Green Sentiment, Stock Returns, and Corporate Behavior*

Marie Brière[1] and Stefano Ramelli[2]

October 2022

Abstract

In this paper, we propose a new method to estimate non-fundamental demand shocks for green financial assets based on the arbitrage activity of exchange-traded funds (ETFs). By estimating the monthly abnormal flows into environment-friendly ETFs, we construct a Green Sentiment Index that captures shifts in investors' appetite for environmental responsibility that is not yet priced in the value of the underlying assets. Our measure of green sentiment differs significantly from the news-based climate indexes proposed by the extant literature, and it has additional explanatory power on both stock returns and corporate decisions. Over the period 2010-2020, shifts in green sentiment anticipate a persistent stock-price out-performance of more environmentally responsible firms, as well as an increase in their capital investments and cash holdings, particularly for more equity-dependent ones.

JEL Classification: G12, G32, G41
Keywords: Climate finance, corporate behavior, ESG, responsible investments, investor sentiment, non-fundamental demand, stock returns

*The authors declare that they have no relevant or material financial interests that relate to the research described in this paper. We thank Jean-Jacques Barberis, Sohnke Bartram, Pascal Blanqué, Stefano Colonnello (discussant), Shaun William Davies, Giuliano De Rossi, Ana Mão de Ferro, Julien Fouquau, Emilia Garcia-Appendini, Francesco Franzoni, Philipp Krüger (discussant), Tegwen Le Berthe, Robert Macrae, Peter Pope, Sébastien Pouget, Steve Satchell, Laurent Trottier, Alexander Wagner, Olivier David Zerbib, and participants to the Inquire Practioner Seminar, 2021 European Commission Summer School on Sustainable Finance, 2021 GRASFI conference, 2021 CREDIT conference, the Liechtenstein Workshop on Sustainable Finance, 2022 CEPR Paris symposium, and the BIS/World Bank/Bank of Canada/ Banca d'Italia 2022 Public Investors conference for insightful comments. We also thank Mathieu Jouanneau for his research assistance.

[1]Amundi, Université Libre de Bruxelles, Solvay Brussels School of Economics and Management, Center Emile Bernheim. Email: marie.briere@amundi.com.

[2]University of St. Gallen and Swiss Finance Institute. Email: stefano.ramelli@unisg.ch.

1 Introduction

Environmental considerations, especially those related to the pressing issue of climate change, are playing an increasingly prominent role in financial markets.[3] Factors driving this trend include the intensification of extreme weather events, increased public awareness of environmental issues, and the regulatory developments of recent years.

Despite a growing emphasis on the importance of green finance by practitioners and policy-makers, our collective understanding of the effect of environmental concerns on financial markets and corporate decisions remains limited. Theoretical works indicate that investors' environmental preferences can affect asset prices and, in turn, corporate behaviors (Heinkel, Kraus, and Zechner, 2001; Pástor, Stambaugh, and Taylor, 2020). From an empirical perspective, however, identifying and studying the real *impact* of investors' environmental preferences is challenging for at least two reasons. First, changes of such environmental preferences are not easily observable and measurable to scholars. Second, it is difficult to disentangle changes in environmental preferences from changes in expectations about a firm's fundamentals (cash flows and uncertainties), which are also influenced by environment-related factors, for instance, regulatory risks.[4]

In this paper, we propose a novel method to estimate changes in investor taste for green assets, which addresses both problems. Our approach is based on the analysis of the arbitrage activity of Exchange Traded Funds (ETFs) -- i.e., the creation and redemption of shares

[3] As of 2020, USD 40.5 trillion of assets were managed to account for environmental, social, and governance (ESG) factors screening, representing close to 25% of total managed assets in the US and 50% in Europe. See `http://www.gsi-alliance.org/trends-report-2018/`.

[4] For instance, Krüger, Sautner, and Starks (2020) provide clear survey evidence that institutional investors consider climate risks, particularly regulatory ones, to have material financial implications for their portfolios.

in the ETF primary markets, which leads to observable flows in or out of ETFs -- that previous works show to reflect non-fundamental investor demand shocks (see, in particular, Ben-David, Franzoni, and Moussawi, 2017; Brown, Davies, and Ringgenberg, 2021; Davies, 2020). The main reason why ETFs are likely to be more exposed to non-fundamental demand shocks than their underlying securities is, as their ownership structure is more tilted towards retail clients and short-term institutional investors.[5] The main interest of our paper is on ETFs with explicit environment-friendly features -- which we define as ''green ETFs''. In our sample, these green ETFs have a median institutional ownership of approximately 24%, compared to roughly 42% for conventional ETFs and above 70% for individual stocks.

Using data on a comprehensive sample of US equity ETFs from January 2010 through June 2020, we estimate for each month the differential flows into green ETFs relative to flows into conventional ETFs, net of the effects of other fund characteristics. We use the estimated abnormal flows into green ETFs to build our Green Sentiment Index. We present the computation details in Section 2.

We argue that the Green Sentiment Index reflects changes over time in investor taste for green assets that are not motivated by fundamental information. We show that it differs significantly from other proxies of attention to climate change used in the extant literature, such as the Google search activity on ''climate change'' (Choi, Gao, and Jiang, 2020; Ilhan, Sautner, and Vilkov, 2021) and the news-based climate risk indexes adopted by Engle, Giglio, Kelly, Lee, and Stroebel (2020) (EGKLS hereafter). These measures likely reflect an undefined mix of fundamental and non-fundamental information related to climate change

[5]Given the differences in ownership structure, non-fundamental demand shocks impact an ETF's price differently from the net asset value (NAV) of its underlying securities. The resulting wedge incentivizes the ETF's Authorized Participants (APs) to create or redeem ETF shares, generating observable flows.

and the environment. The key advantage of the proposed approach is to identify changes in investor demand for environment-friendly assets that are mostly not motivated by changes in expected firm fundamentals. If they were, the value of ETFs' underlying securities would have adjusted accordingly, not triggering the arbitrage mechanism behind the observed flows into green ETFs.

