002	-0.0003	0.1558***
	(0.171)	(0.081)	(0.048)	(0.067)	(0.046)	(0.060)
Fund size	-0.0097**	0.0139*	-0.0122**	0.0183**	-0.0099*	0.0181**
	(0.005)	(0.008)	(0.006)	(0.009)	(0.006)	(0.008)
Fund size × ESG	-0.0166	-0.0254	0.0038	-0.0143	-0.0004	-0.0205
	(0.026)	(0.020)	(0.009)	(0.014)	(0.010)	(0.014)
Fund return	-0.0370***	-0.0334**	-0.0348***	-0.0327**	-0.0383***	-0.0358**
	(0.011)	(0.016)	(0.011)	(0.016)	(0.011)	(0.016)
Crash × Fund return	-0.0035	0.0837	-0.0052	0.0982	-0.0073	0.1075
	(0.041)	(0.072)	(0.041)	(0.073)	(0.044)	(0.076)
Market return	-0.0594	-0.0856	-0.0617	-0.0810	-0.0632	-0.0871
	(0.044)	(0.056)	(0.044)	(0.056)	(0.044)	(0.056)
Market return volatility	-0.8712***	-0.1543	-0.8591***	-0.1289	-0.8821***	-0.1240
	(0.119)	(0.170)	(0.120)	(0.171)	(0.121)	(0.171)
S&P 500 ESG index return	0.0254	-0.0172	0.0320	-0.0212	0.0247	-0.0270
	(0.047)	(0.058)	(0.047)	(0.058)	(0.047)	(0.058)
Fund liquidity	-0.1016	0.1238	-0.0466	0.3549***	-0.1006	0.1240

(continued)

	(0.127)	(0.103)	(0.119)	(0.112)	(0.126)	(0.103)
Crash × Fund liquidity	-0.0094	-0.0009	-0.0095	-0.0849	-0.0100	-0.0007
	(0.058)	(0.070)	(0.060)	(0.075)	(0.058)	(0.069)
Firm churn ratio	0.1976	0.2143	0.1362	0.2273	0.1984	0.2425
	(0.139)	(0.322)	(0.133)	(0.321)	(0.139)	(0.322)
Crash × Firm churn ratio	-0.1916*	0.0108	-0.0843	0.0127	-0.1931*	-0.0012
	(0.099)	(0.110)	(0.081)	(0.111)	(0.100)	(0.109)
Firm leverage	0.0768	-0.0372	0.0772	-0.0439	0.0834	-0.0387
	(0.080)	(0.111)	(0.081)	(0.111)	(0.080)	(0.110)
Crash × Firm leverage	-0.0621***	0.0052	-0.0599***	0.0053	-0.0643***	0.0063
	(0.018)	(0.025)	(0.018)	(0.026)	(0.018)	(0.025)
Firm liquidity	-0.0284	-0.2375*	-0.0349	-0.2359*	-0.0287	-0.2448*
	(0.073)	(0.142)	(0.073)	(0.143)	(0.073)	(0.143)
Crash × Firm liquidity	-0.0204	0.0138	-0.0239	0.0121	-0.0217	0.0197
	(0.016)	(0.025)	(0.016)	(0.025)	(0.016)	(0.027)
Observations	16,805		16,675		16,801	
R-squared	0.489		0.491		0.489	

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

	Sensitivity of Net Purchases of					
	non-ES stocks	ES stocks	non-ES stocks	ES stocks	non-ES stocks	ES stocks
	(1)	(2)	(3)	(4)	(5)	(6)
by non-ESG funds to:						
Fund Flow/Normal	1.0552***	0.7692***	1.0579***	0.7361***	1.0533***	0.7209***
Fund Flow/Crash	1.3569***	1.0987***	1.3708***	1.1633***	1.3480***	1.1514***
by ESG funds to:						
Fund Flow/Normal	1.0336***	0.7010***	1.0469***	0.8363***	1.0530***	0.8767***
Fund Flow/Crash	1.6840***	0.8544***	1.3843***	0.9822***	1.4596***	0.9342***
Diff-in-Diff (Crash - Normal):						
non-ESG funds/Fund Flow	0.3017***	0.3295***	0.3129***	0.4272***	0.2947***	0.4306***
ESG funds/Fund Flow	0.6504***	0.1533	0.3374***	0.1459**	0.4066***	0.0575
ESG - non-ESG / Fund Flow	0.3487*	-0.1762	0.0245	-0.2813***	0.1118	-0.3730***

