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Run to the -sustainable- hills?

An exploration of ESG fund flows in the US market in response to Flight-To-Safety periods

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ABSTRACT

Funds flowing into Environmental, Social, and Governance (ESG), Non-ESG, and Precious Metal funds (as a proxy to a safe haven asset) are analyzed for 440 such funds in the United States during Flight-To-Safety (FTS) episodes to determine if investors perceive safe-haven-like properties in ESG funds by shifting funds into this group. FTS episodes represent brief rotations of funds into safer assets to preserve capital during burst of market volatility. Looking at data for the last 10 years, the evidence herein suggests that for periods with FTS episodes, ESG funds see increasing flows when compared to the Non-ESG group and decreasing flows when compared to Precious Metals, albeit both results by a small difference, which can be interpreted as investors willing to move funds into ESG investments over Non-ESG, although not yet seeing ESG as an equally suitable safe haven alternative.

Keywords: Sustainable Finance, Fund Flows, Flight-To-Safety, Safe Haven Assets, ESG, VIX

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SECTION 1: INTRODUCTION

You have seen it. You have heard of it. Maybe you even own some of it. From coverage by financial media to involvement by regulators and stakeholders, the presence of the Environmental, Social, and Governance (ESG) approach to finance and investing has become increasingly ubiquitous in the last decade. Reports by the US Sustainable Investing Forum saw an increase of 42% in Assets Under Management (AUM) from 2018 to 2020, from $12 to $17.1 trillion, even as a big portion of these funds do not disclose the specific factors considered (Goby, 2021). Moreover, a Morgan Stanley study in 2021 found 75% of millennial investors to be involved in ESG investments. What has driven the momentum and when did all start?

The start of the ESG investing boom can be traced back to the aftermath of the 2008 financial crisis (Ruggie & Middleton, 2019), an event that reshaped how investors approach and scrutinize the companies they invest in and has since started the paradigm shift seen today, building on top of several initiatives to tackle responsible business sustainability such as the Brundtland Report in 1987, the Kyoto Protocol in 1997, the Paris Agreement in 2015, and the more recent Glasgow Climate Pact of 2021. As for how the ESG investing approach translates to financial markets, research in this area of finance including Lins, Servaes, and Tamayo (2017) for stocks, Kanamura (2021) for high yield bonds, and Pastor and Vorsatz (2020) for mutual funds points to sustainable assets having higher returns and less downside risk than non-ESG counterpart during periods of elevated risk in financial markets like recessions or non-financial related crisis like COVID-19.

If ESG assets -used interchangeably with sustainable assets- indeed behave in the way described by research with respect to how they fare in downturns, particularly during recessions, have investors started to view ESG investments another safe haven asset? Assets of this type are either uncorrelated or negatively correlated to financial markets and on average tend to retain their value during stretches of market turmoil (Ji, Zhang, and Zhao, 2020) safeguarding investor returns, some examples being gold, government bonds, and countercyclical stocks.

The purpose of this paper is to answer this question by means of analyzing the fund flows of ESG instruments during the past 10 years using monthly data, focused mainly on the US landscape, in periods when the market showed Flight-To-Safety (FTS) episodes as measured by the Chicago Board Options Exchange (CBOE) Volatility Index or VIX, a proxy to live market sentiment representing the expected volatility of the S&P 500 index over the next 30 days. These FTS episodes are commonly defined and understood as a swift rebalancing of portfolios from risky to safer assets at the onset of a high-volatility period or high VIX reading (Lehnert, 2022). To the author's knowledge there is no previous work done that relates flights-to-safety and ESG assets, as the area is mainly focused on the bigger events, namely the Great Financial Crisis (GFC) and COVID-19 crisis. This research hence adds to the nascent literature on sustainable investing by expanding the understanding of flows into these assets amid periods of elevated volatility.

To answer the research question stated above, three tests were performed within a panel regression framework controlling for common fund-level variables analyzed by investors and present in academic research. The paper addresses the fund flows dynamics amid FTS episodes between ESG and Non-ESG funds, between ESG and Precious Metal funds -as a proxy to a safe haven asset, and also addressing the returns of ESG and Non-ESG funds during the same FTS episodes.

Using a sample consisting of 440 funds across ESG, Non-ESG, and Precious Metal groups, it finds that, on average, fund flows increase at the tune of USD 250 thousand for ESG funds with respect to their counterpart and decrease by USD 200 thousand with respect to Precious Metal funds, which would seem to defeat the research question. Said results are not definitive conclusions, given this is only significant when flows into ESG funds increase for the prior month and thus cannot fully suggest that investors perceive safe haven characteristics in ESG investments. As for the returns between ESG and Non-ESG funds, no difference statistically significant from zero is found amid FTS episodes between the two groups.

The rest of the paper divides in the following scheme: Section 2 discusses the literature review of fundamental papers related to what drives ESG investing, flows during

past crisis, and what defines a flight-to-safety episode; Section 3 sets up the hypotheses to be tested; Section 4 covers the data collection and empirical methodology; Section 5 goes over the descriptive statistics for both the indices (S&P 500, VIX, and UMCSENT) and fund groups (ESG, Non-ESG, and Precious Metals); Section 6 analyses the results arrived from the tests; Section 7 discusses the limitation and delimitations in this study; and finally Section 8 ventures into the conclusion and final remarks.

SECTION 2: LITERATURE REVIEW

As an active research area, ESG investing research features works that finds ESG investments offering improved performance over conventional investments during moments of market stress, and research that finds no clear linkage of this dynamic. As such, this literature covers relevant past research in this topic, as well as literature on fund flows and Flight-To-Safety episodes, central to the discussion of the present work.

2.1 ON THE RISE OF ESG INVESTING

What is driving investing in ESG instruments? This question has been tackled exhaustively by research, with no categorical conclusion reached. One such reason is ESG funds have slowly caught up to their traditional counterparts with regards to returns, in what is called "the most persuasive driver for doubters" (Ruggie & Middleton, 2019) who see ESG investments as low-return assets. This at the same time when an important generational wealth transfer is occurring from the Baby Boomer generation (born between 1946-1964) to Millennials (1980 and 1996) and the Generation Z (1996-2012), generations more aware and conscious about matters related to ESG, with consulting firm Ernst & Young (2017) estimating said transfer in around $30 trillion over the next decades.

Society has also become more sensitive to problems surrounding environmental and climate issues, which according to Ricart and Rey (2022) is reflected in the several international initiatives moved forward since the 80s, from the Brundtland Report in 1987 to the more recent Glasgow Climate Pact of 2021, with investors increasingly taking into

consideration ESG factors as part of their investment decisions. As Marie-Laure Schaufelberger, head of stewardship at the Pictet Group notes, ESG has become a new dimension through which understand the viability of businesses. In this regard, the stakeholder theory applied to ESG (Daugaard & Ding, 2022) states that a good performance here creates long term firm value by lowering explicit costs, improving operational efficiency, corporate reputation, as well as competitiveness.

This last bit of information relates to investor's preferences. As the increase in socially responsible investments (another proxy to ESG) continues its steady rise, there is a group of investors that are willing to forgo financial returns if in doing so they revendicate their social motivations (Riedl & Smeets, 2017; Hartzmark & Sussman, 2019), whereas some others may hold this relationship more on par, caring both for return and its source (Cowton, 2018), and of course, the other extreme with investors whose decisions are not affected by ESG concerns. To this, institutional investors may be pressured by their stakeholders to either hold highly rated sustainable assets or cut lower rated ones, as discussed in Hartzmark and Sussman (2019), on top of investors that follow nonpecuniary motives. Matallín-Sáez, Soler-Domínguez, Navarro-Montoliu, and de Mingo-López (2022) suggest a potential disposition bias to the latter, where investors strongly attached to nonpecuniary motivations are less prone to disinvest sustainable funds even if performance is lower than their counterpart, as in Riedl and Smeets (2017).

Transparency is another core driver of ESG investing, and Big Data is at the center. Leading rate providers like Morningstar, Sustainalytics, and Morgan Stanley Capital International (MSCI) now cover thousands of companies with over a thousand different ESG data points, creating "previously unknowable levels of transparency" (Ruggie & Middleton, 2019), with big efforts being made to address the prevalent greenwashing problem by using Artificial Intelligence to derive information from documents and even social media posts, as reported by Responsible Investor in their ESG Yearbook for 2022.