We use our Green Sentiment Index to establish two key results on the role of investor green sentiment. First, in Section 3, we study how green sentiment influences the value that investors attach to corporate environmental responsibility as priced by the stock market. We use the environmental score from the ESG data provider Sustainalytics as in EGKLS. We find that a one-standard-deviation higher green sentiment is associated with an out-performance of a one-standard-deviation more environmentally responsible firm of approximately 27 basis points over a one-month horizon and 53 basis points over a six-month horizon, net of the effects of other firm characteristics and sector.

Importantly, the effect of green sentiment is independent of -- and in addition to -- the effect of the news-based climate risk index used by EGKLS. Indeed, the EGKLS's climate risk measure and green sentiment predict an out-performance of environmental responsibility, but for different reasons. While the former also predicts a positive revision in analysts' earnings forecasts on environmentally responsible firms, green sentiment does not, further confirming the validity of our approach. We also confirm that our results are not mechanically driven by the price pressure created by the re-balancing of ETFs themselves, the propagation challenge explored in Ben-David et al. (2018).

Second, in Section 4, we use the Green Sentiment Index to study the effects of investor environmental preferences on *real* corporate decisions. We find that in quarters with a higher green sentiment, environmentally responsible firms increase both their capital investments and cash holdings. A one-standard-deviation higher green sentiment is associated with 0.21% higher Capex and 0.31% higher cash holdings -- equal to approximately 5% and 3.4% of their respective sample means -- for a one-standard-deviation higher environmental score. We do not observe any effect of green sentiment on firms' R&D activities.

Interestingly, the "real impact" of green sentiment on Capex and cash holdings appears heterogeneous across firms based on their access to capital, as proxied by their credit rating. In particular, the influence of green sentiment on Capex is focused on low- (non-investment grade) and medium-rated firms ("BBB", "BBB+", and "BBB-", based on the S&P scale). Conversely, the influence on cash holdings is focused on low-, and to a less extent, high-rated firms. These results confirm the importance of financial frictions in mediating the impact of responsible investing on firm behavior.

Our paper contributes to three strands of research. First, we add to the literature on the effects of environmental preferences on financial markets. Several theoretical works suggest that investors' green preferences affect stock prices (Heinkel et al., 2001; Fama and French, 2007; Gollier and Pouget, 2014; Landier and Lovo, 2020; Luo and Balvers, 2017; Oehmke and Opp, 2020; Pástor et al., 2020; Pedersen et al., 2020; Zerbib, 2020). In particular, the model in Pástor et al. (2020) predicts that green assets should over-perform following unexpected upward shifts in investors' environmental preferences (even though, *in equilibrium*, green assets should experience lower returns -- the opposite of what happens with "sin stocks", Hong and Kacperczyk, 2009). Battiston et al. (2021) and Gourdel et al. (2021) provide climate stress tests of the financial system and simulate how investors' expectations affect climate policy effectiveness. However, from an empirical perspective, identifying those shifts is far from obvious. Approaches based on climate-related attention and news-based measures (e.g., Choi et al., 2020; Engle et al., 2020; Huynh and Xia, 2020) are likely to partially or primarily reflect the arrival of new fundamental information.[6] In a contemporaneous work, Pastor et al. (2021) use the spread between German green and non-green bonds to study the asset-pricing effects of changes in climate concerns, although they do not aim at disentangling the fundamental and non-fundamental drivers of green demand. Van der Beck (2021) estimates that the performance of ESG investments is strongly driven by price pressure arising from flows toward sustainable funds. The ETF-based approach that we propose has the advantage of specifically capturing shifts in investor taste for green assets that are *not driven* by firm-fundamental considerations. In addition to this methodological contribution, our paper applies the proposed approach to shed new light on the effects of investor environmental preferences on firm value and real corporate decisions, confirming some key predictions of theory (Pástor et al., 2020) and contributing to the flourishing empirical literature on climate finance (e.g., Anderson and Robinson, 2020; Bartram et al., 2020; Bolton and Kacperczyk, 2021a,b; Ceccarelli et al., 2021; Choi et al., 2020; Ilhan et al., 2021; Pankratz and Schiller, 2019; Ramelli et al., 2021).

Second, we contribute to the literature on the effects of investor sentiment(s). Several papers identify a significant role of sentiment in influencing both the stock market overall and the cross-section of stock returns (e.g., Baker and Wurgler, 2006; Ben-Rephael et al., 2012; Qiu and Welch, 2004; Lemmon and Portniaguina, 2006; Stambaugh et al., 2012). Sentiment

[6]Other recent works analyzing news-based measures of attention to climate change include Bessec and Fouquau (2020), Faccini et al. (2021), and Santi (2020). Other papers propose to capture firm-level exposures to climate risks -- but not changes in investor environmental sentiment -- based on the text analysis of corporate earnings calls (Sautner et al., 2020; Li et al., 2020) or adopting machine learning techniques on annual reports (Bingler et al., 2021).

is also known to affect firms' financing and investment decisions (Baker and Wurgler, 2000; Henderson et al., 2006; Kim and Weisbach, 2008). Da et al. (2015) measures market-level sentiment based on Google search behavior. They are, of course, different types of investor sentiment. For instance, Baker et al. (2012) and Ben-Rephael et al. (2019) study the effects of foreign sentiment. We contribute to this literature by measuring and studying a new class of investor sentiment, the one pertaining to environment-related considerations. Again, the main advantage of our approach based on ETF is its ability to control for changes in expectations about firm fundamentals. By studying how green sentiment influences corporate decisions, we also link to the debate on the real effects of financial markets (e.g., Morck et al., 1990; Luo, 2005; Bakke and Whited, 2010; Bond et al., 2012; Dessaint et al., 2019).