Table 4: Net Purchases by Star-rated funds

The table reports regressions for Net Purchases at the fund level (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-ES stocks, and in column (4) it is Net Purchases of ES stocks. The sample is composed of all U.S. actively managed equity funds. The sample period is from January 2020 to June 2020. The variable *Crash* takes the value of one in February and March. All variables are defined in the Appendix (see Table A1). All models are estimated by ordinary least squares and include a constant term, but the coefficient is not reported. Standard errors are White-corrected for heteroskedasticity and clustered at the fund level. Quarter and fund fixed effects included. *p*–values are in parentheses. * indicates significance at 1% (***), 5% (**), 10% (*).

Panel A: Coefficient estimates

	Star ratings			
VARIABLES	(1)	(2)	(3)	(4)
			non-ES stocks	ES stocks
Crash	-0.0663***	-0.0591***	0.0172	-0.0181
	(0.010)	(0.010)	(0.022)	(0.031)
Crash × High-rated funds	-0.0772	-0.0532	0.0042	-0.1310
	(0.062)	(0.059)	(0.061)	(0.111)
Crash × Fund Flow	0.3925***	0.3487***	0.3475***	0.3467***
	(0.030)	(0.028)	(0.047)	(0.057)
Crash × Fund Flow × High-rated funds	-0.2606	-0.2518	0.0019	-0.0276
	(0.178)	(0.179)	(0.195)	(0.268)
Crash × Fund size	0.0032***	0.0030***	0.0013*	0.0004
	(0.000)	(0.000)	(0.001)	(0.001)
Crash × Fund size × High-rated funds	0.0039	0.0026	-0.0002	0.0069
	(0.003)	(0.003)	(0.003)	(0.006)
Fund Flow	0.9416***	0.9555***	1.0449***	0.7679***
	(0.016)	(0.017)	(0.021)	(0.040)
Fund Flow × High-rated funds	0.2787	0.2882	-0.0549	-0.0624
	(0.203)	(0.205)	(0.167)	(0.205)
Fund size	0.0194***	0.0001	-0.0130**	0.0178**
	(0.007)	(0.008)	(0.005)	(0.008)
Fund size × High-rated funds	0.0262*	0.0233*	0.0044	-0.0111
	(0.013)	(0.013)	(0.023)	(0.026)
Fund return		-0.0435***	-0.0357***	-0.0318*
		(0.017)	(0.011)	(0.017)
Crash × Fund return		0.0226	0.0073	0.0681
		(0.034)	(0.043)	(0.072)
Market return		-0.0083	-0.0945**	-0.0587
		(0.025)	(0.047)	(0.057)
Market return volatility		-0.6521***	-0.8643***	-0.1865
		(0.092)	(0.125)	(0.168)
S&P 500 ESG index return		-0.0307	0.0612	-0.0370

(continued)

		(0.034)	(0.050)	(0.059)
Fund liquidity		0.1170	-0.2135*	0.4207***
		(0.074)	(0.120)	(0.138)
Crash × Fund liquidity		0.0662**	-0.0188	-0.1028
		(0.034)	(0.055)	(0.085)
Firm churn ratio			0.1238	0.3384
			(0.140)	(0.335)
Crash × Firm churn ratio			-0.0960	-0.0071
			(0.080)	(0.110)
Firm leverage			0.0885	-0.0626
			(0.083)	(0.114)
Crash × Firm leverage			-0.0531***	0.0170
			(0.019)	(0.026)
Firm liquidity			-0.0323	-0.2394
			(0.075)	(0.147)
Crash × Firm liquidity			-0.0172	0.0175
			(0.017)	(0.026)
Observations	8,609	8,260	15,798	
R-squared	0.752	0.767	0.485	