There is of course a group of research that dissents from the literature referenced above and finds no clear relationship between ESG investing and hedging properties. Taking a contrarian stance to Lins et al. (2017), Berkman, Li, and Liu (2020) found no evidence that

firms with high Corporate Social Responsibility (CSR) ratings outperformed low-rated ones when controlling for industry, this using a similar sample construction methodology to Lins et al. (2017), also finding that the apparent outperformance of high-rated CSR firms does not translate to other international markets. On the impact of ESG ratings, Demers, Hendrikse, Joo, and Lev (2021) concluded through a multiple regression analysis and Owen-Shapley decomposition on the COVID-19 crisis that ESG rating contributes only 1% of the variation in returns, whereas investments in intangible assets proved to be statistically significant in explaining variations. Interestingly, for longer periods of time they found that high ESG performers also do not outperform low performers when controlling for several accounting and market-based factors, with other research reaching similar conclusions (Hallbritter & Dorfleitner, 2015; Shanaev & Ghimire, 2022; Naffa & Fain, 2022).

Dissent also makes itself present towards the pillars of ESG, with Folger-Laronde, Pashang, Feor, and ElAlfy (2020) pointing to the shallow scope that the three ESG pillars offer as backdrop to determine sustainability-lead performance, as social aspects are thinly incorporated in the different rating methodologies, providing a counterpoint to Ruggie and Middleton (2019).

2.2 ON FUND FLOWS

What about flows during crisis? These come mainly as investors "find refuge in the ESG approach as it focuses on the long-run sustainability of firms" (Singh, 2020) and due to their known hedging or return resiliency property (Lins et al, 2017; Kanamura, 2021). To better understand fund flows, a definition is provided by Pastor and Vorsatz (2020) in the form of variations in Total Net Assets of a fund between period t and t-1. In line with current research, the latter authors found that when compared with the S&P500 and during the COVID19 period, flows from investors went to highly rated ESG funds and those that actively exclude noncompliant stocks. Similarly, Albuquerque, Koskinen, and Santioni (2021) found that during 2020 ESG funds became aggressive buyers in response to inflows more so than non-ESG funds, to what Bollen (2007) and Renneboog (2008) refer as a clientele effect that sees fund managers selling a smaller portion of ESG stocks relative to conventional stocks when facing a downturn. Climate risk is another catalyst of fund flows and investors are

increasingly aware of it, according to Reboredo and Otero (2021) who show that flows react negatively to increases in low-carbon transition risk exposure, with Døskeland and Pedersen (2016) supporting the idea that funds that reduce exposure to climate related risks experience inflows coming from funds that experience the opposite.

2.3 ON FLIGHT-TO-SAFETY EPISODES

To provide a more formal definition of a flight-to-safety episode, such episodes coincide with large returns in bonds accompanied by large equity returns of the opposite sign, negative correlation between both, and elevated equity volatility (Baele, Bekaert, Inghelbrecht, & Wei, 2019; Adrian, Crump, & Vogt, 2019; Lehnert, 2022). These episodes can also be traced back to increases in the VIX, together with a decrease in consumer sentiment and appreciation of currencies such as the US dollar, the Swiss franc, and the Japanese yen (Baele et al. 2019). Along the same lines, Boscaljon and Clark (2013) found that FTS episodes occur following a 25% increase in the VIX over its 75-day moving average, this when focusing in the gold and silver market. Interestingly, as quick as these events are to manifest, they fade just as quick, as the reaction by investors is driven by a temporary price pressure that elevates aggregate -or in this case focused- stock prices and reverts shortly thereafter and are preceded by a general rebalancing towards risky assets (Lehnert, 2019), which suggests that at the onset of a FTS episode investors see flows into usual shelters (bonds, gold, Bitcoin, etc.) and -potentially- sustainable stocks as a risk-off strategy, given that these firms "are expected to bear the brunt in a more effective manner" (Singh, 2020).

SECTION 3: SETTING THE HYPOTHESIS

This research seeks to find if investors perceive SR funds as a "safe-haven" relative to the rest of the market, as is the case with other asset classes like gold or government bonds. Given that research points out to the return resiliency property of socially responsible funds during market downturns and research that accounts for positive market reaction towards gold and certain industry sectors during FTS periods (Boscaljon & Clark, 2013), the tested hypothesis is thus:

H1: FTS periods correspond to an increase in ESG fund flows compared to conventional funds.

H1.1: FTS periods correspond to an increase in ESG fund flows aligned with safe haven assets, as proxied by precious metal funds.

Then as an additional layer of robustness, and in line with the focus of past research, the paper sets to dig into the return differentials between SR and conventional funds, testing the following hypothesis:

H2: FTS periods are associated with greater return differentials for SR/ESG funds compared to conventional funds.

SECTION 4: DATA AND METHODOLOGY

The data collected for the purpose of this research includes fund-level data on the three different fund groups (ESG, its Non-ESG counterpart, and Precious Metals as proxy for safe-haven assets) totaling USD 2.4 trillion, as well as data for the indices used to confirm an FTS episode, namely the VIX, the S&P 500, and the Consumer Sentiment index by the University of Michigan. The methodology employed takes the form of three unbalanced panel regressions that capture the dynamics between ESG and both Non-ESG and Precious Metal funds, and the dynamics between ESG and Non-ESG fund returns. This methodology closely follows the methods employed by previous research focused on investment funds, with the goal of understanding how Fund Flows, the dependent variable, react to periods with high market stress, especially in the case of ESG funds.

4.1 DATA COLLECTION

4.1.1 FUND GROUPS

The fund groups studied for this paper cover three main areas: ESG, Non-ESG as its counterpart, and Precious Metals representing safe-haven assets. To build up the sample of ESG funds universe of Electronically Traded Funds (ETF) on Bloomberg was used. Certain

filters were employed in line with previous research, narrowing down the universe of funds to funds domiciled in the US that call ESG as their general strategy, with USD 15M or more in AUM, and an inception date of at least two years before the current date, i.e. up to 2020. Leveraged/inverse funds were left out. The former filter relating to fund launch date is to limit the sample being prone to Evan's (2008) incubation bias, where funds are first offered privately before authorization for a ticker is obtained. Funds of this nature usually outperform nonincubated ones for a brief period following the inception date. After introducing these filters, the universe narrows down to 50 such funds representing USD 74.1 billion in Assets Under Management (AUM). Given that for some variables ESG ETFs lack data because of their recency, 102 ESG mutual funds are included to cover the empty spaces, representing USD 138 billion in AUM altogether.

For both Non-ESG and Precious Metal funds the sampling methodology was alike, filtering by domicile, AUM, and strategy. In the case of Non-ESG funds, the sample covers all such ETFs that are neither ESG nor Precious Metal related, nor any other safe-haven type fund, further leaving out leveraged/inverse strategies. This leaves 267 funds representing USD 2.3 trillion in AUM, with the notable size difference with respect to their ESG counterpart stemming from their mature state. For Precious Metal funds, these include mainly gold, silver, and palladium. After going through the aforementioned filters, the sample is composed of 21 ETFs representing USD 128 billion in AUM.

At the fund level, data is obtained from Bloomberg and Thomson Reuters Eikon, depending on availability by the provider. Said data is controlled according to similar research for fund's Fund Flows, Expense Ratio, Age (measured in months since inception), Lagged Monthly Returns, 30-Day Volatility, Traded Volume, Size, and Turnover Rate, measured as the month-to-month fund replacement of holdings. Fund Flows data for the Non-ESG group were not available on neither Bloomberg nor Thomson Reuters Eikon due to limited data access, although Eikon did provided the convention used by their mutual fund research service, Refinitiv Lipper, and thus flows for the group were calculated according to the convention:

$$FF_{i,t} = AUM_t - \left(\frac{AUM_{t-1}}{1 - r_t}\right) \quad (1)$$

where fund flows $FF_{i,t}$ are defined as the change in AUM between t and t-1 adjusted for the performance r_t at time t.

