CEIS Tor Vergata Research Papers

Università di Roma Tor Vergata

ISSN 2610-931X

CEIS Tor Vergata

RESEARCH PAPER SERIES

Vol. 19, Issue 8, No. 524 – November 2021

Herding and Anti-Herding Across ESG Funds

Rocco Ciciretti, Ambrogio Dalò, Giovanni Ferri

Herding and Anti-Herding Across ESG Funds

Rocco Ciciretti,[†] Ambrogio Dalò,[‡] and Giovanni Ferri[§]

September 20, 2021

Abstract

We investigate to what extent ESG funds present an herding/anti-herding behavior, and the consequences of their investment strategies in terms of both systematic risk exposure and risk-adjusted returns. Our findings document that ESG funds pursue an anti-herding strategy that leads to higher risk-adjusted returns. Specifically, a one standard deviation increase in ESG score at the fund-level is associated with an increase in fund performance of about 3.74 basis points per year. Moreover, we document that such an enhanced performance does not come at the cost of higher systematic risk exposure but instead reduces it. A possible explanation behind our findings is that after the catching-up phase previously documented by the literature, ESG funds are now able to put to good use enhanced stock-picking skills built over the years.

Keywords: ESG investing, Equity Funds, Herding, Anti-Herding, Risk-Adjusted Returns.

JEL: G11, C58

Acknowledgments: this research is partially funded by Morningstar (contract n. OPP635370), and Etica Sgr (ref. n. R01-2019).

[†]Tor Vergata University of Rome, CEIS and RCEA-Rimini, Italy. e-mail: *rocco.ciciretti@uniroma2.it*.

[‡]University of Groningen, The Netherlands. e-mail: *a.dalo@rug.nl*.

[§]LUMSA, CERBE and MoFIR, Italy. e-mail: *g.ferri@lumsa.it*

1 Introduction

Socially responsible investments (SRI) have known a dramatic increase in recent years. Consistent with such a trend, the US Social Investment Foundation (2020, 2018) reports the total value of assets under management (AUM) in the US subject to SRI screening amounted to $17.1 trillion in 2020 – an increase of 42% relative to 2018. Globally, it reached $35.3 trillion, an increase of 15% since 2018 (Global Sustainable Investment Alliance, 2020, 2018). United States and Europe represent the 80% of the SRI in the period 2018/2020.[1] Such a form of investing incorporates firms' environmental, social, and governance (ESG) characteristics in investment decisions. The incorporation of the ESG characteristics into the funds investment decisions reflects three main reasons: (1) they reflect investor preferences, unrelated to risk and return (Luo and Balvers, 2017; Hong and Kacperczyk, 2009), (2) they relate to a lower systematic risk exposure (Albuquerque et al., 2019; Becchetti et al., 2018), or (3) they ensure better performance during the systemic crisis and lower the systemic risk exposure (Cerqueti et al., 2021; Lins et al., 2015).

Within this framework, the current state of the art on asset pricing and ESG investing has focused its attention on understanding if and to what extent ESG funds deliver higher/lower risk-adjusted returns at the expense of higher/lower systematic risk exposure. The literature that tries to dissect the risk/return relation among ESG investments may be broadly divided into three strands, and the results provided so far are mixed. The first strand of literature finds that investing in firms with higher ESG scores leads to greater risk-adjusted returns (Statman and Glushkov, 2009; Kempf and Osthoff, 2007; Bauer et al., 2005a). The second strand of literature finds that investing in firms with lower ESG scores leads to lower risk-adjusted returns (Albuquerque et al., 2019; Luo and Balvers, 2017; Hong and Kacperczyk, 2009; Galema et al., 2008; Renneboog et al., 2008; Bauer et al., 2007). The third strand of literature instead finds that there is no difference in terms of returns between ESG and conventional investing (Bauer et al., 2007, 2006; Hamilton et al., 1993).

None of these papers investigate if and to what extent the increasing interest for responsible assets that we observe on the financial market could generate an herding/anti-herding behavior among ESG funds, and what role play such behavior in explaining the risk-adjusted performance and systematic risk exposure of ESG funds. Intuitively, an investor can be said to herd if she/he decides to buy or sell a specific asset after observing other investors' actions. Hence, risk and

[1] The most common sustainable investment strategy is ESG integration, followed by negative screening, corporate engagement and shareholder action, norms-based screening and sustainability-themed investment. (Global Sustainable Investment Alliance, 2020).

return considerations do not enter into the investment decision process. This form of herding is called *intentional herding/anti-herding*. Several reasons can motivate an investor to imitate or not other investors' actions. First, other investors trades may reveal hidden information (Avery and Zemsky, 1998, Bikhchandani et al., 1992, and Welch, 1992). Hence, funds have an incentive to copy the actions of their competitors to take advantage of such an additional piece of information. Second, due to reputation or compensation concerns, asset managers then try to tide their performance with their more skilled competitors (Graham, 1999, Prendergast and Stole, 1996, and Roll, 1992). Third, more skilled or experienced managers are more likely to deviate from past actions and exhibit an anti-herding behavior (Jiang and Verardo, 2018,Menkhoff et al., 2006).

In our context, after the initial catching-up phase respect to conventional funds as documented by Bauer et al. (2005a), ESG funds can now exploit the know-how acquired over the years to achieve better performances in terms of both risk and return. In turn, this could have three effects. First, ESG informed funds follow anti-herding investment strategies. Second, through those strategies, ESG informed funds gain superior returns. Third, by tilting their portfolios towards assets with better ESG performance ESG funds indirectly benefit of the risk reduction effect previously documented by the literature (Albuquerque et al., 2019).

Our aim is to verify if ESG funds exhibit a herding/anti-herding behavior, and the impact of both fund's responsibility and herding/anti-herding behavior on their risk-adjusted and systematic risk exposure. Using a dataset of 10,456 unique ESG funds investing worldwide from February 2012 to June 2018, with detailed information at the holding level, we show that ESG funds show an anti-herding behavior. In line with Jiang and Verardo (2018), by adopting an anti-herding behavior, ESG funds increase the fund performance by about 3.74 basis points per year. Hence, after the catching-up phase documented by Bauer et al. (2005a), ESG funds are now able to put to good use enhanced stock-piking skills. Moreover, the higher performance does not come at the cost of higher risk exposure. Indeed, in line with the literature showing a mitigating effect on risk for ESG investments, we show that by tilting their portfolios towards high ESG assets, ESG funds can reduce their systematic risk exposure (Cerqueti et al., 2021, Albuquerque et al., 2019).

The remainder of this paper is structured as follows. In Section 2, we explain the methodology used. In Section 3, we describe our data set and provide descriptive statistics. Section 4 reports the results and robustness check, and Section 5 concludes.

2 Methodology

Motivated by the increasing AUM subjects to ESG constraints, our primary aim is to verify if the fund's preference for such assets results into a herding/anti-herding behavior among ESG funds. To do so, we start from the standard methodology proposed by Jiang and Verardo (2018) and compute the change in the number of shares of stock i in the portfolio of mutual fund j during month t ($Trade_{i,j,t} = (N_{i,j,t} - N_{i,j,t-1})/N_{i,j,t-1}$), and the change in the aggregate institutional ownership of stock i in month $t-1$ ($\Delta IO_{i,t-1} = N_{i,j,t-1}/N^{out}_{i,j,t-1} - N_{i,j,t-2}/N^{out}_{i,j,t-2}$). As in Jiang and Verardo (2018), we then model the inter-temporal trading patterns by using following cross-sectional model:

$$Trade_{i,j,t} = \gamma_{0,j,t} + \gamma_{1,j,t}\Delta IO_{i,t-1} + \gamma_{2,j,t} lME_{i,t-1} + \gamma_{3,j,t} lBtM_{i,t-1} + \gamma_{4,j,t} MoM_{i,t-1} + \nu_{i,j,t} \qquad (1)$$

where $lME_{i,t-1}$ logarithm of market capitalization for stock i in month $t-1$, $lBtM_{i,t-1}$ is the logarithm of the book-to-market, $MoM_{i,t-1}$ is the cumulative return from month $t-11$ to month $t-1$. Such regression control for three stock characteristics representing the most common investment styles documented by the literature (Carhart, 1997, Daniel and Titman, 1997). The estimate of the slope coefficient, $\hat{\gamma}_{1,j,t}$, captures the association between manager j's trades in the current month and institutional trades in the previous month. We next construct the measure of fund-level herding ($FH_{j,t}$) that captures the average tendency of fund j to follow past institutional trades as:

$$FH_{j,t} = \frac{\sum_{h=1}^{t} \frac{1}{h} \hat{\gamma}_{1,j,t-h+1}}{\sum_{h=1}^{t} \frac{1}{h}} \qquad (2)$$

that attributes more weights to the more recent estimates to reflects the fund's most recent trading decisions. We additionally compute other control variables commonly used in the mutual fund literature. Specifically, the turnover ($Turnover$) is the minimum of aggregated sales or aggregated purchases of securities, divided by the average 12-month AUM of the fund, the growth rate of AUM after adjusting for the appreciation ($Flows$), and the fund's age is the number of years since its inception (Age).