Finally, the paper also contributes to the growing literature on ETFs. Although ETFs represent one of the most important financial innovations of the last decades, research on this market remains relatively scarce. Ben-David et al. (2017) provides an interesting review of the early literature. Ben-David et al. (2018) show that the arbitrage mechanism of ETFs propagates liquidity shocks to the underlying securities, increasing their volatility. Glosten et al. (2021) find that ETF activity increases informational efficiency for stocks with weak information environments and imperfectly-competitive equity markets. Ben-David et al. (2021) find that specialized ETFs compete for flows by catering to the attention of unsophisticated investors, and delivering negative risk-adjusted returns. Rather than studying the direct effects of ETFs, in our paper, we exploit their unique arbitrage mechanism to proxy a market sentiment. Works applying a similar approach are Brown et al. (2021) and Davies (2020). Brown et al. (2021) show theoretically and empirically that the creation and redemption of ETF shares provide observable signals of non-fundamental pressure on prices. Davies (2020) exploits the arbitrage activity of leveraged ETFs to build a "speculation sentiment index" proxying for the magnitude and direction of speculative demand shocks. In a similar spirit, we exploit the arbitrage activity on green ETFs to proxy for the magnitude and direction of shocks of non-fundamental demand for green financial assets. Given the popularity of these financial products among retail investors, they are particularly likely to reflect non-fundamental demand pressure for environment-friendly assets. Our paper aims to provide insight into the desirable and undesirable consequences of green sentiment.

2 Identifying green sentiment from ETF arbitrage activity

This section presents the proposed methodology to identify green sentiment based on ETF flows, describes the data used in the empirical investigation, and illustrates the main properties of the estimated Green Sentiment Index.

2.1 Empirical strategy

Exchange-traded funds (ETFs) are pooled investment vehicles that track an index or a basket of underlying securities. They represent one of the most important financial innovations of the last decades. As of year-end 2020, the ETF market had more than USD 7.9 trillion of assets under management worldwide, with 69% concentrated in the approximately 2,200 ETFs domiciled in the US (Investment Company Institute, 2021). ETFs account for approximately 18% of all assets managed by US investment companies, progressively eroding the space traditionally held by mutual funds. [7] The ETF market is also very liquid, with average trading equal to approximately 26% of the trading of US securities (Investment Company Institute, 2021). We refer to Ben-David et al. (2017), Lettau and Madhavan (2018), Ben-David et al. (2018), and Pagano et al. (2019) for a more comprehensive overview of ETFs and some of their documented effects on financial markets.

A key feature of ETFs is their arbitrage mechanism. In the secondary market, ETFs are traded like ordinary stocks, without involving any trading of the underlying securities. The price at which an ETF is exchanged can freely deviate from the asset-weighted net asset value (NAV) of the underlying securities. This potential mispricing is corrected by the activity of third-party arbitrageurs -- known as the "authorized participants" (APs) -- which can demand the ETF to issue or redeem shares, causing observable flows of capital into or out the ETF.

Brown, Davies, and Ringgenberg (2021) show theoretically and empirically that ETF arbitrage activities reflect non-fundamental demand shocks. The main reason for this result is that ETFs have an ownership structure that is usually quite different from the ownership of the underlying securities, with a larger component of retail (non-sophisticated) investors. Given the difference in ownership structure, non-fundamental demand shocks are likely to affect the price of ETF more than the value of its underlying securities. The resulting mispricing between the ETF and the NAV (a premium or a discount) incentivizes APs to create or redeem ETF shares in the primary market, causing observable ETF flows. These flows -- contrary to the flows in, e.g., mutual funds -- reveal the presence of non-fundamental

[7] See, e.g., Bloomberg, "Mutual funds bleed $469 billion as ETFs triumph in zero-sum 2020", December 13, 2020.

demand shocks, otherwise hard to disentangle from the effect of new fundamental information.

Our main intuition is to exploit the unique features of the ETF market, in the spirit of Brown, Davies, and Ringgenberg (2021) and Davies (2020), to measure changes in green non-fundamental demand shocks, i.e., shifts in investors' appetite for environmental responsibility not yet incorporated in the values of the underlying assets. We do that by studying the primary market of "green" ETFs, i.e., ETFs allowing environmentally-conscious investors to replicate a basket of environmentally-responsible securities.

Investors' appetite for ESG investments has been growing rapidly in recent years. The assets under management of ESG-focused funds worldwide have risen from around USD 340 billion in 2015 to over USD 1.6 trillion in 2020. The size of the US-domiciled ESG funds market has doubled since 2015 and now accounts for over 230 billion, with over 15% in the form of ETFs (Morningstar, 2020). As for sustainable funds, the size of the green ETF market has grown tremendously. The US segment of the green ETF market was, for example, multiplied by 3.6 between January 2015 and June 2020 (from USD 1.1 to 4.1 billion).

The main assumption behind our approach is that the demand for green ETFs is more sensitive to non-fundamental information than the demand for individual stocks. There are good reasons to believe this assumption to be true. In general, ETFs are predominantly used by retail investors (Ben-David et al., 2017; Brown et al., 2021; Ben-David et al., 2021), with average institutional ownership significantly lower than the institutional ownership of individual stocks. Following Stambaugh (2014)'s argument that uninformed traders are mostly present among retail investors, this suggests a higher density of liquidity traders in the ETF investor base.

This is even more true for specialized products such as green ETFs, particularly appealing to retail and sentiment-driven investors (Ben-David et al., 2021). The average share of institutional ownership of the green ETFs in our sample is 31%, significantly lower than for conventional equity ETFs (49%). The dominant presence of retail investors, combined with the fact that, like other ETFs, green ETFs can be used by institutional investors to gain short-term exposure to the green segment of the market, may contribute to making green ETFs more sensitive to non-fundamental demand shocks than the underlying green securities. A shock related to exceptionally high demand for green investment can give rise to relative mispricing, and the subsequent creation or redemption of ETF shares to correct it. The segmentation of investors between green ETFs and the underlying green stocks' markets is likely to create a wedge (a premium or discount) between the price of green ETFs and the value of the underlying securities, triggering a change in flows to green ETFs.