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

	Sensitivity of Net Purchases			
			of non-ES stocks	of ES stocks
	(1)	(2)	(3)	(4)
by non-ESG funds to:				
Fund Flow/Normal	0.9416***	0.9555***	1.0449***	0.7679***
Fund Flow/Crash	1.3342***	1.3042***	1.3925***	1.1146***
by ESG funds to:				
Fund Flow/Normal	1.2203***	1.2438***	0.9900***	0.7055***
Fund Flow/Crash	1.3523***	1.3406***	1.3395***	1.0246***
Diff-in-Diff (Crash - Normal):				
Low-rated funds/Fund Flow	0.3925***	0.3487***	0.3475***	0.3467***
High-rated funds/Fund Flow	0.1319	0.0968	0.3495*	0.3191
High-rated - Low-rated / Fund Flow	-0.2606	-0.2518	0.0019	-0.0276

Table 5: Investor horizon and Net Purchases of ES and non-ES stocks

The table reports regressions for Net Purchases at the fund level (Panel A) and *t*-test on linear combinations of parameters (Panel B). The dependent variables in Panel A are Net Purchases of ES stocks and of non-ES stocks. The sample is composed of all U.S. actively managed equity funds. The sample period is from January 2020 to June 2020. The variable *Crash* takes the value of one in February and March. All variables are defined in the Appendix (see Table A1). All models are estimated by ordinary least squares and include a constant term, but the coefficient is not reported. Standard errors are White-corrected for heteroskedasticity and clustered at the fund level. Quarter and fund fixed effects included. *p*–values are in parentheses. * indicates significance at 1% (***), 5% (**), 10% (*).

Panel A: Coefficient estimates

	ESG (prospectus)		ESG (Globe ratings)		ESG (Low Carbon)	
VARIABLES	(1)		(2)		(3)	
	non-ES stocks	ES stocks	non-ES stocks	ES stocks	non-ES stocks	ES stocks
Crash	0.0368*	-0.0151	0.0021	-0.0067	0.0374	-0.0145
	(0.022)	(0.029)	(0.024)	(0.031)	(0.023)	(0.031)
Crash × ESG	0.1199*	-0.0751	0.0672**	-0.0185	0.0046	-0.0006
	(0.072)	(0.054)	(0.027)	(0.034)	(0.028)	(0.031)
Crash × Fund Flow	0.3051***	0.3298***	0.3133***	0.4267***	0.3014***	0.4324***
	(0.041)	(0.055)	(0.052)	(0.071)	(0.048)	(0.066)
Crash × Fund Flow × ESG	0.3626*	-0.1813	0.0330	-0.2775***	0.1002	-0.3733***
	(0.197)	(0.124)	(0.084)	(0.098)	(0.092)	(0.094)
Crash × Fund churn ratio	-0.0725**	-0.0013	-0.0294	0.0177	-0.0891**	-0.0052
	(0.033)	(0.024)	(0.033)	(0.038)	(0.038)	(0.027)
Crash × Fund churn ratio × ESG	-0.1815	0.1213	-0.0875	-0.0567	0.0643	-0.0097
	(0.165)	(0.105)	(0.068)	(0.053)	(0.055)	(0.048)
Crash × Fund size	0.0010	0.0004	0.0021***	0.0000	0.0010	0.0005
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Crash × Fund size × ESG	-0.0054	0.0035	-0.0029**	0.0009	-0.0005	-0.0004
	(0.003)	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)
Fund Flow	1.0532***	0.7686***	1.0571***	0.7363***	1.0509***	0.7180***
	(0.021)	(0.038)	(0.026)	(0.048)	(0.026)	(0.047)
Fund Flow × ESG	-0.0100	-0.0691	-0.0153	0.0994	0.0074	0.1524**
	(0.176)	(0.078)	(0.046)	(0.067)	(0.046)	(0.061)
Fund churn ratio	-0.0899	0.0864	-0.0738	0.1126	-0.1311	0.1852**
	(0.104)	(0.091)	(0.126)	(0.132)	(0.117)	(0.091)
Fund churn ratio × ESG	1.3943**	-0.3353	0.2106	-0.1999	0.4554**	-0.5738**
	(0.603)	(0.531)	(0.165)	(0.196)	(0.206)	(0.267)
Fund size	-0.0101**	0.0143*	-0.0124**	0.0187**	-0.0114**	0.0202**
	(0.005)	(0.008)	(0.006)	(0.010)	(0.006)	(0.008)
Fund size × ESG	-0.0268	-0.0248	0.0033	-0.0147	-0.0038	-0.0169
	(0.028)	(0.020)	(0.009)	(0.014)	(0.010)	(0.013)
Fund return	-0.0358***	-0.0338**	-0.0344***	-0.0330**	-0.0376***	-0.0355**
	(0.011)	(0.016)	(0.011)	(0.016)	(0.011)	(0.016)
Crash × Fund return	0.0031	0.0838	-0.0022	0.0971	0.0037	0.1090