The purpose of our first hypothesis is to verify if the increasing interest for ESG investing implies a herding/anti-herding behavior among funds tilting their portfolio towards ESG assets.

To asses if and two what extent ESG funds show a herding/anti-herding tendency towards ESG assets in the first place, we run the following model:

$$FH_{j,t} = \theta_0 + \theta_1 ESG_{j,t} + \Theta^\top Fc_{j,t} + \lambda_t + \mu_j + \epsilon_{j,t} \tag{3}$$

where $ESG_{j,t}$ is the ESG score for fund j at time t, and $Fc_{j,t}$ represents the matrix of fund characteristics and includes: logarithm of the asset under management ($lAUM$), logarithm of the fund age ($lAge$), the net annual expense ratio ($Expenxes$), the funds flows ($Flows$), and the turnover ($Turnover$). λ_t and μ_j captures the time and investment area fixed effect, respectively.

We then make one step ahead and try to verify if and to what extent both the funds'responsibility level, their herding/counter-herding behavior, or the combination of the two are associated to higher financial performances. The increasing demand for such assets indeed might generate positive realized returns even though expected long-run return goes down, or more skilled managers could be better in stock-picking. Hence, our second hypothesis instead aims to verify if such herding/anti-herding behavior has an impact on risk-adjusted return for those ESG funds that integrate the new information coming from the release of ESG scores from the rating agencies. To test such hypothesis, we first estimate the net and gross risk-adjusted returns for each fund using the Carhart (1997) model estimated over the past two years of monthly returns as follows:

$$R^e_{j,t} = \alpha_{j,t} + \beta_{m,j,t} R^e_{m,t} + \beta_{s,j,t} SMB_t + \beta_{h,j,t} HML_t + \beta_{w,j,t} WML_t + \epsilon_{j,t} \tag{4}$$

where $R^e_{j,t}$ is the fund excess return for fund j in month t, $\alpha_{j,t}$ is the risk-adjusted return estimated using two years of monthly data, $R^e_{m,t}$ is the excess return of the market, SMB_t is the size risk factor, HML_t is the value risk factor, WML_t the momentum risk factor. We then relate the fund risk-adjusted returns to its responsibility levels, his herding tendency, and the combined effect of the two by estimating the following model:

$$\hat{\alpha}_{j,t} = \omega_0 + \omega_1 FH_{j,t} + \omega_2 ESG_{j,t} + \omega_3 ESG_{j,t} \times FH_{j,t} + \Omega^\top Fc_{j,t} + \lambda_t + \mu_j + \epsilon_{j,t} \tag{5}$$

that includes all the variables already described in model (3) and (4) respectively. The parameter ω_1, ω_2, and ω_3 aim to capture the impact of funds herding/counter-herding behavior, responsibility level, and the combined effect of the two on funds risk-adjusted returns.

Our third and final hypothesis seeks to verify if, by pursuing a herding/anti-herding strategy, ESG funds can lower their systematic risk exposure. In this respect, it is reasonable to assume that the more a fund follows the herd, the higher should be its systematic risk exposure. In this framework, ESG investments can conversely lower the systematic risk exposition due to their lower degree of co-movements with the market (Albuquerque et al., 2019). To verify if and to what extent ESG has a mitigating role on funds systematic risk exposure, we then estimate the following model:

$$\hat{\beta}_{j,m,t} = \psi_0 + \psi_1 FH_{j,t} + \psi_2 ESG_{j,t} + \psi_3 ESG_{j,t} \times FH_{j,t} + \Psi^{\top} Fc_{j,t} + \lambda_t + \mu_j + \epsilon_{j,t} \tag{6}$$

that includes all the variables already described in model (3) and (4) respectively. The parameter ψ_1, ψ_2, and ψ_3 aim to capture the impact of funds herding/counter-herding behavior, responsibility level, and the combined effect of the two on funds systematic risk exposure.

3 Data & Descriptive Evidences

Data at the fund share class level are retrieved from Morningstar Direct (MD). From here, we able to retrieve the monthly Asset Under Management (AUM), the Annual Net Expenses Ratio ($Expense$), and the historical sustainability score (ESG) at the fund level. Following Patel and Sarkissian (2017), we aggregate share class-level observations to one fund-level observation using the unique fund identifier ($FundId$) in MD. We additionally eliminate all the observations before the inception date to avoid the incubation bias (Evans, 2010). The resulting sample consists of $10,456$ unique open-end equity mutual funds rated on ESG aspects and investing globally or in specific macro geographic areas from February 2012 to June 2018 (77 months).

We then match Morningstar Direct funds with Morningstar European Data Warehouse (EDW) to retrieve portfolio holdings-level information related to the funds' portfolio constituencies. To complete our dataset at holding-level variables, we retrieve from Refinitiv (DATASTREAM) the following variables on an annual basis: market value of equity; common equity; total assets; deferred taxes; net sales or revenues; selling, general, and administrative expenses; interest expense on debt; and cost of goods sold. We use these variables to create size (ME), book-to-market (BE/ME), and momentum (MoM) characteristics following the Fama and French (2012, 2017) approach. Furthermore, we collect monthly return indexes.[2] We then filter out ADRs, units, preferred shares, and stapled securities. The resulting sample consists of $37,181$ unique holdings over the same sample period.

From the Fama and French (2012, 2017) global risk-factor database, we obtain the monthly excess

[2]The data types of the variables retrieved are: $WC08001$ (market value of equity), $WC03501$ (common shareholders' equity), $WC03263$ (deferred taxes), RI (Return Index).

return of the market ($R^e_{m,t}$), the one-month T-bill rate (R_f), the size risk factor (SMB), the value risk factor (HML), the momentum risk factor (WML), the profitability risk factor (RMW), and the investment risk factor (CMA).[3]

Table I reports the descriptive statistics for our set of variables at fund-level.[4] The average fund in our sample manages 583 million dollars, has a growth of 0.89% in terms of AUM, and a monthly turnover of 0.26% (Panel A, column 1-3). It achieves a monthly return of 0.67%, is almost 10 years old, and has an annual expense ratio of 1.40% (column 5-7). Moreover, on a theoretical scale from 0 to 100, it has an ESG score of 48.31 (column 8) and shows a slight tendency to follow past institutional trades (column 4). Overall, the correlations between fund characteristics are relatively low (Panel B). Remarkably, funds ESG scores are negatively correlated with the Jiang and Verardo (2018) herding measure (column 4). This evidence indicates that the more responsible the fund is, the less it follows past institutional trades. Hence, funds with higher ESG levels tend to diversify their portfolios differently from their competitors. Moreover, the ESG scores are negatively correlated with fund's returns (R), turnover ($Turnover$), and the year-end expense ratio ($Expences$), while positively correlated with funds size (AUM) and funds flow ($Flows$, column 1-7). The positive correlation between ESG scores and funds'flows could indicate that investors appear to be able to target more responsible funds (El Ghoul and Karoui, 2017), while not worry too much about returns since the correlation between ESG score and returns appear to be negative. Hence, ESG inventors do not appear to be driven exclusively by pecuniary motivations (Luo and Balvers, 2017; Bollen, 2007).