To measure the creation/redemption activity by APs in the ETF market, we define $Flows_{i,t}$ as the monthly percentage change in ETF shares outstanding for fund i at time t:

$$Flows_{i,t} = \frac{SharesOutstanding_{i,t}}{SharesOutstanding_{i,t-1}} - 1$$

We measure green sentiment as the differential inflows in green ETFs (non-fundamental demand on green ETFs) compared to the inflows of other ETFs, net of the effects of other observable ETF characteristics. Specifically, for every month in our sample, we run the following T cross-sectional regressions of monthly ETF flows:

$$Flows_{i,t} = c_t + \gamma_t \times GreenETF_{i,t} + \delta_t \times controls_{i,t} + \epsilon_{i,t}, \forall t \tag{1}$$

where *GreenETF* is an indicator for green ETFs and *controls* is a vector of ETF characteristics: past month ln(NAV), return, and volatility.[8] We define the standardized time series of estimated coefficients on *GreenETF* as our Green Sentiment Index.

2.2 Data

For all equity ETFs domiciled in the US, we retrieve survivorship-bias-free data (shares outstanding, volume traded, net asset value, last price and the percentage of institutional ownership) from Bloomberg.[9] We identify a total of 3,887 individual ETFs (of which, 406 are exchange-traded notes, ETN) over the period from January 2010 through June 2020.

From Morningstar Direct, we obtain information on ETFs' categories, keeping only funds classified as "equity funds" and dropping funds investing exclusively outside the US and long/short equity funds.[10] We also retrieve the following additional information from the ETF Global dataset: inception date, net expenses, creation fees, and whether the fund is levered or not. The final sample includes 1,195 individual ETFs.

Table 1 displays summary statistics for our sample of ETFs over the period from January 2010 through June 2020. The average AUM is nearly USD 2 billion and the average number of shares outstanding is USD 31 billion. Both distributions are highly skewed to the right, confirming the high concentration of the ETFs market (Pagano et al., 2019). Monthly flows represent, on average, 2% of the total number of shares outstanding. Interestingly,

[8] As a robustness check, we added several additional characteristics in the regressions, such as ETF age (number of years since inception), percentage of institutional ownership, net expense ratio, creation fee and a dummy for levered ETFs. As an additional robustness check, we also used weighted least squares (WLS) regressions where observations were weighted by ETFs AUM, with similar results.

[9] Bloomberg is recognized as the most accurate source for ETF data (Ben-David et al., 2018).

[10] More precisely, we drop the following categories: Europe Equity Large Cap, Japan Equity, Latin America Equity, Asia ex-Japan Equity, Asia Equity, Global Emerging Markets Equity, Greater China Equity, Canadian Equity Large Cap, Africa Equity, Thailand Equity, India Equity, Korea Equity, Mexico Equity, Australia & New Zealand Equity, Long/Short Equity.

equity ETFs appear to be equally used by institutional and retail investors, with an average institutional ownership of approximately 49%. Importantly, this institutional ownership is significantly lower than the average institutional ownership of individual stocks (approximately 65%). The average net expense ratio is 46 basis points, and the creation fee is 1,588 USD. Less than 1% of the ETFs in our sample are levered.

[Table 1 here]

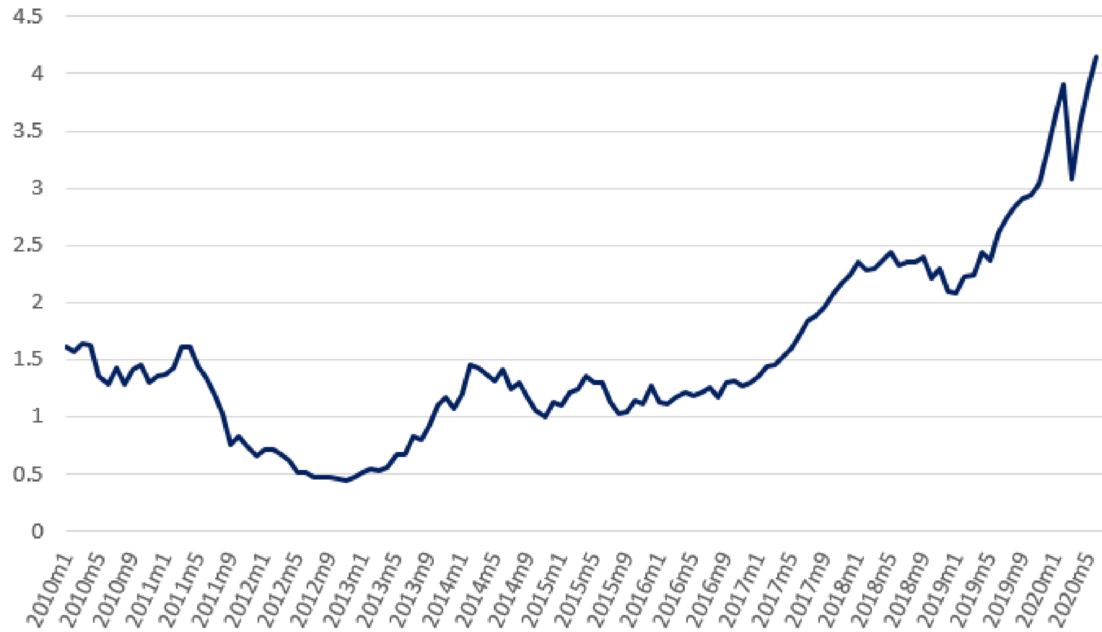
A critical choice in our empirical investigation is how to identify "green ETFs". We classify as green those ETFs whose names include one of the following keywords: "climate", "carbon", "clean", "solar", "fossil", "renewable", "environment", "wind", "ecological", "green energy", "progressive energy". In addition, we perform a manual check on the names and the prospectus of ETFs to ensure not to omit any additional funds with explicit and salient environmentally-conscious features.We identify a total of 23 green ETFs, listed in Table 2.

[Table 2 here]

Importantly, among the identified green ETFs, only one ETF is not classified as "sustainable" on the Morningstar Direct platform. The largest green fund is the iShares Global Clean Energy, with USD 721 million of assets under management as of June 2020. The oldest fund, Invesco WilderHill Clean Energy, was created in 2005.