(continued)

	(0.041)	(0.073)	(0.041)	(0.073)	(0.043)	(0.076)
Market return	-0.0629	-0.0862	-0.0631	-0.0817	-0.0674	-0.0883
	(0.044)	(0.056)	(0.044)	(0.056)	(0.044)	(0.056)
Market return volatility	-0.8577***	-0.1516	-0.8531***	-0.1292	-0.8701***	-0.1040
	(0.120)	(0.171)	(0.120)	(0.172)	(0.121)	(0.170)
S&P 500 ESG index return	0.0297	-0.0174	0.0334	-0.0206	0.0269	-0.0236
	(0.047)	(0.058)	(0.047)	(0.058)	(0.047)	(0.058)
Fund liquidity	-0.0982	0.1261	-0.0491	0.3509***	-0.0978	0.1286
	(0.122)	(0.103)	(0.116)	(0.113)	(0.120)	(0.102)
Crash × Fund liquidity	-0.0081	-0.0005	-0.0139	-0.0871	-0.0033	-0.0045
	(0.058)	(0.071)	(0.057)	(0.074)	(0.059)	(0.070)
Firm churn ratio	0.1775	0.2113	0.1328	0.2284	0.1721	0.2311
	(0.135)	(0.322)	(0.132)	(0.320)	(0.135)	(0.322)
Crash × Firm churn ratio	-0.1059	0.0085	-0.0342	0.0133	-0.0956	0.0010
	(0.082)	(0.111)	(0.084)	(0.113)	(0.081)	(0.110)
Firm leverage	0.0807	-0.0374	0.0763	-0.0445	0.0819	-0.0375
	(0.080)	(0.111)	(0.081)	(0.110)	(0.080)	(0.110)
Crash × Firm leverage	-0.0624***	0.0053	-0.0603***	0.0057	-0.0638***	0.0060
	(0.018)	(0.025)	(0.018)	(0.026)	(0.018)	(0.025)
Firm liquidity	-0.0351	-0.2389*	-0.0411	-0.2393*	-0.0372	-0.2432*
	(0.073)	(0.142)	(0.073)	(0.143)	(0.073)	(0.143)
Crash × Firm liquidity	-0.0172	0.0136	-0.0209	0.0119	-0.0180	0.0201
Observations	16,805		16,675		16,801	
R-squared	0.49		0.492		0.49	