To gauge the time-varying dynamics of the funds herding tendency over time according to their responsibility level, we categorized funds in two groups $Low-ESG$ and $High-ESG$, respectively (see Figure I). The group $Low-ESG$ is composed of all the funds having an average score lower than the 25^{th} percentile of the score distribution. The group $High-ESG$ is composed of all the funds having an average score higher than the 75^{th} percentile of the score distribution. We then compute the two years moving average of the Jiang and Verardo (2018) herding measure for the entire sample. The descriptive evidence shows that the average tendency to follow the crowd increases overtime for the entire sample and the two sub-groups. However, the $High-ESG$ score group of funds has *always* a lower herding tendency in comparison with the $Low-ESG$ score group.

[3]Fama–French web page: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html.

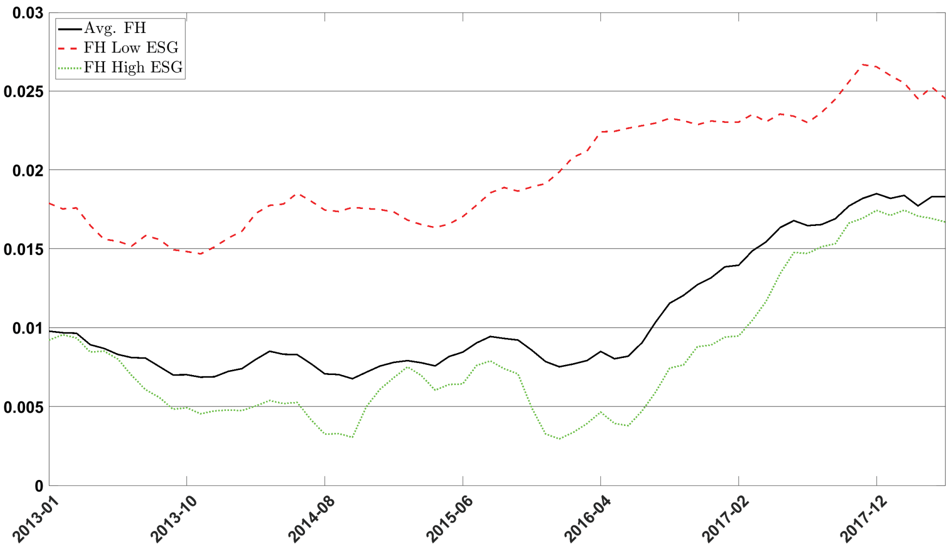
[4]For each variable, values greater than the 0.99 percentile or less than the 0.01 percentile are set equal to the 0.99 and the 0.01 percentile each month.

Table I. Descriptive Statistics for the Fund-Level Variables

The table reports the time-series averages of the cross-sectional distributions for the monthly, yearly and static characteristics of the actively managed funds in our sample. The cross-sectional characteristics are: the month-end asset under management in millions (AUM); the growth rate of AUM after adjusting for the appreciation of the fund's assets ($Flow$); the turnover ratio of the fund ($Turnover$); the Jiang and Verardo (2018) herding measure (FH); the average net monthly fund return in percentage (R); the ESG score (ESG); $Expense$ is the year-end fund's expense ratio; Age is the number of years in which the fund is actively managed. Panel A provides descriptive statistics for the distribution of the characteristics, and Panel B provides correlations. The sample consists of $10,456$ funds investing worldwide for 77 months (February 2012 - June 2018).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A							
	AUM	$Flows$	$Turnover$	FH	R	$Expences$	Age	ESG
$Mean$	583	0.887	0.263	0.013	0.671	1.404	10	48.309
$St.Dev$	175	5.840	2.457	0.184	4.747	0.115	6	0.401
25%	446	-1.325	-0.679	-0.081	-2.013	1.327	5	48.011
50%	575	0.119	0.104	0.012	0.841	1.396	8	48.327
75%	701	2.047	1.022	0.106	3.578	1.483	13	48.619
95%	874	10.540	4.173	0.297	8.081	1.567	23	48.826
	Panel B							
AUM	1.000							
$Flows$	-0.021	1.000						
$Turnover$	-0.009	0.307	1.000					
FH	0.003	0.001	0.002	1.000				
R	-0.015	-0.006	-0.005	-0.004	1.000			
$Expences$	-0.265	-0.020	-0.002	0.002	0.036	1.000		
Age	0.035	-0.112	-0.042	-0.006	-0.007	0.005	1.000	
ESG	0.022	0.018	-0.009	-0.016	-0.010	-0.101	-0.016	1.000

Figure I. Average Herding Frequency Overtime



The figure shows the evolution over time of the average herding tendency, computed using equation (2), for the average fund (black solid line), and for $Low-ESG$ score group of funds (red dashed line) and $High-ESG$ score group of funds (green dotted line). The group $Low-ESG$ is composed by all the funds having an average score lower than the 25^{th} percentile of the score distribution. The group $High-ESG$ is composed by all the funds having an average score higher than the 75^{th} percentile of the score distribution.

All in all, such a descriptive piece of evidence indicates that more responsible funds are bigger in terms of AUM, older, with higher assets growth, and less expensive than the average fund in our sample. More importantly, ESG funds pursue different investment strategies from their competitors. As such, they could generate higher risk-adjusted returns due to a superior stock-picking ability or the temporary rise in the realized return generated by the increasing interest of investors for ESG assets.

4 Results

4.1 Herding Behavior across ESG Funds

With out first hypothesis we verify if and to what extent there exists a herding/antiherding behavior associated with the responsibility level of the fund. On the one hand, fund preference for ESG assets motivated by the peculiar characteristics of such assets could lead to a herding behavior among ESG funds. On the other hand, in the attempt of anticipating the market shift towards ESG assets, ESG funds could show an anti-herding behavior by tilting their portfolio towards assets still not fully priced by the market. As such, ESG funds by exploiting the competitive advantage accumulated over the years could now deliver higher risk-adjusted returns after the initial catching up phase to conventional funds documented by the literature (Bauer et al., 2006).

To disentangle the existing relation between funds herding behavior and their preference for ESG assets, we estimate model (3) and report the results in Table III.[5] Consistent with the low herding tendency of $High-ESG$ funds (see Figure I), the coefficient capturing the tendency of the fund to herd due to its preference for responsible assets appear to be negative and significant for all the model specifications (ESG, column 1-3). While bigger funds in terms of AUM show a pronounced herding tendency (AUM, column 1-3). By contrast, other fund characteristics such as $lAge$, $Expences$, $Flows$, and $Turnover$ do not play a significant clear role in explaining funds herding behavior based on past trades (column 1-3). Together with the anecdotal pieces of evidence provided by Table I and Figure I, our preliminary results show that, under their preference for ESG stocks, responsible funds appear to show an anti-herding behavior. Hence, ESG funds diversify their portfolio differently from their competitors.

The question now is if the anti-herding strategy perused by ESG funds generate higher/lower risk-adjusted returns and if such a strategy leads to a higher/lower systematic risk exposure.

[5]Following Petersen (2009), we base our t-statistics on standard errors clustered at fund-level following.

Table II. Determinant of Fund Herding for Responsible Funds

This table reports the results for estimated coefficients of the model:

$$FH_{j,t} = \theta_0 + \theta_1 ESG_{j,t} + \Theta^\top Fc_{j,t} + \lambda_t + \mu_j + \epsilon_{j,t}$$

where $FH_{j,t}$ is the Jiang and Verardo (2018) herding measure for fund j at time t; ESG is the historical sustainability score for the fund j at time t; $Fc_{j,t}$ represents the matrix of fund characteristics that includes the logarithm of the asset under management ($lAUM$), logarithm of the fund age ($lAge$), the net annual expense ratio ($Expences$), the funds flows ($Flows$), and the turnover ($Turnover$). λ_t captures the time-fixed effects, and μ_j captures the investment area fixed effect. The t-statistics are based on standard errors clustered at fund-level are reported in brackets. ***,** and * denote 1%, 5%, and 10% significance.