The time period covered in this paper spans over the 10 years between April 30th 2012 and April 29th 2022, starting three years after the ending of the GFC according to the US Financial Reserve (2013), a period that by some measures marks the start of the ESG investing momentum (Ruggie & Middleton, 2019) and also where an important amount of research on ESG began to appear. The three year window between the end of the GFC and the start of the sample provides further control for ESG funds launched right after the GFC aftermath. Throughout the whole paper the data used in on a monthly basis, following Albuquerque et al. (2022) use of monthly data to uncover differences between ESG and Non-ESG assets that would otherwise be lost under other time frequencies.

4.1.2 INDICES GROUP

Three indices are used to determine Flight-To-Safety periods, as per Boscaljon and Clark (2013) and Baele et al. (2019). The risk measure chosen is the CBOE's VIX index, a proxy for the 30-day expected volatility favored over other risk measures such as GARCH due to its quick adjustments to events and being the more followed volatility by investors (Copeland & Copeland, 1999). The overall state of the US financial landscape is proxied by the S&P 500, which represents over 80% of the total US stock market and whose returns are inversely correlated to the VIX. Another proxy of volatility or risk, although extending beyond the stock market to the general economy is the Consumer Sentiment index published monthly by the University of Michigan (UMCSENT), a measure of the state of the economy as determined by the consumers following a monthly survey. Higher monthly readings indicate a positive current and future economic outlook as per the opinion of the consumer, and vice versa for lower readings, showing a tendency to move inverse to the VIX. Monthly data on the VIX and S&P 500 is gathered from FactSet and readily available on all data providers, whereas data on the UMCSENT is obtained from the US Federal Reserve database.

4.2 EMPIRICAL METHODOLOGY

4.2.1 ESG FUND FLOWS UNDER FLIGHT-TO-SAFETY EPISODES

The methodology for the present work follows a multiple regression framework using an unbalanced panel dataset at the fund (i) level, centered around the effect FTS episodes have on fund flows pertaining to ESG funds, with fund flows being the dependent variable. To help explain this dynamic, two dummy variables are introduced to distinguish between both funds that are ESG labeled or conventional and whether a period n represents an FTS event or not. Alongside the dummy variables, the three indices discussed so far to determine an FTS event are included, as well as several control variables commonly present in investment fund research and looked at and analyzed by investors. Further, to ease the interpretation of results, the regression takes a difference-in-differences approach by including an interaction term between two dummy variables, ESG_i and FTS_t, that will make possible to capture the specific effect of ESG fund flows during months where FTS episodes occurred. To this end, the goal will be to see whether flows increase given investor's risk-off response to heightened volatility.

The above comprises the first of three tests to be performed, one per hypothesis. To recap, the first test focuses on the dynamics between flows into ESG and conventional funds, with the second test following a similar approach, although distinguishing now between ESG and precious metal funds. This is done to see in more detail how flows into ESG funds may or may not be related to flows into precious metal funds, the latter being a proxy to safe haven assets. Both the three indices and the control variables remain in the model. The paper then moves to third test, analyzing the relationship between ESG fund returns and those of conventional funds like the bulk of previous research has focused on, although heavily focused on two main events, namely the crises of 07-09 and 2020 under COVID-19. Thus, here the distinction lies in covering shorter, more frequent periods that trigger an FTS response by investors over a longer period of time. The regression equations for each of the tests are covered in depth in Section 6.

4.2.2 DEFINING FLIGHT-TO-SAFETY EPISODES

Studying the Flight-To-Safety phenomena has become an active research area, and as such, more than one definition exists for such events. For instance, in Caballero and Krishnamurthy (2008) an FTS episode ensues when market agents face Knightian uncertainty about the state of the economy, shifting from risky assets to assets viewed as safer or of a quality appropriate to sustain a possible downturn. Baele et al. (2019) defines such episodes through as one that satisfies positive bond returns coupled with negative returns for equities under elevated market volatility. These FTS episodes are generally short-lived, lasting up to 3 days and reverting to pre-FTS levels within four to ten months (Baele et al., 2019; Lehnert, 2022) as the price pressures generated by the agents is often lacks a strong fundamental basis.

In defining an FTS episode for the present research, this paper follows the methodology of Boscaljon and Clark (2013) in defining one such episode as a 25% rise in the VIX over its 75-day Moving Average, which at the same time is consistent with previous research by Copeland and Copeland (1999) and finds a positive reaction between increases in the VIX and an FTS response to gold assets. Two other levels of percentage increase, 10% and 50%, are discouraged due to the former being too much noise in capturing investor uncertainty, and the latter captures no new information. Together with the 10-year sample data at hand, 25% increases yield 23 such episodes as listed in Table 1 and Figure 1.

Table 1: Flight-To-Safety Episodes

Month	VIX Level	% Over 75d MA	Month	VIX Level	% Over 75d MA
4/29/2022	33.40	29%	2/28/2018	19.85	43%
2/28/2022	30.15	32%	1/31/2018	13.54	27%
11/30/2021	27.19	45%	10/31/2016	17.06	25%
9/30/2021	23.14	28%	9/30/2015	24.50	31%
1/29/2021	33.09	31%	8/31/2015	28.43	80%
10/30/2020	38.02	43%	6/30/2015	18.23	31%
3/31/2020	53.54	87%	1/30/2015	20.97	26%
2/28/2020	40.11	162%	9/30/2014	16.31	27%
1/31/2020	18.84	40%	7/31/2014	16.95	37%
5/31/2019	18.71	26%	1/31/2014	18.41	33%
12/31/2018	25.42	28%	5/31/2012	24.06	30%
10/31/2018	21.23	43%			

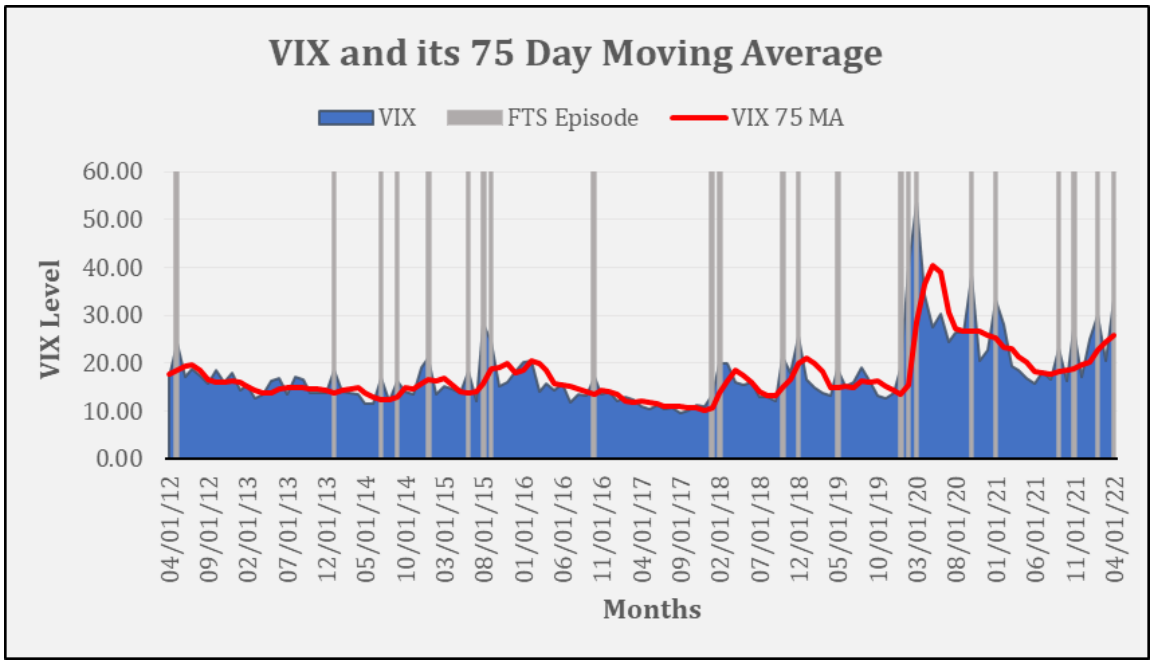

Figure 1: VIX and its 75 day Moving Average (FTS Episodes highlighted in grey)

SECTION 5: DESCRIPTIVE STATISTICS

Descriptive statistics are introduced for the three indices used to confirm FTS episodes, as well for the group of funds chosen, with graphical and tables used for easing interpretations.