As of June 2020, the total assets under management for green ETFs was above USD 4 billion. The size is relatively small compared to conventional equity ETFs (more than USD 4,000 billion), but it has been rapidly growing, with assets under management more than double over our sample period, as shown in Figure 1.

Figure 1: Evolution of Green ETFs' Assets Under Management
This graph presents the evolution of the aggregate assets under management (AUM, in USD billions) of green ETFs domiciled in the US over the period from January 2010 through June 2020.



2.3 The Green Sentiment Index

We here compare the ETF-flows-based Green Sentiment Index estimated based on Equation 1 to two measures of climate-related attention/risk proposed in the existing literature: the "Crimson Hexagon negative climate news" index proposed by EGKLS (and then employed also in Huynh and Xia, 2020 and Ceccarelli et al., 2021) and the Google search volume index (SVI) for the topic "climate change" used, for instance, in Choi et al. (2020) and Ilhan et al. (2021).

The negative climate news index of EGKLS is particularly interesting for our purposes because it is meant to proxy climate risk, that is, climate-related fundamental information.[11]

[11]EGKLS obtain this index from the data provider Crimson Hexagon (CH). The index represents the share

Our Green Sentiment Index aims at capturing the opposite side of the demand for green financial assets, i.e., that is not related to fundamental considerations. The Google SVI is a good proxy for the level of public attention on specific topics, climate change in our case, and it is, therefore, likely to reflect a mix of both fundamental and non-fundamental information.

Figure 2 plots the three indexes, all standardized to facilitate comparison. We observe quite different patterns over time. All three indices spike around the signature of the Paris Agreement in December 2015, but with slightly different timing. *Google climate SVI* and *Green sentiment* reflect the rising awareness on climate change in more recent years (especially after 2018). Interestingly, *Green sentiment* also spikes in early 2020 in correspondence with the COVID-19 crash.[12]

of all news articles in major outlets that are both about ''climate change'' and have a ''negative sentiment'' as categorized by CH. The index is available from January 2008 through May 2018. We thank Stefano Giglio and Johannes Stroebel for making these data available on their websites.

[12]We interpret this evidence as suggesting that the increased investor attention to environmental issues following the outbreak of the pandemic -- that extant research has also identified in terms of stock-price (out-)performance of firm environmental responsibility (Albuquerque et al., 2020; Pástor and Vorsatz, 2020; Garel and Petit-Romec, 2021) -- is not primarily driven by fundamental information and the behavior of institutional investors.

Figure 2: Evolution of the Green Sentiment Index
This graph plots the evolution of various indexes of climate sentiment, all standardized. *Green sentiment* is the standardized Green Sentiment Index computed based on specification (1). *Negative climate news* is the standardized negative climate news index proposed by Engle et al. (2020). *Google climate SVI* is the Google search volume index for the topic "climate change" in the US.

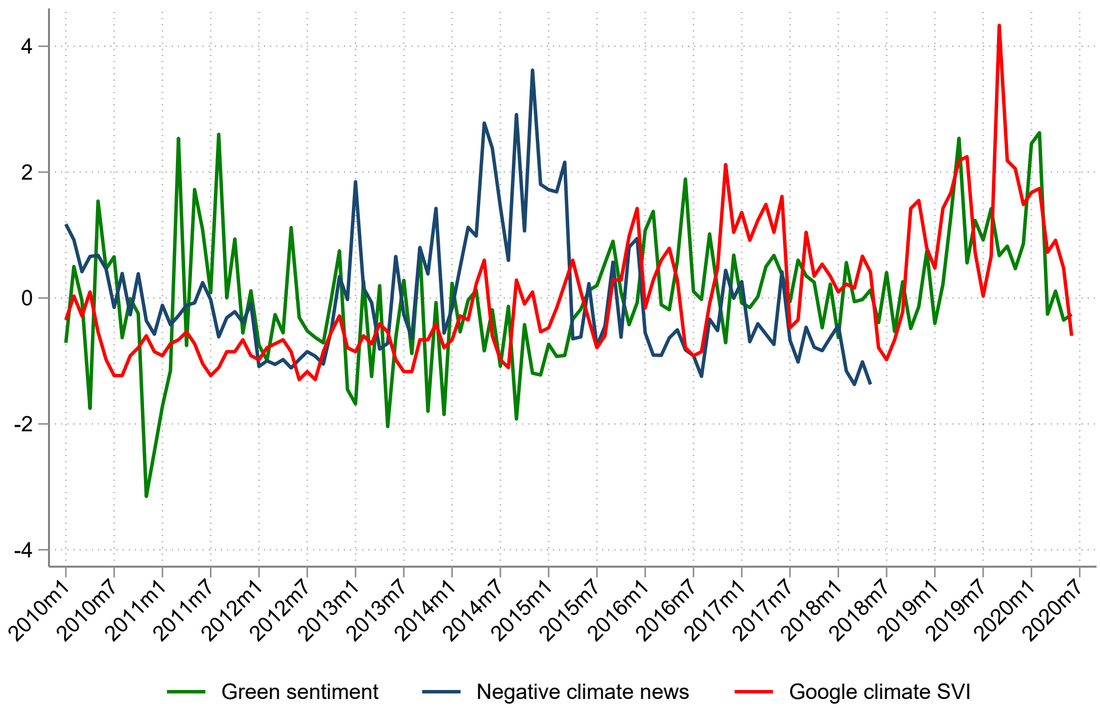


Table 3 shows the pairwise correlation between the three indexes. As expected, *Green sentiment* correlates *positively* with *Google climate SVI* (0.29, $p < 0.001$) but it correlates *negatively* with EGKLS' *Negative climate news* (-0.28, $p < 0.01$). *Google climate SVI* and *Negative climate news* do not significantly correlates with each other (0.08, $p > 0.1$).