	(1)	(2)	(3)
ESG	-0.0015***	-0.0025***	-0.0023**
	[-1.8039]	[-2.6936]	[-2.3837]
$lAUM$	0.0041**	0.0046**	0.0045**
	[2.1149]	[2.3155]	[2.3423]
$lAge$	0.0003	-0.0005	0.0006
	[0.0661]	[-0.1341]	[0.1511]
$Expences$	-0.0018	0.0009	-0.0001
	[-0.3280]	[0.1676]	[-0.0163]
$Flows$	-0.0085	0.0001	-0.0032
	[-0.3565]	[0.0043]	[-0.1403]
$Turnover$	-0.0212	-0.0237	-0.0243
	[-0.6722]	[-0.7470]	[-0.7708]
$Const$	0.0618	0.1059**	0.0959*
	[1.4431]	[2.2263]	[1.9519]
R^2_{adj}	0.0021	0.0033	0.0038
$Obs.$	58,880	58,880	58,880
$Time\ FE$	N	Y	Y
$Area\ FE$	N	N	Y

4.2 *The existing relation among fund herding and financial performance*

Table III reports the results of the model (5) for the net (α_j) and gross (α_j^g) risk-adjusted returns in Panel A and B, respectively. Consistent with El Ghoul and Karoui (2017), the ESG score is negatively related to funds performances for both the net and gross alpha (column 1-2). Such a relation turns to be positive and significant after controlling for both time and fund fixed effect. The different results could be explained by the considerable heterogeneity of our sample regarding the investment area covered. In line with Jiang and Verardo (2018), the fund herding measure (FH) appears to harm both net and gross alphas even though such a relationship is statistically insignificant (column 1-3).

Moreover, the anti-herding strategy combined with the fund preference for ESG assets does not appear to have a meaningful impact on funds' risk-adjusted returns (columns 1-3). Consistent with El Ghoul and Karoui (2017) the size of a fund ($lAUM$) has a positive but significant impact. Similarly, the fund's flow ($Flows$) positively impacts risk-adjusted performance ($Flows$), indicating a smart-money effect, while the $Turnover$ does not a significant impact on risk-adjusted returns. On the other hand, the net annual expense ($Expences$) ratio significantly reduces the investors'returns.

Overall, the results show that ESG funds can anticipate the current shift towards ESG assets. Hence, after the catching-up phase documented by Bauer et al. (2005b), ESG funds are now able to improve their performance by exploiting a niche of the market (Cerqueti et al., 2021). A one-standard-deviation decrease in the ESG scores at fund-level increases the monthly risk-adjusted return by 0.312 basis points ($0.0078 \times 0.40 = 0.312$) that is 3.74 basis points yearly.

To check if and to what extent such improved performances come at the cost of a higher risk exposure, we then estimate the model (6) and report the results in Table IV. Not surprisingly, funds with a higher tendency to follow the crowd and the market also have a higher market risk exposition (FH, column 1-3). Similar consideration holds for funds that frequently trade ($Turnover$, column 1-3). However, in line with the risk-reduction effect previously documented by the literature (Albuquerque et al., 2019; Lins et al., 2015), such an effect is mitigated by the interaction with and ESG investing attitude ($FH \times ESG$, column 1-3).

To sum up, our results show that ESG funds can generate higher risk-adjusted returns, and such enhanced performance does not come at the cost of a higher market risk exposure.

Table III. Determinants of Fund Performance due to Herding Behaviour Across ESG Funds

The table reports the results for the estimated coefficients of the model:

$$\hat{\alpha}_{j,t} = \omega_0 + \omega_1 ESG_{j,t} + \omega_2 FH_{j,t} + \omega_3 ESG_{j,t} \times FH_{j,t} + \Omega^{\top} Fc_{j,t} + \lambda_t + \mu_j + \epsilon_{j,t}$$

$\alpha_{j,t}$ risk-adjusted performance for fund j at time t estimated using the Carhart (1997) model over two years of monthly return; ESG is the historical sustainability score; $FH_{j,t}$ is the Jiang and Verardo (2018) herding measure; $Fc_{j,t}$ represents the matrix of fund characteristics that includes the logarithm of the asset under management ($lAUM$), logarithm of the fund age ($lAge$), the net annual expense ratio ($Expences$), the funds flows ($Flows$), and the turnover ($Turnover$). λ_t captures the time-fixed effects, and μ_j captures the investment area fixed effect. Panel A provides for the risk-adjusted performance estimated using the net returns are dependent variable in the Carhart (1997) model, and Panel B provides for the risk-adjusted performance estimated using the gross returns are dependent variable in the Carhart (1997) model. The t-statistics are based on standard errors clustered at fund-level are reported in brackets. ***,** and * denote 1%, 5%, and 10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A			**Panel B**		
ESG	-0.0005	0.0041*	0.0078***	-0.0007	0.0041*	0.0076***
	[-0.2416]	[1.7799]	[3.4011]	[-0.3633]	[1.8893]	[3.4932]
FH	-0.4186	-0.3985	-0.3317	-0.4200	-0.3971	-0.3300
	[-1.2665]	[-1.2573]	[-1.0947]	[-1.3077]	[-1.2945]	[-1.1252]
$ESG \times FH$	0.0090	0.0087	0.0073	0.0090	0.0086	0.0072
	[1.3332]	[1.3227]	[1.1574]	[1.3760]	[1.3613]	[1.1909]
$lAUM$	0.0375***	0.0290***	0.0340***	0.0369***	0.0284***	0.0332***
	[6.7909]	[5.9668]	[6.9201]	[6.7876]	[5.9617]	[6.9086]
Age	0.0037	-0.0173	-0.0432***	0.0048	-0.0161	-0.0405***
	[0.1985]	[-1.1746]	[-2.7502]	[0.2664]	[-1.1383]	[-2.6744]
$Expences$	-0.0838***	-0.0764***	-0.0511***	-0.0112	-0.0050	0.0193
	[-5.5162]	[-5.4410]	[-3.7884]	[-0.7594]	[-0.3660]	[1.4414]
$Flows$	0.5841***	0.5467***	0.5668***	0.5922***	0.5579***	0.5769***
	[10.8822]	[9.0146]	[9.7174]	[11.2508]	[9.3001]	[9.9871]
$Turnover$	-0.0544	0.0195	-0.0127	-0.0590	0.0133	-0.0163
	[-0.5224]	[0.1885]	[-0.1356]	[-0.6109]	[0.1387]	[-0.1875]
$Const$	-0.2831***	-0.5668***	-0.6916***	-0.2541***	-0.5456***	-0.6678***
	[-2.5133]	[-4.4746]	[-5.5215]	[-2.3227]	[-4.5336]	[-5.5863]
R^2_{adj}	0.0780	0.1476	0.1727	0.0544	0.1277	0.1523
$Obs.$	48706	48706	48706	48854	48854	48854
$Time\ FE$	N	Y	Y	N	Y	Y
$Area\ FE$	N	N	Y	N	N	Y

Table IV. Determinants of Fund Systematic Risk Exposure due to Herding Behavior Across ESG Funds

The table reports the results for the estimated coefficients of the model:

$$\hat{\beta}_{j,m,t} = \psi_0 + \psi_1 ESG_{j,t} + \psi_2 FH_{j,t} + \psi_3 ESG_{j,t} \times FH_{j,t} + \Psi^{\top} Fc_{j,t} + \lambda_t + \mu_j + \epsilon_{j,t}$$

$\hat{\beta}_{j,m,t}$ market risk exposure for fund j at time t estimated using the Carhart (1997) model over two years of monthly returns, ESG is the historical sustainability score; $FH_{j,t}$ is the Jiang and Verardo (2018) herding measure; $Fc_{j,t}$ represents the matrix of fund characteristics that includes the logarithm of the asset under management ($lAUM$), logarithm of the fund age ($lAge$), the net annual expense ratio ($Expences$), the funds flows ($Flows$), and the turnover ($Turnover$). λ_t captures the time-fixed effects, and μ_j captures the investment area fixed effect. The t-statistics are based on standard errors clustered at fund-level are reported in brackets. ***,** and * denote 1%, 5%, and 10% significance.