5.1 SUMMARY STATISTICS FOR INDICES: VIX, S&P 500, AND UMCSENT

Descriptive statistics are provided in Table 2 for the three indices presented in this paper. At the onset of an FTS episode, the VIX mean value becomes is 25.27, with an upper (lower) quartile reading of 36.61 (25.43), whereas excluding FTS episodes the mean and upper (lower) quartiles become 16.01 and 14.05 (11.77), a change of 58%, 161%, and 116% respectively. Higher readings in the VIX imply higher market volatility for the next 30 days.

Under FTS conditions, the S&P 500 had a mean end-of-month return of -4.02% with readings for the upper and lower quartiles of -1.75% and -6.42%. For months that do not account for FTS episodes, the index has a mean monthly increase of 2.17% and an upper (lower) quartile of 3.59% (0.50%). In terms of basis points, there happens to be a 619 basis

points reduction for the S&P 500 during months that feature FTS episodes. This interpretation is aligned with the dynamics in the VIX index, as the volatility index is negatively correlated with the S&P 500, for what it can be understood that as the VIX captures the prevalent volatility in the market, this will translate into lower broad index returns as investors assume a capital preservation stance by cutting losses and shifting funds into safer assets. Said negative returns for months with FTS episodes rarely move into the next month, as FTS episodes are short-lived and investors are quick to recoup losses (Lehnert, 2022). Spikes in volatility may also be related to reasons not strong enough for fund managers to shift strategy for a longer horizon. The dynamics between the indices and FTS episodes are observed graphically in Figure 2.

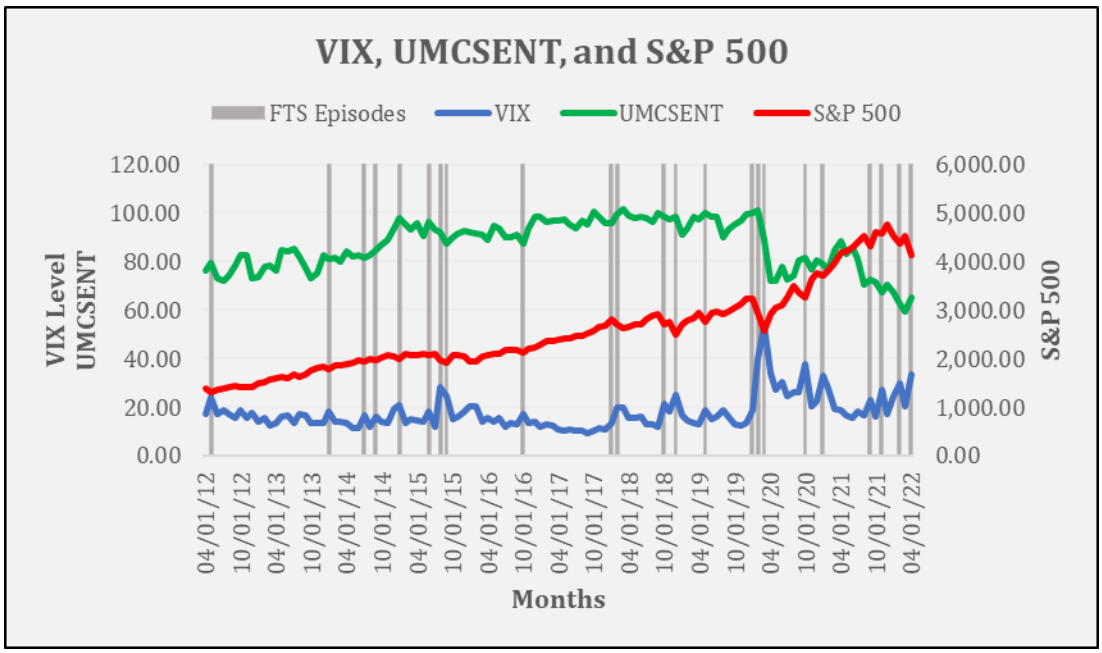

Figure 2: VIX, UMCSENT, and S&P 500 (FTS Episodes highlighted in grey)

The UMCSENT for its part, given that it is not a measure specifically focused on financial markets, has naturally a weaker relationship with respect to the VIX, but nevertheless the inverse relationship is captured by its mean, which decreases -0.02% during FTS episodes, and standard deviation, which increases by 23%. Higher monthly readings for the UMCSENT represent a positive current and future economic outlook by the US consumers, and vice versa for lower readings.

Table 2: Descriptive Statistics for Indices VIX, S&P 500 and UMCSENT

		Mean	Std. Dev.	Q3	Median	Q1
VIX	2012-2022	17.77	6.79	23.95	16.12	13.95
	2012-2022 75 MA	17.22	5.36	22.33	15.84	14.20
	FTS (VIX 25% over 75 MA)	25.27	9.42	36.61	23.14	25.43
	No FTS	16.01	4.53	14.05	15.19	11.77
	Δ between FTS/No FTS	*57.86%*	*108.21%*	*160.53%*	*52.39%*	*116.10%*
S&P 500 (%)	2012-2022	0.98	3.92	3.12	1.75	-0.90
	FTS (VIX 25% over 75 MA)	-4.02	3.81	-1.75	-3.14	-6.42
	No FTS	2.17	2.88	3.59	1.97	0.50
	Δ between FTS/No FTS (basis points)	-619	93	-534	-511	-692
UMCSENT	2012-2022	87.00	10.12	96.10	89.10	79.30
	FTS (VIX 25% over 75 MA)	86.90	11.92	98.20	87.20	80.25
	No FTS	87.03	9.72	95.80	89.80	78.95
	Δ between FTS/No FTS	*-0.15%*	*22.65%*	*2.51%*	*-2.90%*	*1.65%*

5.2 SUMMARY STATISTICS FOR FUNDS: ESG, NON-ESG, AND PRECIOUS METALS

Descriptive statistics for the different fund groups are provided in Table 3 on the Appendix 1 and finds interesting results. Starting with Fund Flows, both Non-ESG and Precious Metal funds show increases of 52% and 2304% in the amount of net fund flows for months that featured FTS episodes with respect to months with no such events, or a multiple of 5.2x and 23x, respectively, with the high multiple for Precious metals explained by its preeminent place as a safe-haven asset. The ESG group had a decrease in netflows of 2.5x, which can be understood as higher inflows for Non-ESG and Precious metals and higher outflows for ESG funds when comparing monthly readings with FTS episodes against months without such episodes. Although Matallín-Sáez et al. (2021) suggest a disposition bias exists where ESG investors are reluctant to disinvest in losing ESG positions, they are more open to do so with profitable ones, as well as the group of investors whose primary investing motives are non-pecuniary, thus increasing the amount of funds leaving ESG vehicles during FTS episodes to increase once again whenever there is no major concern in the markets, as captured by an average monthly netflow increase of USD 1.20M when considering the mean monthly fund flows when no FTS episodes are recorded against the mean of fund flows across the full 10 years of data. For the Non-ESG and Precious Metal group this difference between fund flows in months without FTS episodes and mean for the 10 years of data results in a decrease of USD -3.97M and USD -11.58M.

As for returns, Precious Metals shows the highest return differential among the three fund groups when comparing months with FTS episodes against months with no FTS episodes with a differential of 221 basis points, followed by ESG Funds with 51 and Non-ESG funds with 47. Excluding FTS episodes and comparing non-FTS months against the mean across the 10 years of data, all three groups found negative mean returns, with Precious Metals averaging a -42 basis points decrease, followed by the ESG and Non-ESG groups with -12 and -11 basis points. Turnover rate shows both ESG and Precious Metals funds showing increases in this measure of 4.58% and 4.29% respectively under FTS episodes, indicating that flows into these vehicles are more quickly translated into shares bought by the fund managers, whereas the Non-ESG group had a -3.56% decrease, indicating that although having higher inflows than their ESG counterpart, it translated into slower share purchases by the managers. For months with no FTS episodes turnover rate is minimal for Non-ESG and precious metal funds, 0.93% and -0.98%, as under lesser prevailing market volatility conditions managers do not tend to make major changes to their portfolios.