[**Table 3 here**]

Overall, this descriptive evidence supports the claim that the Green Sentiment Index captures investor demand for green assets not driven by hedging-climate-risk purposes or changes in expectations about firms' fundamentals. If it were -- reflecting, for instance, the potential benefit of green ETFs in facilitating "price discovery" after fundamental shocks (Glosten et al., 2021) -- we would have observed a positive correlation with news-based climate risk measures capturing the arrival of financially material information.

In the next sections, we investigate what are the effects of this type of investor sentiment on both firm value and corporate behavior.

3 Effects of green sentiment on stock returns

In this section, we use the Green Sentiment Index to shed light on the channels behind the effects of corporate environmental responsibility on stock prices. The theoretical literature on responsible investing predicts that a decrease should follow shifts in investor environmental preferences in the cost of capital of more environmentally-responsible firms (Heinkel et al., 2001; Fama and French, 2007; Pástor et al., 2020). Our approach to measuring green sentiment provides a powerful tool to empirically test whether this is really the case, net of the effects of changes in expectations about firm fundamentals.

3.1 Data

We retrieve monthly stock prices for common shares listed on US major stock exchanges (NYSE, NYSE Arca, AMEX, and NASDAQ) from January 2010 through June 2020, from the Compustat Capital IQ North America Daily database. We adjust prices for dividends through the monthly multiplication factor and the price adjustment factors provided by Compustat. In cases of dual listings, we keep only the firm's security with the highest market capitalization. For every month, we trim returns at the 1st and 99th percentiles to reduce the impact of outliers. We also use monthly returns to compute buy-and-hold returns in windows of up to 6 months (e.g., *Cumulative return t+6*).

For each stock, we estimate the *Market beta* from regressions of monthly returns over the 1-month Treasury-bill rate on the excess market return using a 36-month moving window, when at least 24 months of non-missing returns are available. We use the excess returns on the market factor available from Kenneth French's website. For each stock-month observation, we also compute *Momentum* as the average individual stock return from month t-12 to t-2, as in Bessembinder et al. (2019).

From Compustat, we also retrieve the following firm annual accounting characteristics: *Leverage* (long-term debt plus debt in current liabilities, divided by total assets, in percentage points: (dltt + dlc) $\times$ 100/at), *Size* i.e., *Log(market cap)* (ln(prcc_f $\times$ csho)), *Book-to-market* (book value of equity divided by market valuation: ceq/(prcc_f $\times$ csho)), and *Profitability* (annual income before extraordinary items over total assets: ib$\times$100/at).

We merge the above Compustat data with the firms' ESG scores from Sustainalytics, which are also employed in EGKLS.[13] To facilitate the economic interpretation of the results, we standardize the environmental scores from Sustainalytics to have mean 0 and unit standard deviation. As an alternative proxy for environmental responsibility, we compute the firms' environmental score using the MSCI KLD database.[14] Specifically, *ENV (kld)* is defined as the fraction of covered environmental "strengths" indicators equal to one minus the fraction of covered environmental "concerns" indicators equal to one, following a common practice in

[13]Given that the Sustainalytics scores at our disposal are available for the period from 2010 through 2017, we expand the latest available score through June 2020, relying on the stickiness of ESG scores.

[14]The MSCI KLD dataset, which we access through WRDS, provides a series of dummy variables indicating, for each firm and year, the presence of strengths or concerns on several environmental, social, and governance factors.

the ESG literature (e.g., Krüger, 2015; Lins et al., 2017).

We have a sample of approximately 95,000 firm-month observations from January 2010 through June 2020 with available stock returns, accounting information, and environmental scores. Table 4 reports descriptive statistics of the main variables used in our analyses. We omit a detailed discussion of these statistics for the sake of brevity.

[**Table 4 here**]

3.2 Main results on stock returns

Table 5 reports the result of OLS regressions of individual stock returns on the interaction between the Green Sentiment Index and the firm's environmental score, as well as standard firm characteristics (*Leverage*, *Market beta*, *Log(market cap)*, *Book-to-market*, *Profitability* and *Momentum*).[15] The regressions also include sector fixed effects based on the GICS industry group classification (comprising a total of 26 industries). We cluster standard errors at the firm level to control for the correlation of residuals within firms.[16]

[**Table 5 here**]

The coefficient of interest is on the interaction between *Green sentiment* and the firm's environmental performance, *Env score*. We observe that in months with a one-standard-deviation higher green sentiment, firms with one-standard-deviation stronger environmental

[15]We control for firm characteristics instead of a stock's estimated loadings on the size, value, and quality factors following Kelly et al. (2019) and Bessembinder et al. (2019). However, we obtain similar results when controlling for factor loadings instead of firm characteristics, or even using model-adjusted returns on the left-hand side of the regressions.

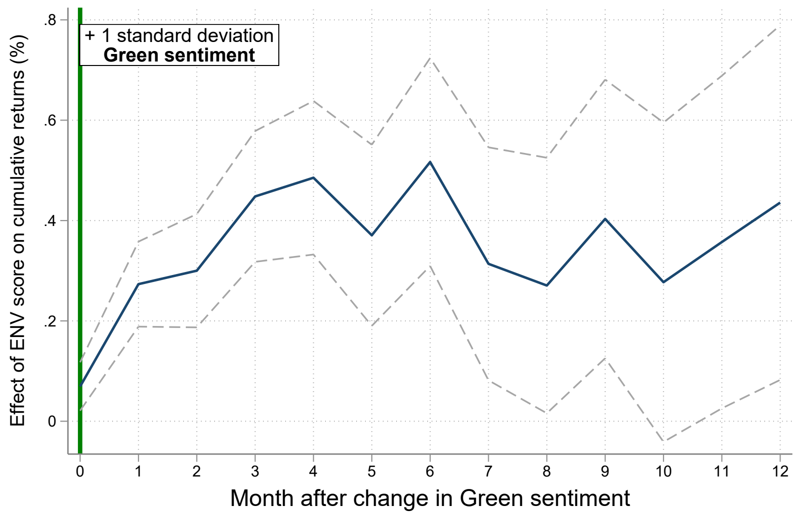
[16]As discussed in Section 3.5, our findings remain statistically significant even when double-clustering standard errors both at the firm and time dimensions (Petersen, 2009; Thompson, 2011). We present our main results clustering at the firm level because, given the relatively short period analyzed, clustering standard errors (also) at the time level risks being excessively restrictive.

performance experience 7 basis points higher return (Column 1 of Table 5). The effect is statistically significant but economically small. We interpret this result as indicating that the pressure on the price of environmentally-responsible shocks caused directly by green ETFs' arbitrage activity -- a channel similar to the one documented in Ben-David et al. (2018) -- is, in our setting, limited. Indeed, not all environmentally-responsible firms are included in green ETFs and hence directly affected by their arbitrage activity. We confirm this intuition in Section 3.4 by directly controlling for Green ETFs' ownership.