	(1)	(2)	(3)
ESG	0.0007	-0.0010	-0.0016
	[0.6275]	[-0.8870]	[-1.3511]
FH	0.2642*	0.2724**	0.2498*
	[1.9302]	[2.0636]	[1.9485]
$ESG \times FH$	-0.0054**	-0.0055**	-0.0051**
	0.0027	0.0026	0.0025
	[-1.9895]	[-2.1272]	[-2.0230]
$lAUM$	0.0020	0.0046*	0.0033
	[0.7526]	[1.8452]	[1.2717]
Age	0.0126	0.0141*	0.0255**
	[1.3354]	[1.7293]	[2.8902]
$Expences$	0.0501	0.0453	0.0352
	[6.5499]	[6.1669]	[4.8925]
$Flows$	-0.0298	-0.0056	-0.0162
	[-1.2172]	[-0.2386]	[-0.6940]
$Turnover$	0.1538***	0.1452***	0.1516***
	[3.5283]	[3.5022]	[3.7713]
$Const$	0.9091***	1.0133***	1.0169***
	[15.1968]	[15.7839]	[15.5272]
R^2_{adj}	0.0476	0.0810	0.1014
$Obs.$	48706	48706	48706
$Time\ FE$	N	Y	Y
$Area\ FE$	N	N	Y

4.3 Robustness: Lags and Quartile Categorization of the ESG Score

In order to verify the stability of our evidence, we run two different sets of robustness checks. First, to control for endogeneity due to reverse causality, we run the same model (3), (5) and (6) but using the lagged values for the ESG score and controls at fund-level.[6] This first check is motivated by the idea that higher risk-adjusted returns could increase the amount of AUM at the fund-level to be re-invested in assets with the same or higher ESG scores. Similar reasoning applies to the systematic risk, where the lower market risk exposure of ESG assets lowers their capital cost. The extra fund could then be used to boost the investment in better ESG practices at the firm-level. Hence, in such a scenario, the ESG funds benefit indirectly from the lower systematic risk exposure at firm-level. We the second check, we control for the sensitivity of investors to fund-level holding measure (Agarwal et al., 2014, Huang and Kale, 2013 and Kacperczyk and Seru, 2007). This second check is motivated by the premise that investors, based on their interaction with fund managers and advisors, are more likely to have a relative rather than an absolute perceptions of fund responsibility. Hence, we assign funds to ESG-sorted quartiles and use the new quartile dummies instead of the ESG score to estimate again the model (3), (5) and (6), respectively. The quartile dummies are Q_1, Q_2, Q_3, Q_4 where Q_1/Q_4 takes value one if the fund has an ESG score lower/higher than the $25^{th}/75^{th}$ percentile and zero otherwise. The Q_2 and Q_3 dummies are defined using a similar procedure.

Table V shows the results for the model (3) using the lagged ESG score and control variables at the fund-level. The results are qualitatively similar to those reported in Table II. Specifically, the impact of the lagged ESG score is always negative and significant, indicating that funds tilting their portfolios towards assets with lower ESG scores have a lower tendency to follow the crowd. Similar considerations hold for the quartile specification of the ESG scores in Table VI. Specifically, the quartile ESG dummies present negative and decreasing coefficients as we move from the fourth to the second dummy, but statistically significant only for the fourth dummies representing funds with a score higher the 75^{th} percentile of the score distribution (Q_4).

Table VII and VIII show the results for the model (5) using the lagged ESG score at fund-level and the quartile specification on both the gross and net risk-adjusted returns at fund-level. Specifically, ESG funds appear to deliver higher net and gross risk-adjusted returns even when using the lagged ESG score (Table VII) or the ESG score quartile specification (Table VIII). Moreover, Table IX and X show the result for the model (6) on funds systematic risk exposure using the lagged

[6]Notice that the issue of endogeneity due to omitted variables is already tackled by using time and investment area fixed-effects.

Table V. Determinant of Fund Herding for Responsible Funds – Lagged Variables

This table reports the results for estimated coefficients of the model:

$$FH_{j,t} = \theta_0 + \theta_1 ESG_{j,t-1} + \Theta^\top Fc_{j,t-1} + \lambda_t + \mu_j + \epsilon_{j,t}$$

where $FH_{j,t}$ is the Jiang and Verardo (2018) herding measure for fund j at time t; ESG is the historical sustainability score at time $t-1$; $Fc_{j,t}$ represents the matrix of fund characteristics that includes the logarithm of the asset under management ($lAUM$), logarithm of the fund age ($lAge$), the net annual expense ratio ($Expences$), the funds flows ($Flows$), and the turnover ($Turnover$). λ_t captures the time-fixed effects, and μ_j captures the investment area fixed effect. The t-statistics are based on standard errors clustered at fund-level are reported in brackets. ***,** and * denote 1%, 5%, and 10% significance.

	(1)	(2)	(3)
ESG	-0.0016*	-0.0026***	-0.0024**
	[-1.8567]	[-2.7424]	[-2.4462]
$lAUM$	0.0044**	0.0049**	0.0048**
	[2.2417]	[2.4486]	[2.4606]
$lAge$	0.000	-0.0009	0.0003
	[-0.0021]	[-0.2381]	[0.0818]
$Expences$	-0.003	0.0002	-0.001
	[-0.5342]	[0.0403]	[-0.1869]
$Flows$	-0.0078	0.0014	-0.0018
	[-0.320]	[0.0589]	[-0.0789]
$Turnover$	0.0137	0.0111	0.0101
	[0.4394]	[0.3532]	[0.3241]
$Const$	0.0631	0.1094**	0.0984**
	[1.4533]	[2.2599]	[1.9719]
R^2_{adj}	0.0018	0.0024	0.0039
$Obs.$	56,161	56,161	56,161
$Time\ FE$	N	Y	Y
$Area\ FE$	N	N	Y

ESG score and control variables at the fund level and the quartile specification of the ESG score, respectively. Consistent with the results provided by Table IV the better performance of funds with higher ESG scores does not come at the cost of greater systematic risk exposure.

Table VI. Determinant of Fund Herding for Responsible Funds – Quartile Specification for the ESG Score

This table reports the results for estimated coefficients of the model:

$$FH_{j,t} = \theta_0 + \sum_{k=2}^{4} \theta_{k-1} Q_{j,k} + \Theta^{\top} Fc_{j,t} + \lambda_t + \mu_j + \epsilon_{j,t}$$

where $FH_{j,t}$ is the Jiang and Verardo (2018) herding measure for fund j at time t; $Q_{j,k}$ are the quartile dummies for the ESG score for $k = 4, 3, 2$; $Fc_{j,t}$ represents the matrix of fund characteristics that includes the logarithm of the asset under management ($lAUM$), logarithm of the fund age ($lAge$), the net annual expense ratio ($Expences$), the funds flows ($Flows$), and the turnover ($Turnover$). λ_t captures the time-fixed effects, and μ_j captures the investment area fixed effect. The t-statistics are based on standard errors clustered at fund-level are reported in brackets. ***,** and * denote 1%, 5%, and 10% significance.

	(1)	(2)	(3)
Q_4	-0.0181	-0.0285**	-0.0285**
	[-1.6085]	[-2.1658]	[-2.1655]
Q_3	-0.0034	-0.0094	-0.0094
	[-0.3361]	[-0.9026]	[-0.9007]
Q_2	-0.0054	-0.0063	-0.0062
	[-0.6971]	[-0.7934]	[-0.7783]
$lAUM$	0.0041**	0.0044**	0.0045**
	[2.1317]	[2.2233]	[2.3404]
Age	0.0004	0.000	0.0007
	[0.0996]	[-0.0039]	[0.1855]
$Expences$	-0.0015	0.0006	0.0001
	[-0.2677]	[0.1148]	[0.0233]
$Flows$	-0.0102	-0.0029	-0.0052
	[-0.4263]	[-0.1271]	[-0.2249]
$Turnover$	-0.0193	-0.0189	-0.0213
	[-0.6153]	[-0.5992]	[-0.678]
$Const$	-0.005	-0.0063	-0.0068
	[-0.2696]	[-0.3482]	[-0.3715]
R^2_{adj}	0.0019	0.0028	0.0036
$Obs.$	58,880	58,880	5,8880
$Time\ FE$	N	Y	Y
$Area\ FE$	N	N	Y

Table VII. Determinants of Fund Performance due to Herding Behavior Across ESG Funds – Lagged Variables

The table reports the results for the estimated coefficients of the model:

$$\hat{\alpha}_{j,t} = \omega_0 + \omega_1 ESG_{j,t-1} + \omega_2 FH_{j,t-1} + \omega_3 ESG_{j,t-1} \times FH_{j,t-1} + \Omega^\top Fc_{j,t-1} + \lambda_t + \mu_j + \epsilon_{j,t}$$

$\alpha_{j,t}$ risk-adjusted performance for fund j at time t estimated using the Carhart (1997) model over two years of monthly returns, $FH_{j,t-1}$ is the Jiang and Verardo (2018) herding measure at time $t-1$; ESG is the historical sustainability score; $Fc_{j,t-1}$ represents the matrix of fund characteristics that includes the logarithm of the asset under management ($lAUM$), logarithm of the fund age ($lAge$), the net annual expense ratio ($Expences$), the funds flows ($Flows$), and the turnover ($Turnover$). λ_t captures the time-fixed effects, and μ_j captures the investment area fixed effect. Panel A provides for the risk-adjusted performance estimated using the net returns are dependent variable in the Carhart (1997) model, and Panel B provides for the risk-adjusted performance estimated using the gross returns are dependent variable in the Carhart (1997) model. The t-statistics are based on standard errors clustered at fund-level are reported in brackets. ***,** and * denote 1%, 5%, and 10% significance.