SECTION 6: ANALYSIS OF RESULTS

In analyzing the results, the first test goes over the relationship between fund flows for ESG and Non-ESG funds and the way both react to FTS episodes, with the hypothesis being that if ESG investments are perceived as an alternative to known safe-haven assets such as treasuries and Precious Metals, FTS episodes should coincide with higher net fund flows into ESG funds than their Non-ESG counterpart, behavior present in classical safe-havens. The setting for his first test takes the form of the following unbalanced panel regression:

$$FF_{i,t} = b_0 + b_1\, ESG_i + b_2\, FTS_t + b_3\, AGE_i + b_4\, EXPRATIO_i + b_5\, SP500_t + b_6\, SENT_t + b_7\, VIX_t + b_8\, RETURN_{i,t-1} + b_9\, RETURN_{i,t} + b_{10}\, FF_{i,t-1} + b_{11}\, VOL_{i,t} + b_{12}\, lnVOLUME_{i,t} + b_{13}\, lnSIZE_{i,t} + b_{14}\, lnTURNRATE_{i,t} + b_{15} ESGxFTS_{i,t} + b_{16}\, ESGxFTSxFF_{i,t-1} + b_{17}\, ESGi\ x\ FTSt\ x\ RET_{i,t} + b_{18}\, ESGxFTSxRET_{i,t-1} + \varepsilon_{i,t} \quad (2)$$

where fund flows of fund i at time t, $FF_{i,t}$, is the dependent variable, ESG_i and FTS_t are dummy variables taking the value of 1 if fund i is an ESG fund and 0 if it is Non-ESG and equal to 1 if

an FTS episode occurs at time t or 0 otherwise. AGE_t is a time-invariant measure of the months between inception date for fund i and April 29th 2022; $EXPRATIO_i$ is the expense ratio of fund i; $SP500_t$ is the monthly return for the S&P 500 index at time t; $SENT_t$ is the monthly change for the Consumer Sentiment Index at time t, as is VIX_t for the CBOE Volatility Index; $RETURN_{i,\,t-1}$ and $RETURN_{i,\,t}$ are the return of fund i lagged by one month at time t-1 and at t, respectively; $FF_{i,\,t-1}$ is the one month lagged fund flow at time t-1; $VOL_{i,t}$ is the 30-day volatility of fund i at time t; $lnVOLUME_{i,t,}$ $lnSIZE_{i,t}$, and $lnTURNRATE_{i,t}$ are the log of fund i's traded volume, size measured by AUM, and turnover rate at time t, with the turnover rate defined as the percentage of holdings replaced given a period of time (in this case a month), respectively. ESGxFTSi,t is introduced as an interaction term capturing the specific effect of funds during FTS episodes and the three other interactions aim at capturing this effect given lagged fund flows, $FF_{i,t-1}$, returns for period t, $RET_{i,t}$, and lagged returns, $RET_{i,t-1}$. b_0 is a constant and $\varepsilon_{i,t}$ is the error term.

For all three tests Random Effects are applied to assess the effect of the time-invariant variables, ESG_i and FTS_t, which are central to the present work. Opting for Fixed Effects would have hindered the results by removing one of the two.

As seen in Table 4, when controlling only for the dummy variables, ESG_i and FTS_t, only ESG_i is found to be significant with a -37.36 beta which suggests ESG funds suffer greater net outflows when compared to Non-ESG funds irrespective of the presence of a FTS episode. This result, however, reverses when controlling for fund level characteristics and variables so that, by themselves, neither dummy variable is statistically significant in explaining changes to fund flows. When testing the full model, fund returns (at time t and t-1), fund size, and fund turnover rate are the only statistically significant fund level variables, with coefficients 484.87, 201.47, 59.76, and 24.79, respectively. This comes to no surprise as it is intuitive to think more flows will go to more established funds that show positive returns for the period.

Table 4: Regression Results for Test 1

Explanatory Variables	Dummy Variables	Adding: Fund Characteristics	Adding: Indices	Adding: Fund Variables and Interaction
ESG	-37.36***	1.17	1.00	-33.48
	(10.47)	(8.92)	(8.94)	(21.34)
FTS	-18.18	-18.18	3.83	-9.39
	(17.06)	(17.15)	(5.90)	(9.37)
AGE		0.02	0.03	-0.77***
		(0.06)	(0.06)	(0.29)
EXPRATIO		-6629.52***	-6695.52***	-5892.37*
		(1583.72)	(1593.83)	(3244.31)
SP500			356.51*	219.38
			(187.68)	(358.08)
SENT			9.26	-10.87
			(50.30)	(85.03)
VIX			2.37	5.93
			(11.39)	(18.37)
RET				484.87***
				(163.58)
RET t-1				201.47**
				(93.24)
FF t-1				-0.13
				(0.11)
VOL				-2.87
				(31.09)
lnVOLUME				-9.05
				(7.31)
lnSIZE				59.76***
				(18.56)
lnTURNRATE				24.79***
				(7.05)
ESGxFTS				26.47
				(18.10)
ESGxFTSxFF t-1				0.25*
				(0.13)
ESGxFTSxRET				-590.71**
				(270.88)
ESGxFTSxRET t-1				-223.01
				(233.01)
Constant	45.62***	61.22***	52.40***	-76.66**
	(10.17)	(11.73)	(11.31)	(34.97)
N =	400	396	396	293
R^2 =	0.001	0.003	0.003	0.03
S.E. of regression =	567.4702	568.26	569.03	695.63
Hausman =	0.09	0.07	0.13	0.00

*Notes: *** p-value ≤ 0.01; ** p-value ≤ 0.05; * p-value ≤ 0.10. Robust standard errors in parenthesis.*

Now looking at the interaction terms included, which are the relevant portion in the model, it is interesting to see that holding everything else constant the interaction term

$ESGxFTS_{i,t}$ is not significant although $ESGxFTSxFF_{i,t-1}$ is at the 10% level, suggesting ESG funds see a slight increase in average flows of USD 250 thousand under FTS episodes for funds whose flows increased the month prior, compared to their conventional counterpart. Fund flows are certainly not a measure of fund performance, but from this result it could be argued that ESG investors may be swayed by funds with more recent activity. Something worth mentioning is that, although the model shows significance for one interaction term the R^2 for the test is very low at only 3%, making it incorrect to imply that the model explains to a great extent the fund flows dynamic within those short-lived bursts of market volatility.

Test 2 follows the same structure of Test 1, that is keeping equation (2), with the ESG dummy now equal to 1 if fund i is an ESG fund and 0 if a precious metal fund. Here the goodness of the model improves with R^2 now 27%, and the FTS_t variable is significant by itself at the 5% with coefficient 25.81 in the full model, suggesting FTS episodes increase flows by an average of USD 25.8 million for this sample group. Looking at the interaction terms, $ESGxFTS_{i,t}$ is again not significant, whereas $ESGxFTSxFF_{i,t-1}$ is significant at the 1% level, this time with a negative coefficient of -0.2, meaning increasing flows into ESG funds at t-1 lead to net outflows of USD 200 thousand in favor of the precious metal group at time t if during this time an FTS episode ensues. This is to say that against a pure play safe haven such as Precious Metals, ESG funds may not be a suitable substitute. Table 5 shows the full results.

Table 5: Regression Results for Test 2

Explanatory Variables	Dummy Variables	Adding: Fund Characteristics	Adding: Indices	Adding: Fund Variables and Interaction
ESG	-12.47	1.74	0.56	-74.98
	(9.87)	(10.48)	(10.87)	(56.47)
FTS	19.11**	18.51**	6.22	25.81**
	(9.44)	(9.40)	(4.50)	(12.23)
AGE		-0.1***	-0.1***	-0.16
		(0.02)	(0.02)	(0.11)
EXPRATIO		-182.71**	-171.38**	260.32
		(79.84)	(76.72)	(182.11)
SP500			-2.9*	-3.13
			(1.49)	(4.48)
SENT			-148.58**	-359.23**
			(67.22)	(179.84)
VIX			-14.90	-6.58
			(13.01)	(20.22)
RET				529.09
				(421.22)
RET t-1				155.32
				(155.46)
FF t-1				0.49***
				(0.01)
VOL				-23.56
				(31.97)
lnVOLUME				6.56
				(3.99)
lnSIZE				7.20
				(8.78)
lnTURNRATE				31.71**
				(13.14)
ESGxFTS				-0.36
				(21.04)
ESGxFTSxFF t-1				-0.2***
				(0.02)
ESGxFTSxRET				-188.41
				(247.59)
ESGxFTSxRET t-1				116.26
				-164.8
Constant	13.70	38.86***	44.39***	-36.44
	(9.53)	(11.16)	(11.55)	(50.22)
N =	173	173	173	70
R^2 =	0.001	0.006	0.007	0.27
S.E. of regression =	245.66	245.10	245.55	326.79
Hausman =	0.03	0.51	0.01	0.00