When looking at the effect in *t+1* (column 2), we find that green sentiment predicts a strong out-performance associated with a firm's environmental responsibility. One-standard-deviation higher green sentiment leads to approximately 27 basis points per additional standard deviation of environmental responsibility. The effect is highly statistically significant.

Interestingly, the effect does not appear to revert in the following months (columns 3 to 7). It slightly increases in magnitude through *t+4* and remains stable in *t+5* and *t+6*. One-standard-deviation higher green sentiment in t leads to an out-performance of one-standard-deviation more environmentally-responsible firms approximately equal to 0.53% through *t+6*. Figure 3 illustrates the evolution of this effect using cumulative returns through *t+12*. Even when looking at such an extended time frame, the stock-price effect of green sentiment persists, with only a mild reversal.

Figure 3: Effect of Green Sentiment on the pricing of corporate environmental responsibility
This figure shows the evolution of the estimated effect of the interaction between the Green Sentiment Index and the firm's environmental score on cumulative returns, using the same regression specification as in Table 5 (which controls for leverage, market beta, size, book-to-market, profitability, momentum, and sector). The cumulation of returns starts at month 0. The dashed lines indicate 90% confidence intervals based on standard errors clustered at the firm level.



One may have expected the stock-price effects of green sentiment to be only temporary, as for other forms of investor sentiment (Baker and Wurgler, 2006). However, as also noticed in Pástor et al. (2020), shifts in green tastes, although not driven by fundamental considerations, are likely to be persistent and, hence, drive a long-lasting effect on stock prices.

3.3 Green sentiment vs. climate risk

We here conduct three tests further supporting the claim that the effect of green sentiment on the value of corporate climate responsibility is not driven by new fundamental environment-related information.

First, in Table 6, we split the sample period between before and after the United Nations

Framework Convention on Climate Change (UNFCCC) Paris Agreement signed in December 2015. Previous works document that the Paris Agreement significantly increased the salience and materiality of climate transition risks for institutional investors (Bolton and Kacperczyk, 2021b; Delis et al., 2019; Seltzer et al., 2021). We expect the effect of green sentiment to be independent of such an important regulatory development. Table 6 shows that this is actually the case: Green sentiment mediates the value of environmental responsibility both before and after the Paris Agreement.

[Table 6 here]

Second, in Table 7, we re-run our regressions of individual stock returns by also including the interaction between the environmental score and the negative climate news index of EGKLS, aimed at capturing variation in (perceived) climate risk (the sample is reduced because the EGKLS' measure is available only through May 2018). Even when accounting for news-based climate risk, green sentiment is associated with a significant increase in the value of corporate environmental responsibility. We observe that the negative climate news measures have important effects on stock prices, in line with what is documented by EGKLS. The results are particularly striking when recalling that *Green sentiment* and *Negative climate news* correlate negatively with each other (see Table 3), suggesting that they impact stock prices through different channels.

[Table 7 here]

Third, we shift our attention from stock prices to analysts' earnings forecasts, which are meant to reflect changes in cash flow expectations (Brown and Rozeff, 1978). Although stock prices and forecast revisions are generally highly positively correlated (Kothari et al., 2016), we expect green sentiment to drive a divergence of the two dimensions, i.e., to cause an increase in stock prices that is not accompanied by a positive update of earnings forecasts.

For this exercise, we retrieve data on earnings forecasts from the IBES Summary Statistics database, which provides snapshots as of the day before the third Friday of each month of individual firms' expected earnings per share (EPS) at different horizons. For each firm-month observation, we compute the monthly change in average earnings forecasts, Δ *EPS forecast*, at 1-, 2-, and 3-year horizons as done, e.g., in Landier and Thesmar (2020).[17]

[Table 8 here]

Table 8 shows the results of OLS regressions of forecast revisions between months t and $t{+}1$ on green sentiment in month t interacted with firms' environmental scores, controlling for firm characteristics, as well sector and month fixed effects. The regressions also include the interaction between the environmental score and the EGKLS' negative climate news index. As expected, green sentiment does not appear to have any explanatory power on the revisions of earnings forecasts, despite its effects on stock returns. Conversely, the EGKLS' negative climate news index is associated with a statistically significant increase in the average forecast at the 2-year and 3-year horizons.

[17]Specifically, for each horizon h and firm i, we compute the earnings revisions as $\Delta EPSforecast_{i,h} = \frac{\mathbb{E}_{t+1}[EPS_{i,h}]-\mathbb{E}_t[EPS_{i,h}]}{\mathbb{E}_t[EPS_{i,h}]} \times 100$, when $\mathbb{E}_t[EPS_{i,h}] > 0$. We trim the resulting values at the 1st and 99th percentiles. The horizon is computed based on the distance between the forecast's statistical period (variable "statpers") of the end date of the accounting period covered by the forecast (variable "fpedats"): 1 year (fiscal year ending between 1 and 12 months after the forecast's statistical period), 2 years (fiscal year ending between 1 and 2 years after the forecast's statistical period), 3 years (fiscal year ending between 2 and 3 years after the forecast's statistical period).

3.4 Green sentiment vs. ETF price pressure

Throughout the paper, we use the observed abnormal flows into green ETFs as a proxy for the market-wide green sentiment. In particular, we argue that the observed stock-price effect of green sentiment results from changes in investor appetite for environmental responsibilities, and not merely of the price pressure exerted directly by the ETF arbitrage activity, the propagation mechanism identified by Ben-David et al. (2018).