	Panel A			Panel B		
ESG	-0.0006	0.0040*	0.0077**	-0.0008	0.0041*	0.0076***
	[-0.2952]	[1.7120]	[3.2769]	[-0.4126]	[1.8264]	[3.3785]
FH	-0.4829	-0.4625	-0.3901	-0.4786	-0.4567	-0.3844
	[-1.4124]	[-1.4106]	[-1.2458]	[-1.4369]	[-1.4368]	[-1.2656]
$ESG \times FH$	0.0103	0.0099	0.0084	0.0102	0.0098	0.0083
	[1.4690]	[1.4611]	[1.2934]	[1.4976]	[1.4904]	[1.3181]
$lAUM$	0.0357***	0.0277***	0.0327***	0.0352***	0.0272***	0.0320***
	[6.2328]	[5.5355]	[6.4632]	[6.2385]	[5.5383]	[6.4636]
Age	0.0043	-0.0173	-0.0425***	0.0055	-0.0160	-0.0396**
	[0.2248]	[-1.1461]	[-2.6337]	[0.2963]	[-1.0964]	[-2.5460]
$Expences$	-0.0825***	-0.0744***	-0.0495***	-0.0091	-0.0025	0.0215
	[-5.2472]	[-5.1737]	[-3.5787]	[-0.6007]	[-0.1751]	[1.5766]
$Flows$	0.5763***	0.5374***	0.5582***	0.5808***	0.5445***	0.5639***
	[10.4238]	[8.5935]	[9.2284]	[10.7003]	[8.8149]	[9.4310]
$Turnover$	-0.0294	0.0548	0.0184	-0.0296	0.0527	0.0197
	[-0.2786]	[0.5273]	[0.1942]	[-0.2880]	[0.5198]	[0.2144]
$Const$	-0.2706***	-0.5634***	-0.6873***	-0.2436***	-0.5446***	-0.6665***
	[-2.3385]	[-4.3388]	[-5.3422]	[-2.1686]	[-4.4185]	[-5.4344]
R^2_{adj}	0.0751	0.1459	0.1720	0.0527	0.1272	0.1529
$Obs.$	46,600	46,600	46,600	46,752	46,752	46,752
$Time\ FE$	Y	N	Y	Y	N	Y
$Area\ FE$	N	Y	Y	N	Y	Y

Table VIII. Determinants of Fund Performance due to Herding Behavior Across ESG Funds – Quartile Specification for the ESG Score

The table reports the results for the estimated coefficients of the model:

$$\hat{\alpha}_{j,t} = \omega_0 + \sum_{k=2}^{4} \omega_{k-1} Q_{j,k} + \omega_4 FH_{j,t-1} + \sum_{k=2}^{4} \omega_{k+3} Q_{j,k} \times FH_{j,t} + \Omega_4^{\top} Fc_{j,t-1} + \lambda_t + \mu_j + \epsilon_{j,t}$$

$\alpha_{j,t}$ risk-adjusted performance for fund j at time t estimated using the Carhart (1997) model over two years of monthly returns, $FH_{j,t-1}$ is the Jiang and Verardo (2018) herding measure for fund j at time $t-1$; $Q_{j,k}$ are the quartile dummies for the ESG score for $k = 4, 3, 2$; $Fc_{j,t-1}$ represents the matrix of fund characteristics that includes the logarithm of the asset under management ($lAUM$), logarithm of the fund age ($lAge$), the net annual expense ratio ($Expences$), the funds flows ($Flows$), and the turnover ($Turnover$). λ_t captures the time-fixed effects, and μ_j captures the investment area fixed effect. Panel A provides for the risk-adjusted performance estimated using the net returns are dependent variable in the Carhart (1997) model, and Panel B provides for the risk-adjusted performance estimated using the gross returns are dependent variable in the Carhart (1997) model. The t-statistics are based on standard errors clustered at fund-level are reported in brackets. ***,** and * denote 1%, 5%, and 10% significance.

	Panel A			Panel B		
Q_4	-0.0309 [-1.3228]	0.0649** [2.4160]	0.0706*** [2.7414]	-0.0332 [-1.4505]	0.0641** [2.4702]	0.0694*** [2.7843]
Q_3	0.0695*** [2.5632]	0.1640*** [5.9793]	0.1668*** [6.2231]	0.0677* [2.5806]	0.1629*** [6.2317]	0.1654*** [6.4748]
Q_2	0.1128*** [5.4265]	0.1241*** [6.6485]	0.1212*** [6.5647]	0.1089*** [5.3179]	0.1212*** [6.6266]	0.1184*** [6.5457]
FH	-0.0727 [-1.1758]	-0.0612 [-1.0767]	-0.0554 [-1.0003]	-0.0717 [-1.1776]	-0.0599 [-1.0746]	-0.0538 [-0.9900]
$Q_4 \times FH$	0.1003 [1.3527]	0.0996 [1.4074]	0.0886 [1.2884]	0.0969 [1.3307]	0.0954 [1.3790]	0.0842 [1.2511]
$Q_3 \times FH$	0.1555 [1.6476]	0.1339 [1.4373]	0.1168 [1.2864]	0.1618 [1.7519]	0.1402 [1.5422]	0.1234 [1.3919]
$Q_2 \times FH$	0.1379* [1.7950]	0.1245* [1.7347]	0.1138* [1.6557]	0.1316* [1.7173]	0.1182* [1.6582]	0.1083 [1.5860]
$lAUM$	0.0376*** [6.8857]	0.0296*** [6.2175]	0.0343*** [7.0678]	0.0369*** [6.8603]	0.0290*** [6.1949]	0.0335*** [7.0362]
Age	0.0066 [0.3584]	-0.0172 [-1.1932]	-0.0411*** [-2.6573]	0.0075 [0.4244]	-0.0161 [-1.1582]	-0.0385*** [-2.5824]
$Expences$	-0.0793*** [-5.4060]	-0.0695*** [-5.1358]	-0.0477*** [-3.6624]	-0.0070 [-0.4962]	0.0014 [0.1087]	0.0224* [1.7295]
$Flows$	0.5738*** [10.8428]	0.5347*** [8.9941]	0.5597*** [9.7056]	0.5812*** [11.2038]	0.5451*** [9.2686]	0.5687*** [9.9651]
$Turnover$	-0.0486 [-0.4833]	0.0263 [0.2660]	-0.0115 [-0.1239]	-0.0514 [-0.5518]	0.0218 [0.2369]	-0.0131 [-0.1524]
$Const$	-0.3606*** [-6.3579]	-0.4674*** [-9.0025]	-0.4183*** [-8.0553]	-0.3385*** [-6.1239]	-0.4421*** [-8.7649]	-0.3975*** [-7.9150]
R^2_{adj}	0.0943	0.1660	0.1870	0.0712	0.1468	0.1672
$Obs.$	48,706	48,706	48,706	48,854	48,854	48,854
$Time\ FE$	Y	N	Y	Y	N	Y
$Area\ FE$	Y	N	Y	Y	N	Y

Table IX. Determinants of Fund Systematic Risk Exposure due to Herding Behavior Across ESG Funds – Lagged Variables

The table reports the results for the estimated coefficients of the model:

$$\hat{\beta}_{j,m,t} = \psi_0 + \psi_1 ESG_{j,t-1} + \psi_2 FH_{j,t-1} + \psi_3 ESG_{j,t-1} \times FH_{j,t-1} + \Psi^\top Fc_{j,t-1} + \lambda_t + \mu_j + \epsilon_{j,t}$$

$\hat{\beta}_{j,m,t}$ market risk exposure for fund j at time t estimated using the Carhart (1997) model over two years of monthly returns, ESG is the historical sustainability score at time $t-1$; $FH_{j,t-1}$ is the Jiang and Verardo (2018) herding measure; $Fc_{j,t-1}$ represents the matrix of fund characteristics that includes the logarithm of the asset under management ($lAUM$), logarithm of the fund age ($lAge$), the net annual expense ratio ($Expences$), the funds flows ($Flows$), and the turnover ($Turnover$). λ_t captures the time-fixed effects, and μ_j captures the investment area fixed effect. The t-statistics are based on standard errors clustered at fund-level are reported in brackets. ***,** and * denote 1%, 5%, and 10% significance.