*Notes: *** p-value ≤ 0.01; ** p-value ≤ 0.05; * p-value ≤ 0.10. Robust standard errors in parenthesis.*

The third and last test sees the return of ESG funds regressed against those of its Non-ESG counterpart, comparison that is often found in research studying ESG investments. To

do this, the regression equation takes a more direct approach and controls for only the dummy variables ESG_i and FTS_t, and $RETURN_{i,t-1}$, the one-month lagged returns of fund i, to see how the returns for both fund types relate to each other and the effect that an ESG label and a FTS episode have. The regression equation is thus

$$RET_{i,t} = b_0 + b_1\, ESG_i + b_2\, FTS_t + b_3\, RET_{i,t-1} + b_4\, ESGxFTS_{i,t} + b_5\, ESGxFTSxRET_{i,t-1} + \epsilon_{i,t} \quad (3)$$

Where ESG_i is a dummy variable equal to 1 if fund i is ESG and 0 if the fund is conventional, and FTS_t is another dummy variable equal to 1 if an FTS episode occurs at time t and 0 otherwise, and $RET_{i,t-1}$ is the one month lagged return of fund i. Interaction terms are introduced for ease of interpretation as seen in Table 6 and hold the same interpretation as previous tests. $\epsilon_{i,t}$ is the error term.

Table 6: Regression Results for Test 3

Explanatory Variables		Dummy Variables	Adding: Fund Variables and Interactions
ESG		-0.003***	-0.004***
		(0.00)	(0.00)
FTS		-0.06***	-0.06***
		(0.00)	(0.00)
RET t-1			-0.09***
			(0.01)
ESGxFTS			0.01***
			(0.00)
ESGxFTSxRET t-1			0.21***
			(0.03)
Constant		0.01***	0.02***
		(0.00)	(0.00)
N	=	400	400
R^2	=	0.15	0.23
S.E. of regression	=	0.05	0.04
Hausman	=	0.00	0.00

*Notes: *** p-val ≤ 0.01; ** p-val ≤ 0.05; * p-val ≤ 0.10. Robust standard errors in parenthesis.*

When regressing fund returns instead of fund flows, it comes under no surprise seeing that the beta coefficients for the model are statistically significant as returns at time t are often related to returns at t-1. What is interesting is the positive sign of the coefficient for both interaction terms, 0.01 and 0.21, given that they would suggest that for months featuring FTS episodes ESG funds gain an average of 1% over conventional funds when fund flows increase at t-1 by one unit (USD millions) and 21% given a 1% increase in returns for that same ESG fund the month prior, both results assuming everything else constant. This result would fall in line with previous research such as Lins et al. (2017) and Kanamura (2021) in highlighting the apparent risk hedging properties of sustainable investments.

Granted, this model may be too simplistic in explaining this relationship. Table 7 in Appendix 2 includes another regression run with the controls used thus far, hence following equation (2) but with $RET_{i,t}$ now as the dependent variable, and as the controls are added the interaction variables become statistically insignificant, for what it could be interpreted that no discernible difference exists between returns for both groups during months that feature FTS episodes, although the beta coefficients for ESGxFTS and ESGxFTSxRET_{t-1} keep their positive sign.

SECTION 7: LIMITATIONS AND DELIMITATIONS

A few caveats must be made going forward with regards to the limitations and delimitations present in this paper. As mentioned initially, this paper focuses mainly on the US financial landscape, with FTS being rather short-lived moments feed by country-specific factors (Baele et al. 2019), and thus an FTS episode in the US does not have to be in direct concurrence with an FTS episode in some other country and should that be the case, the response by investors in the US towards ESG investing does not have to be equal to the response of investors from other countries and often is not (Berkman et al. 2020).

On the empirical methodology followed, the definition of FTS episodes goes in accordance with Boscaljon and Clark (2013) given the similar approach followed by this author, although said approach is granted one of the first attempts at studying the

relationship between FTS episodes and safe-haven assets (gold, in this case). The author believes that different insights may be achieved if employing other methodologies.

Finally, in carrying out this research the author used monthly observations following Albuquerque et al (2021) to capture differences between ESG and Non-ESG funds, recognizing that FTS periods are short-lived and that financial markets are relatively quick to revert to their pre-FTS episode levels (see Baele et al.2019; Lehnert, 2022), reason why the results presented in this work may differ to those obtained if studying the fund flow response at shorter time periods (i.e. weekly) instead of months.

SECTION 8: CONCLUSION

Environmental, Social, and Governance issues have had a palpable influence in the investment landscape since the Great Financial Crisis of 07-09, with USD billions going into sustainable investments each year and governments pushing for business reforms with sustainable development at the forefront. This has opened the door to researchers to study the dynamics between investments labeled as ESG-compliant and those that are not, ergo conventional investment instruments. Given the risk-hedging properties that research has found in sustainable investments, especially during volatile markets, this paper studied whether investors see safe-haven properties in ESG investments as measured by their fund flows, the net amount of cash inflows and outflows, via regressing on an unbalanced panel that included ESG, Non-ESG, and precious metal funds.

Taking the three tests performed in perspective, the results provide no definitive proof to suggest investors move funds into ESG investments during volatile market conditions, as is the case with Precious Metals, although an argument could be made in favor of investors moving funds to ESG investments before doing so to conventional funds. This group, ESG funds, saw average net outflows of USD 200 thousand significant at the 1% level when compared to a safe-haven asset class, Precious Metals. Against Non-ESG investments, however, the relationship sees average net inflows increasing by USD 250 thousands significant at the 10% level, although the explanatory power of the model is very low, thus

the significance could be erased as other controls are introduced. If the result is considered sufficient given the relatively low coefficients, then it would suggest both pecuniary and non-pecuniary motivated investors are behind the increase in net flows, contrary to the disposition bias described in Matallín-Saez et al. (2021) where nonpecuniary motivated ESG investors drive outflows during market stress periods by disinvesting in profitable positions alongside pecuniary motivated investors while keeping the losing ones. This said, ESG funds also did not showed a statistically significant return resiliency against Non-ESG funds for the period studied, as the interaction coefficient was only significantly different from zero under the restricted model shown in Table 6 and becomes immaterial when controlling for fund-level variables. This represents an opposite view to the hedging properties found on Lins et al. (2019).

As the present work represents one of the first papers to study ESG fund flows dynamics during Flight-To-Safety episodes, the author believes this can become an insightful area of research, with ESG investing becoming more relevant and ubiquitous. This said, the results showed herein are not to be taken as categorical given the limitations faced during the process. Future research done with exhaustive data would be sure to arrive at more compelling insights.

REFERENCES

Adrian, T., Crump, R. K. & Vogt, E. (2019). Nonlinearity and Flight-to-Safety in the Risk-Return Trade-Off for Stocks and Bonds, *Journal of Finance*, (John Wiley & Sons, Inc.), 74(4), pp. 1931–1973. doi: 10.1111/jofi.12776

Albuquerque, R., Koskinen, Y., & Santioni, R. (2021). Mutual Fund Loyalty and ESG Stock Resilience During the COVID-19 Stock Market Crash, *European Corporate Governance Institute – Finance Working Paper*, 782/2021, Available online: http://dx.doi.org/10.2139/ssrn.3908464

Baele, L., Bekaert, G., Inghelbrecht, K., & Wei, M. (2020). Flights to Safety, *The Review of Financial Studies*, 33(2), pp. 689-746. Available online: https://doi.org/10.1093/rfs/hhz055

Berkman, H., Li, M., & Lu., (2020). Trust and the Value of CSR during the Global Financial Crisis, *Accounting & Finance*, 61(3), pp. 4955-4965, Available online: https://doi.org/10.1111/acfi.12721

Bollen, N. P. B. (2007). Mutual fund attributes and investor behavior, *Journal of Financial and Quantitative Analysis*, 42(3), pp. 683–708. Available online: https://ssrn.com/abstract=899382