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

	Sensitivity of Net Purchases of					
	non-ES stocks	ES stocks	non-ES stocks	ES stocks	non-ES stocks	ES stocks
	(1)	(2)	(3)	(4)	(5)	(6)
by non-ESG funds to:						
Fund Flow/Normal	1.0532***	0.7686***	1.0571***	0.7363***	1.0509***	0.7180***
Fund Flow/Crash	1.3584***	1.0985***	1.3703***	1.1630***	1.3523***	1.1504***
Fund churn ratio/Normal	-0.0899	0.0864	-0.0738	0.1126	-0.1311	0.1852**
Fund churn ratio/Crash	-0.1624	0.0852	-0.1032	0.1303	-0.2202*	0.1801*
by ESG funds to:						
Fund Flow/Normal	1.0432***	0.6996***	1.0418***	0.8357***	1.0583***	0.8704***
Fund Flow/Crash	1.7110***	0.8481***	1.3881***	0.9849***	1.4599***	0.9295***
Fund churn ratio/Normal	1.3045**	-0.2488	0.1367	-0.0874	0.3242*	-0.3886
Fund churn ratio/Crash	1.0505*	-0.1288	0.0198	-0.1263	0.2994*	-0.4034

(continued)

Diff-in-Diff (Crash - Normal):						
non-ESG funds/Fund Flow	0.3051***	0.3298***	0.3133***	0.4267***	0.3014***	0.4324***
ESG funds/Fund Flow	0.6678***	0.1485	0.3462***	0.1492**	0.4016***	0.0590
ESG - non-ESG / Fund Flows	0.3626*	-0.1813	0.0330	-0.2775***	0.1002	-0.3733***
non-ESG/Fund churn ratio	-0.0725**	-0.0013	-0.0294	0.0177	-0.0891**	-0.0052
ESG/Fund churn ratio	-0.2540	0.1200	-0.1169*	-0.0390	-0.0248	-0.0148
ESG - non-ESG / churn ratio	-0.1815	0.1213	-0.0875	-0.0567	0.0643	-0.0097

Appendix A.

Table A1: Variable definitions.

Crash	A dummy variable that takes a value of one during February and March 2020 (when global financial markets experienced collapsed) and zero otherwise.
ESG Globe Rating	A dummy variable that takes a value of one if the fund receives, at December 2019, a Sustainability rating of 4 and 5 Globes and zero otherwise. 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 Low-Carbon Designation	A dummy variable that takes a value of one if the fund has, at December 2019, a Low-Carbon Designation and zero otherwise. This is based on two metrics, Morningstar Portfolio Carbon Risk Score and The Morningstar Portfolio Fossil Fuel Involvement. Funds may receive the Low-Carbon Designation, which allows investors to easily identify low-carbon funds within the global universe. 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)
ESG Prospectus	A dummy variable that takes a value of one if the fund incorporates environmental, social, and governance (ESG) principles into the investment process or through engagement activities and zero otherwise. (Source: Morningstar Direct)
Firm Churn Ratio	The weighted average of the churn ratios of firm j's investors. (Source: Morningstar historical holdings and Direct)
Firm Leverage	The book value of debt divided by the book value of total assets as of December 2019. (Source: Morningstar Direct)
Firm Liquidity	The value of cash divided by the book value of total assets as of December 2019. (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). This variable is measured in the period ending in month t. (Source: Morningstar historical holdings)
Fund Liquidity	Cash (i.e., currency and coins, negotiable checks, and balances in bank accounts) divided by net assets under management in month $t-1$. (Source: Morningstar Direct)
Fund Flow	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)
Fund Size	Total net asset value of the fund in log of USD millions in month t. (Source: Morningstar Direct)
Fund return	The return of the fund as provided by Morningstar in month $t-1$. (Source: Morningstar Direct)
Market Return	The return of the reference index as defined in the prospectus or provided by Morningstar in month t. (Source: Morningstar Direct)
Market Return Volatility	The standard deviation of the market daily returns during month t. (Source: Morningstar Direct)
Net Purchases	The net dollar 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)
Refinitiv Environment and Social score	A dummy variable that takes a value of one if the stock receives an ES Score above the top quartile of the distribution and zero otherwise. The ES Score is the average between the Environment and the Social scores as of December 2019. (Source: Refinitiv)
S&P 500 ESG index return	The return of the S&P 500 ESG index as provided by Morningstar in month t. (Source: Morningstar Direct)

(continued)

Star Rating	A dummy variable that takes a value of one if the fund receives, at December 2019, a Star rating of 4 and 5 Stars and zero otherwise. 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)