	(1)	(2)	(3)
ESG	0.0008	-0.0010	-0.0015
	[0.7360]	[-0.8680]	[-1.1929]
FH	0.0816	0.0965	0.0985
	[0.9094]	[1.1420]	[1.1339]
$ESG \times FH$	-0.0014	-0.0017	-0.0018
	[-0.8378]	[-1.0521]	[-1.0521]
$lAUM$	0.0017	0.0039	0.0028
	[0.6198]	[1.5111]	[1.0431]
Age	0.0125	0.0145*	0.0251**
	[1.2948]	[1.7336]	[2.7697]
$Expences$	0.0497***	0.0443***	0.0351***
	[6.4097]	[5.9521]	[4.7908]
$Flows$	-0.0388	-0.0144	-0.0239
	[-1.5684]	[-0.5958]	[-1.0042]
$Turnover$	0.1625***	0.1519***	0.1581***
	[3.8043]	[3.7802]	[4.0232]
$Const$	0.9088***	1.0205***	1.0181***
	[14.7570]	[15.4575]	[15.0563]
R^2_{adj}	0.0446	0.0795	0.0985
$Obs.$	46,567	46,567	46,567
$Time\ FE$	Y	N	Y
$Area\ FE$	N	Y	Y

Table X. Determinants of Fund Systematic Risk Exposure due to Herding Behavior Across ESG Funds – Quartile Specification for the ESG Score

The table reports the results for the estimated coefficients of the model:

$$\hat{\beta}_{j,m,t} = \psi_0 + + \sum_{k=2}^{4} \omega_{k-1} Q_{j,k} + \psi_5 FH_{j,t-1} + \sum_{k=2}^{4} \omega_{k+4} Q_{j,k} \times FH_{j,t} \psi_1 ESG_{j,t-1} + \Psi^{\top} Fc_{j,t-1} + \lambda_t + \mu_j + \epsilon_{j,t} \quad (7)$$

$\hat{\beta}_{j,m,t}$ market risk exposure for fund j at time t estimated using the Carhart (1997) model over two years of monthly returns, ESG is the historical sustainability score at time $t-1$; $FH_{j,t-1}$ is the Jiang and Verardo (2018) herding measure; $Fc_{j,t-1}$ represents the matrix of fund characteristics that includes the logarithm of the asset under management ($lAUM$), logarithm of the fund age ($lAge$), the net annual expense ratio ($Expences$), the funds flows ($Flows$), and the turnover ($Turnover$). λ_t captures the time-fixed effects, and μ_j captures the investment area fixed effect. The t-statistics are based on standard errors clustered at fund-level are reported in brackets. ***,** and * denote 1%, 5%, and 10% significance.

	(1)	(2)	(3)
$Q_{4,ESG}$	0.0241**	-0.0035	-0.0066
	[2.0173]	[-0.2562]	[-0.4926]
$Q_{3,ESG}$	-0.0362***	-0.0606***	-0.0614***
	[-3.0473]	[-4.5701]	[-4.6803]
$Q_{2,ESG}$	-0.0633***	-0.0608***	-0.0596***
	[-6.6420]	[-6.4507]	[-6.2904]
FH	0.0160	0.0130	0.0114
	[0.8961]	[0.7398]	[0.6603]
$Q_{4,ESG} \times FH$	-0.0163	0.0097	0.0144
	[-0.3349]	[0.1923]	[0.3041]
$Q_{3,ESG} \times FH$	-0.0476**	-0.0430*	-0.0420*
	[-2.0605]	[-1.9369]	[-1.9006]
$Q_{2,ESG} \times FH$	-0.0116	-0.0066	-0.0065
	[-0.4588]	[-0.2711]	[-0.2694]
$lAUM$	0.0020	0.0043*	0.0031
	[0.7678]	[1.7707]	[1.2402]
Age	0.0109	0.0131**	0.0239**
	[1.1942]	[1.6493]	[2.7789]
$Expences$	0.0479***	0.0427***	0.0335***
	[6.5225]	[5.9548]	[4.7510]
$Flows$	-0.0213	-0.0034	-0.0150
	[-0.7930]	[-0.1323]	[-0.5814]
$Turnover$	0.1479***	0.1415***	0.1486***
	[3.5286]	[3.5014]	[3.7407]
$Const$	0.9691***	1.0004***	0.9775***
	[34.5411]	[36.4045]	[35.6219]
R^2_{adj}	0.0723	0.1001	0.1191
$Obs.$	48,706	48,706	48,706
$Time\ FE$	Y	N	Y
$Area\ FE$	N	Y	Y

5 Conclusion

Several reasons could push ESG funds to copy or deviate from each other. First, other funds' trades may reveal hidden information. Second, asset managers try to tide their performance with their more skilled competitors due to reputation or compensation concerns. Third, skilled or experienced managers are more likely to deviate from past actions and exhibit anti-herding behavior. Independently from the motivations behind a herding/anti-herding behavior among ESG funds, such phenomena could be exacerbated by the increasing importance that ESG investing has gained in financial markets. With this study we show: (1) if there exists a herding/anti-herding behavior among ESG funds in the first place, (2) if such herding/anti-herding behavior generates higher or lower risk-adjusted returns, and (3) if such herding/anti-herding behavior generates higher or lower systematic market risk exposition.

Using a dataset of $10,456$ unique ESG funds investing worldwide from 2012 to 2018, enriched by detailed monthly information for 37,181 holdings, we find that ESG funds exhibit an anti-herding behavior. Moreover, we show that, after a catching up-phase, ESG funds become able to generate higher risk-adjusted returns and that such an enhanced performance does not come at the cost of higher systematic risk exposure. Our results are relevant for both investors and asset managers. The former can now invest in such funds without necessarily sacrifice a portion of their returns in the name of their preferences for assets that better comply with ESG standards. The latter may now benefit from an exposition to market fluctuations by tilting their portfolio towards more responsible assets.

Our findings of anti-herding behavior by ESG funds may also justify further analyses addressing the mechanism of price discovery in financial markets. For example, O'Hara (2003) discusses at length how the difference between informed vs uninformed traders is needed to explain how the market microstructure works. For O'Hara, informed traders take advantage of their superior information leading them to choose the same assets as uniformed traders, but assigning larger weights to information-intensive assets compared to the weights chosen by uninformed traders. In the author's reasoning, this squares up incentives allowing informed traders to gain higher returns and, at the same time, perform price discovery by delivering asset prices better aligned to the full information equilibrium, so raising market efficiency. In the context of ESG investing, perhaps we might envisage that better informed funds take the lead in over-weighting the holdings of those assets featuring higher information asymmetry. In turn, this could have three effects. First, informed funds might follow anti- herding investment strategies. Second, through those strategies, informed funds could gain superior returns. Third, by doing that, informed funds might help to disseminate private information and, so, support the market's price discovery mechanism. To be sure, vis-á-vis traditional assets, ESG assets and investing may feature a high degree of opacity and information asymmetry (e.g., Reiser and Tucker, 2019; Van Heijningen, 2019). For example, studying the impact of ESG factor materiality on stock performance of firms, Van Heijningen (2019) finds that the more detailed and less transparent ESG information that makes up the company ESG scores has better predictive power. In practice, compared to traditional assets, where financial reporting is typically sufficient to evaluate the underlying company, evaluating ESG assets implies exploiting less widely used metrics and involves factoring in more private information. These hypotheses could be addressed within future research.