Boscaljon, B., & Clark, J. (2013). Do Large Shocks in VIX Signal a Flight-to-Safety in the Gold Market? *Journal of Applied Finance*, 23(2), 120–131. Available online: https://ssrn.com/abstract=2685826

Caballero, R.J., Krishnamurthy, A. (2008). Collective Risk Management in a Flight to Quality Episode, *The Journal of Finance*, 63(5), Available online: https://economics.mit.edu/files/3679

Chatterjee, S. (2018). Fund Characteristics and Performances of Socially Responsible Mutual Funds: Do ESG Ratings Play a Role?, *Journal of Accounting and Finance*, Available online: 10.33423/jaf.v18i6.449

Copeland, M. M. & Copeland, T. E. (1999). Market Timing: Style and Size Rotation Using the VIX, *Financial Analysts Journal*, 55(2), pp. 73–81, Available online: https://www.jstor.org/stable/4480156

Cowton, C. (2018). Socially Responsible Investing. In A. Lewis (Ed.), *The Cambridge Handbook of Psychology and Economic Behaviour*, pp. 285-304

Daugaard, D., Ding, A. (2022). Global Drivers for ESG Performance: The Body of Knowledge, Sustainability, 14(4), pp. 1-21, Available online: https://doi.org/10.3390/su14042322

Demers, E., Hendrikse, J., Joos, P., & Lev, B. (2021). ESG did not immunize stocks during the COVID-19 crisis, but investments in intangible assets did, *Journal of Business Finance & Accounting*, 48(3-4), pp. 433-462, Available online: https://doi.org/10.1111/jbfa.12523

Døskeland, L.J. & Pedersen, L.J.T. (2016). Investing with Brain or Heart? A Field Experiment on Responsible Investment, *Management Science*, 62(6), pp. 1632-1644. Available online: https://doi.org/10.1287/mnsc.2015.2208

Evans, R.B., (2010). Mutual Fund Incubation, *The Journal of Finance*, 65(4), pp. 1581-1611. Available online: 10.1111/j.1540-6261.2010.01579.x

Federal Reserve System. (2013). The Great Recession and Its Aftermath, Available online: https://www.federalreservehistory.org/essays/great-recession-and-its-aftermath#:~:text=The%20recession%20ended%20in%20June,remained%20at%20historically%20elevated%20levels.

Folger-Laronde, Z., Pashang, S., Feor, L., & ElAlfy, A., (2022). ESG ratings and financial performance of exchange-traded funds during the COVID-19 pandemic, *Journal of Sustainable Finance and Investment*, 12(2), Available online: https://doi.org/10.1080/20430795.2020.1782814

Goby. (2021). ESG funds set a new record inflow by doubling in 2021. Available online: https://www.gobyinc.com/esg-funds-new-record-inflow-

2021/#:~:text=According%20to%20Bloomberg%2C%20global%20ESG,projected%20total%20assets%20under%20management

Hartzmark, S.M., & Sussmann, A.B., (2019). Do Investors Value Sustainability? A Natural Experiment Examining Ranking and Fund Flows, *The Journal of Finance*, Available online: https://doi-org.ludwig.lub.lu.se/10.1111/jofi.12841

Hallbritter, G., & Dorfleitner,G., (2015). The wages of social responsibility — where are they? A critical review of ESG investing, *Review of Financial Economics*, 26(1), pp. 25-35. Available online: https://doi.org/10.1016/j.rfe.2015.03.004

Ji, Q., Zhang, D., & Zhao, Y. (2020). Searching for safe-haven assets during the COVID-19 pandemic, *International Review of Financial Analysis*, 71, Available online: https://doi.org/10.1016/j.irfa.2020.101526

Kanamura, T. (2021). Risk Mitigation and Return Resilience for High Yield Bond ETFs with ESG Components. *Finance Research Letters*, Available online: https://doi.org/10.1016/j.frl.2020.101866 [Accessed March 5 2022]

Lehnert, T. (2022). Flight-to-safety and retail investor behavior, *International Review of Financial Analysis*, 81. Available online: https://doi.org/10.1016/j.irfa.2022.102142

Lins, K.V., Servaes, H. & Tamayo, A. (2017). Social Capital, Trust, and Firm Performance: The Value of Corporate Social Responsibility during the Financial Crisis. *The Journal of Finance*, Available online: https://doi.org/10.1111/jofi.12505

Matallín-Sáez, J. C., Soler-Domínguez, A., Navarro-Montoliu, S., & de Mingo-López, D. V. (2022). Investor behavior and the demand for conventional and socially responsible mutual funds. *Corporate Social Responsibility and Environmental Management*, 29(1), 46– 59. Available online: https://doi-org.ludwig.lub.lu.se/10.1002/csr.2172

Naffa, H., Fain, M. (2022). A factor approach to the performance of ESG leaders and laggards, *Finance Research Letters*, 44. Available online: https://doi.org/10.1016/j.frl.2021.102073

Pastor, L. & Vorsatz, B. (2020). Mutual Fund Performance and Flows During the COVID-19 Crisis, *Chicago Booth Research Paper*, 20(18). Available online: http://dx.doi.org/10.2139/ssrn.3648302

Pavlova, I., de Boyre, M.E., (2022). ESG ETFs and the COVID-19 stock market crash of 2020: Did clean funds fare better?, *Finance Research Letters*, 44. Available online: https://doi.org/10.1016/j.frl.2021.102051

Reboredo, J., Otero, L., (2021). Are investors aware of climate-related transition risks? Evidence from mutual fund flows, *Ecological Economics*, 189. Available online: https://doi.org/10.1016/j.ecolecon.2021.107148

Renneboog, L., Ter Horst, J., & Zhang, C. (2008). Socially responsible investments: Institutional aspects, performance, and investor behavior, *Journal of Banking and Finance*, 32(9), pp. 1723–1742. Available online: https://doi.org/10.1016/j.jbankfin.2007.12.039

Ricart, J.E. & Rey, C. (2022). Purpose in Corporate Governance: The Path towards a More Sustainable World, *Sustainability*, 14(8), pp. 1-11. Available online: 10.3390/su14084384

Riedl, A. & Smeets, P. (2017). Why Do Investors Hold Socially Responsible Mutual Funds?, *The Journal of Finance*, 72: 2505-2550. Available online: https://doi-org.ludwig.lub.lu.se/10.1111/jofi.12547

Ruggie, J.G. & Middleton, E.K. (2019). Money, Millennials and Human Rights: Sustaining 'Sustainable Investing, *London School of Economics and Political Science*, 10(1), pp. 144-150. Available online: https://doi.org/10.1111/1758-5899.12645

Singh, A. (2020). COVID-19 and safer investment bets, *Finance Research Letters*, 36. Available online: https://doi.org/10.1016/j.frl.2020.101729

Shanaev, S., Ghimire, B., (2022). When ESG meets AAA: The effect of ESG rating changes on stock returns, *Finance Research Letters*, 46(A), Available online: https://doi.org/10.1016/j.frl.2021.102302

SustainFi. (2022). 30 ESG and Sustainable Investing Statistics. Available online: https://sustainfi.com/articles/investing/esg-statistics/#:~:text=2.,from%20the%20end%20of%202020.