References

Agarwal V., Gay G., and Ling L. Window dressing in mutual funds. *The Review of Financial Studies*, 27(11):3133–3170, 2014.

Albuquerque R., Koskinen Y., and Zhang C. Corporate social responsibility and firm risk: Theory and empirical evidence. *Management Science*, 65(10):4451–4469, 2019.

Avery C. and Zemsky P. Multidimensional uncertainty and herd behavior in financial markets. *American economic review*, pages 724–748, 1998.

Bauer R., Derwall J., Guenster N., and Koedijk K. The eco-efficiency premium puzzle. *Financial Analysts Journal*, 61(2):51–63, 2005a.

Bauer R., Koedijk K., and Otten R. International evidence on ethical mutual fund performance and investment style. *Journal of Banking & Finance*, 29(7):1751–1767, 2005b.

Bauer R., Otten R., and Rad A. Ethical investing in australia: Is there a financial penalty? *Pacific-Basin Finance Journal*, 14(1):33–48, 2006.

Bauer R., Derwall J., and Otten R. The ethical mutual fund performance debate: New evidence from canada. *Journal of Business Ethics*, 70(2):111–124, 2007.

Becchetti L., Ciciretti R., and Dalò A. Fishing the corporate social responsibility risk factors. *Journal of Financial Stability*, 37:25 – 48, 2018.

Bikhchandani S., Hirshleifer D., and Welch I. A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of political Economy*, 100(5):992–1026, 1992.

Bollen N. Mutual fund attributes and investor behavior. *Journal of Financial and Quantitative Analysis*, 42(3):683–708, 2007.

Carhart M. On persistence in mutual fund performance. *Journal of Finance*, 52(1):57–82, 1997.

Cerqueti R., Ciciretti R., Dalò A., and Nicolosi M. Esg investing: A chance to reduce systemic risk. *Journal of Financial Stability*, 54, 2021.

Daniel K. and Titman S. Evidence on the characteristics of cross sectional variation in stock returns. *Journal of Finance*, 52(1):1–33, 1997.

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

Evans R. Mutual fund incubation. *The Journal of Finance*, 65(4):1581–1611, 2010.

Fama E. and French K. Size, value, and momentum in international stock returns. *Journal of Financial Economics*, 105(3):457–472, 2012.

Fama E. and French K. International tests of a five-factor asset pricing model. *Journal of Financial Economics*, 123(3):441–463, 2017.

Galema R., Plantinga A., and Scholtens B. The stocks at stake: Return and risk in socially responsible investment. *Journal of Banking & Finance*, 32(12):2646–2654, 2008.

Global Sustainable Investment Alliance. Global sustainable investment review. Technical report, 2018.

Global Sustainable Investment Alliance. Global sustainable investment review. Technical report, 2020.

Graham J. R. Herding among investment newsletters: Theory and evidence. *The Journal of Finance*, 54(1):237–268, 1999.

Hamilton S., Jo H., and Statman M. Doing well while doing good? the investment performance of socially responsible mutual funds. *Financial Analysts Journal*, 49(7):62 – 66, 1993.

Hong H. and Kacperczyk M. The price of sin: The effects of social norms on markets. *Journal of Financial Economics*, 93(1):15–36, 2009.

Huang L. and Kale J. Product market linkages, manager quality, and mutual fund performance. *Review of Finance*, 17(6):1895–1946, 2013.

Jiang H. and Verardo M. Does herding behavior reveal skill? an analysis of mutual fund performance. *The Journal of Finance*, 73(5):2229–2269, 2018.

Kacperczyk M. and Seru A. Fund manager use of public information: New evidence on managerial skills. *The Journal of Finance*, 62(2):485–528, 2007.

Kempf A. and Osthoff P. The effect of socially responsible investing on portfolio performance. *European Financial Management*, 13(5):908–922, 2007.

Lins K., Servaes H., and Tamayo A. Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis. *Working Paper*, 2015.

Luo A. and Balvers R. Social screens and systematic investor boycott risk. *Journal of Financial and Quantitative Analysis*, 52(1):365–399, 2017.

Menkhoff L., Schmidt U., and Brozynski T. The impact of experience on risk taking, overconfidence, and herding of fund managers: Complementary survey evidence. *European economic review*, 50(7):1753–1766, 2006.

O'Hara M. Presidential address: Liquidity and price discovery. *The Journal of Finance*, 58(4): 1335–1354, 2003.

Patel S. and Sarkissian S. To group or not to group? evidence from mutual fund databases. *Journal of Financial and Quantitative Analysis*, 52(5):1989–2021, 2017.

Petersen M. A. Estimating standard errors in finance panel data sets: Comparing approaches. *The Review of Financial Studies*, 22(1):435–480, 2009.

Prendergast C. and Stole L. Impetuous youngsters and jaded old-timers: Acquiring a reputation for learning. *Journal of political Economy*, 104(6):1105–1134, 1996.

Reiser D. B. and Tucker A. Buyer beware: Variation and opacity in esg and esg index funds. *Cardozo L. Rev.*, 41:1921, 2019.

Renneboog L., Ter Horst J., and Zhang C. The price of ethics and stakeholder governance: The performance of socially responsible mutual funds. *Journal of Corporate Finance*, 14(3):302–322, 2008.

Roll R. A mean/variance analysis of tracking error. *The Journal of Portfolio Management*, 18(4): 13–22, 1992.

Statman M. and Glushkov D. The wages of social responsibility. *Financial Analysts Journal*, 65 (4):33–46, 2009.

US Social Investment Foundation. The impact of sustainable and responsible investment. Technical report, 2018.

US Social Investment Foundation. Report on us sustainable and impact investing trends. Technical report, 2020.

Van Heijningen K. The impact of esg factor materiality on stock performance of firms. *Erasmus Platform for Sustainable Value Creation working paper*, 2019.

Welch I. Sequential sales, learning, and cascades. *The Journal of finance*, 47(2):695–732, 1992.

RECENT PUBLICATIONS BY *CEIS Tor Vergata*

Experimental Analysis of Endogenous Institutional Choice: Constantly Revealing versus Ad-hoc Contracting
Daniela Di Cagno, Lorenzo Ferrari, Werner Güth and Vittorio Larocca
CEIS Research Paper, 523, November 2021

Institutions and Economic Developent: New Measurements and Evidence
Leonardo Becchetti and Gianluigi Conzo
CEIS Research Paper, 522, November 2021

Institutions and Economic Development: New Measurements and Evidence
Esther Acquah, Lorenzo Carbonari, Alessio Farcomeni and Giovanni Trovato
CEIS Research Paper, 521, November 2021

The Transmission Mechanism of Quantitative Easing: A Markov-Switching FAVAR Approach
Luisa Corrado, Stefano Grassi and Enrico Minnella
CEIS Research Paper, 520, October 2021

Keeping the Agents in the Dark: Private Disclosures in Competing Mechanisms
Andrea Attar, Eloisa Campioni, Thomas Mariotti and Alessandro Pavan
CEIS Research Paper, 519, October 2021

Modelling Cycles in Climate Series: the Fractional Sinusoidal Waveform Process
Tommaso Proietti and Federico Maddanu
CEIS Research Paper, 518, October 2021

Modelling and Estimating Large Macroeconomic Shocks During the Pandemic
Luisa Corrado, Stefano Grassi and Aldo Paolillo
CEIS Research Paper, 517, October 2021

Three Liquid Assets
Nicola Amendola, Lorenzo Carbonari and Leo Ferraris
CEIS Research Paper, 516, October 2021

Efficient Nonparametric Estimation of Generalized Autocovariances
Alessandra Luati, Francesca Papagni and Tommaso Proietti
CEIS Research Paper, 515, October 2021

Partnership Dissolution with Cash-Constrained Agents
Guillaume Pommey
CEIS Research Paper, 514, October 2021