Yu, B., Wu, S., & Lenard, M.J., (2022). Do Ethical Companies Have High Stock Prices or High Returns? *Journal of Risk and Financial Management*, 15(2):81, Available online: https://doi.org/10.3390/jrfm15020081

APPENDIX

Appendix 1. Table 3: Descriptive Statistics for Fund Groups ESG, Non-ESG, and Precious Metals

		N	Mean	Std. Dev.	Q3	Median	Q1
ESG Funds	Fund Flows (USDm)	152	1.359	26.136	3.106	-2.628	-7.455
	FTS (VIX 25% over 75 MA)		-3.757	12.387	-0.974	-4.276	-8.639
	No FTS		2.559	28.330	5.423	-1.861	-6.932
	Δ between FTS/No FTS		*-246.81%*	*-56.28%*	*-117.95%*	*129.76%*	*24.62%*
	Return (%)	152	0.38%	3.35%	2.10%	0.62%	-1.04%
	FTS (VIX 25% over 75 MA)		0.89%	3.24%	2.85%	1.64%	-0.11%
	No FTS		0.26%	3.34%	1.95%	0.57%	-1.20%
	Δ between FTS/No FTS (basis points)		*63*	*-10*	*91*	*108*	*109*
	Volatility	152	0.132	0.069	0.157	0.115	0.096
	FTS (VIX 25% over 75 MA)		0.131	0.053	0.176	0.124	0.090
	No FTS		0.132	0.072	0.151	0.115	0.096
	Δ between FTS/No FTS		*-1.00%*	*-26.82%*	*16.92%*	*8.03%*	*-6.58%*
	Volume (in millions)	50	0.932	0.969	0.962	0.511	0.359
	FTS (VIX 25% over 75 MA)		0.733	0.784	0.589	0.509	0.418
	No FTS		0.979	1.005	1.213	0.512	0.324
	Δ between FTS/No FTS		*-25.19%*	*-21.99%*	*-51.45%*	*-0.56%*	*29.03%*
	Size (in millions)	152	946.220	239.670	950.288	834.456	806.751
	FTS (VIX 25% over 75 MA)		873.452	123.999	920.755	828.323	808.131
	No FTS		963.298	256.952	952.416	837.663	806.960
	Δ between FTS/No FTS		*-9.33%*	*-51.74%*	*-3.32%*	*-1.12%*	*0.14%*
	Turnover Rate (%)	50	2.60%	35.71%	25.80%	-2.18%	-17.50%
	FTS (VIX 25% over 75 MA)		*4.58%*	*37.62%*	*20.71%*	*0.77%*	*-12.74%*
	No FTS		*2.14%*	*35.43%*	*25.97%*	*-3.02%*	*-19.36%*
	Δ between FTS/No FTS (basis points)		*245*	*219*	*-526*	*379*	*662*
Non-ESG	Fund Flows (USDm)	267	44.284	72.966	84.823	45.438	7.077
	FTS (VIX 25% over 75 MA)		61.201	58.312	110.086	59.046	16.456
	No FTS		40.314	75.707	81.784	44.427	7.688
	Δ between FTS/No FTS		*51.81%*	*-22.98%*	*34.61%*	*32.91%*	*114.06%*
	Return (%)	267	0.57%	3.51%	2.47%	0.98%	-0.82%
	FTS (VIX 25% over 75 MA)		1.05%	3.11%	2.74%	1.42%	0.18%
	No FTS		0.47%	3.59%	2.36%	0.87%	-0.93%
	Δ between FTS/No FTS (basis points)		*58*	*-48*	*38*	*55*	*111*
	Volatility	267	0.161	0.069	0.168	0.143	0.130
	FTS (VIX 25% over 75 MA)		0.192	0.121	0.193	0.166	0.141
	No FTS		0.153	0.048	0.164	0.141	0.130
	Δ between FTS/No FTS		*25.03%*	*153.23%*	*17.94%*	*17.42%*	*8.58%*
	Volume (in millions)		39.63	12.35	46.78	36.85	30.24
	FTS (VIX 25% over 75 MA)		41.83	13.77	49.87	44.35	30.89
	No FTS		39.12	12.01	45.97	36.58	30.12
	Δ between FTS/No FTS		*6.95%*	*14.59%*	*8.48%*	*21.22%*	*2.57%*
	Size (in millions)	267	5,439.38	1,593.02	5,993.31	5,463.33	4,454.17
	FTS (VIX 25% over 75 MA)		4,941.87	1,479.31	5,859.87	4,669.59	4,133.19
	No FTS		5,556.14	1,603.32	6,056.79	5,553.62	4,574.43
	Δ between FTS/No FTS		*-11.06%*	*-7.73%*	*-3.25%*	*-15.92%*	*-9.65%*
	Turnover Rate (%)	267	0.11%	26.65%	17.24%	-1.66%	-16.00%
	FTS (VIX 25% over 75 MA)		-3.56%	24.94%	13.56%	0.01%	-26.07%
	No FTS		0.93%	26.96%	18.27%	-2.17%	-14.79%
	Δ between FTS/No FTS (basis points)		*-449*	*-202*	*-470*	*218*	*-1128*

Table 3: Descriptive Statistics for Fund Groups ESG, Non-ESG, and Precious Metals (Cont.)

Precious Metals	Fund Flows (USDm)	21	8.933	150.012	89.606	1.437	-67.690
	FTS (VIX 25% over 75 MA)		58.257	144.332	87.054	29.421	-20.253
	No FTS		-2.644	149.675	91.784	-8.851	-90.463
	Δ between FTS/No FTS		*2303.65%*	*-3.57%*	*-5.15%*	*-432.41%*	*-77.61%*
	Return (%)	21	-0.45%	3.93%	1.96%	-0.15%	-2.87%
	FTS (VIX 25% over 75 MA)		1.33%	3.99%	3.75%	1.03%	-0.13%
	No FTS		-0.87%	3.82%	1.57%	-0.87%	-3.31%
	Δ between FTS/No FTS (basis points)		*221*	*17*	*218*	*190*	*318*
	Volatility	21	0.232	0.083	0.272	0.214	0.171
	FTS (VIX 25% over 75 MA)		0.230	0.075	0.266	0.239	0.167
	No FTS		0.233	0.085	0.271	0.213	0.172
	Δ between FTS/No FTS		*-1.34%*	*-12.38%*	*-2.16%*	*12.13%*	*-3.14%*
	Volume (in millions)	21	36.664	18.519	44.434	30.034	24.380
	FTS (VIX 25% over 75 MA)		35.664	21.350	40.863	30.331	21.284
	No FTS		36.899	17.905	46.150	29.916	24.748
	Δ between FTS/No FTS		*-3.35%*	*19.24%*	*-11.46%*	*1.39%*	*-14.00%*
	Size (in millions)	21	3,946.38	1,418.50	5,297.79	3,315.28	2,893.85
	FTS (VIX 25% over 75 MA)		3,973.26	1,584.05	4,900.59	3,371.86	2,835.56
	No FTS		3,940.07	1,385.61	5,295.29	3,288.20	2,897.97
	Δ between FTS/No FTS		*0.84%*	*14.32%*	*-7.45%*	*2.54%*	*-2.15%*
	Turnover Rate (%)	21	0.02%	27.57%	15.05%	-0.72%	-18.57%
	FTS (VIX 25% over 75 MA)		4.29%	25.93%	21.51%	0.36%	-14.34%
	No FTS		-0.98%	27.97%	13.63%	-1.11%	-18.29%
	Δ between FTS/No FTS (basis points)		*527*	*-204*	*788*	*147*	*395*

Appendix 2. Table 7: Regression results for Test 3, model with control variables

Explanatory Variables	Dummy Variables	Adding: Fund Characteristics	Adding: Indices	Adding: Fund Variables and Interaction
ESG	-0.003***	0.00	-0.001*	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
FTS	-0.06***	-0.06***	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
AGE		-0.00***	0.00	0.00***
		(0.00)	(0.00)	(0.00)
EXPRATIO		-0.11	-0.13*	0.10
		(0.07)	(0.07)	(0.15)
SP500			0.91***	0.98***
			(0.00)	(0.03)
lnSENT			0.01***	0.02***
			(0.00)	(0.00)
lnVIX			0.002***	0.004***
			(0.00)	(0.00)
RET t-1				0.00
				(0.01)
FF				0.00
				(0.00)
FF t-1				0.00
				(0.00)
VOL				0.00
				(0.00)
lnVOLUME				-0.002***
				(0.00)
lnSIZE				0.001***
				(0.00)
lnTURNRATE				0.00
				(0.00)
ESGxFTS				0.01
				(0.05)
ESGxFTSxRET t-1				0.04
				(0.04)
ESGxFTSxFF				-0.00
				(0.00)
ESGxFTSxFF t-1				-0.00
				(0.00)
Constant	0.02***	0.02***	-0.002***	0.001***
	(0.00)	(0.00)	(0.00)	(0.00)
N =	400	396	396	293
R^2 =	0.22	0.23	0.57	0.58
S.E. of regression =	0.04	0.04	0.03	0.03
Hausman =	0.00	0.00	0.35	0.00

*Notes: *** p-val ≤ 0.01; ** p-val ≤ 0.05; * p-val ≤ 0.10. Robust standard errors in parenthesis.*