To rule out the possibility that our results are mechanically driven by (green) ETFs' arbitrage activity, in Table 9, we replicate our main regressions by interacting the green sentiment index also with the percentage of common stocks held by green ETFs (*Green ETF ownership*). To compute this variable, we first retrieve green ETFs' portfolio holdings from the CRSP survivor-bias-free US mutual fund database. For each stock-month observation, we then divide the sum of green ETFs holdings in USD over the total market capitalization.

[**Table 9 here**]

Green sentiment does not appear to predict any stock-return effect on green ETFs' constituents, at least not over our sample period. On the contrary, green sentiment continues to have a significant predicting power on the pricing of environmental responsibility, in line with our main results.

3.5 Additional robustness checks

This subsection investigates the robustness of the stock-price effects of green sentiment in four relevant dimensions.

First, Appendix Table A1 shows that our estimates remain statistically significant even when we double-cluster standard errors at the firm and the month levels to allow for potential correlation of residuals across both dimensions (Petersen, 2009; Thompson, 2011).[18]

Second, Appendix Table A2 shows that our results are robust to including month fixed effects to account for the potential effect of macroeconomic conditions on the pricing of environmental responsibility.[19] Notice that in these regressions, the direct effect of *Green sentiment* is absorbed by the month indicators.

Third, given the diffuse concerns on the disagreement between ESG scores from different providers (Berg et al., 2020; Gibson et al., 2020), in Appendix Table A3, we replicate our results using the alternative definition of environmental responsibility based on the MSCI KLD dataset (*Env score (kld)*).[20] Note that in these regressions, the sample is considerably larger, given the broader coverage offered by the MSCI KLD database. Despite these differences, we obtain regression estimates that are statistically and economically similar to the ones obtained with our main proxy of environmental responsibility.

4 Effects of green sentiment on corporate behavior

One of the most common narratives in the ESG industry is that sustainable investing can trigger positive societal change by influencing a firm's cost of capital, which in turn should allow more socially-responsible firms to make more and better investments than other firms.

[18]With this double-clustering, the specification nests the classical Fama-MacBeth procedure (Fama and MacBeth, 1967) which controls for time effect in the correlation of residuals, but not for potential firm effect.

[19]For instance, Bansal et al. (2018) argue that stocks of socially-responsible firms outperform in good economic times, whereas Lins et al. (2017) and Albuquerque et al. (2020) provide evidence that stocks of socially-responsible firms performance relatively well in crisis times.

[20]In our sample, the environmental scores from Sustainalytics and MSCI KLD have a correlation of .58, statistically significant at 1% level.

The above "financing channel mechanism" of responsible investing is identified and discussed in several theoretical works (Heinkel et al., 2001; Pástor et al., 2020; Oehmke and Opp, 2020; Landier and Lovo, 2020; De Angelis et al., 2020), but related empirical evidence remains scarce. In this section, we exploit the properties of our ETF-based Green Sentiment Index to shed light on the effects of investor non-fundamental demand shocks for green assets on corporate behavior.

4.1 Main results on corporate behavior

We focus on two important corporate decisions: investment and saving, and we examine the impact of green sentiment on the level of capital investments and the level of cash holdings, useful for precautionary (Bates et al., 2009; Almeida et al., 2014) and repurchase motives (Wang and Nyborg, 2020), but also to finance future investment (Bolton et al., 2013).

Based on the Compustat Accounting Quarterly database, we compute the variable *Capex/PPE* as the percentage of capital investments scaled by lagged Property, Plant and Equipment (capexq $\times$ 100/L1.ppentq), the variable *Cash/Assets* as the percentage of cash holdings over total assets (chq$\times$100/atq), and the variable *R&D/Assets* as the percentage of research & development expenses over total assets (xrdq$\times$100/atq).[21] We trim these variables at 1-99 percentiles to control for extreme values. For the purposes of this analysis, we bring our data from the monthly to the quarterly level. Summary statistics on *Capex/PPE*, *Cash/Assets*, and *R&D/Assets* are reported in Table 4.

In Table 10, we report the results of OLS regressions of quarterly Capex (column 1), cash

[21] We normalize Capex by the lagged property, plant, and equipment following Dessaint et al. (2019). However, our results are robust to normalizing Capex by lagged total assets.

holdings (column 2), and R&D (column 3) on the average quarterly green sentiment, the firm's environmental score, and the interaction of the two. The regressions also control for firm characteristics and sector fixed effects (we obtain similar results when adding quarter fixed effects, absorbing the direct effect of the green sentiment index). Standard errors are clustered at the firm level to account for the correlation of error terms across firms.[22]

The results indicate that a higher green sentiment in a given quarter is associated with higher capital investments and accumulation of cash for more environmentally responsible firms, consistent with the idea that firms make more investments and hold larger cash balances when access to funds is easier (e.g. Dittmar et al., 2003). The effect is economically important: One standard deviation higher green sentiment is associated with 0.21% higher Capex and 0.31% higher cash holdings for one standard deviation higher environmental score (compared to an average capex of 9% and cash holdings of 4%, this represents a 5% and 3% relative increase respectively). We do not observe any effect of green sentiment on green firms' R&D activity.

[Table 10 here]

4.2 Heterogeneity across credit ratings

What types of firms is green sentiment more likely to influence? The existing literature suggests that managers of more equity-dependent / credit-constrained firms are more likely to be influenced by stock prices in their decision-making (Baker et al., 2003; Hau and Lai, 2013). We expect this principle to apply also in the context of the real impacts of responsible

[22] The estimated coefficients remain statistically significant even if we double-cluster standard errors at both the firm and quarter levels (Petersen, 2009; Thompson, 2011).

investing. Intuitively, the effects of green sentiment on corporate decisions should vary with a firm's ability to raise funds outside the stock market.[23]

To test for the heterogeneity of the effect of green sentiment on real corporate decisions, we split our sample based on corporate credit rating, which we use as a proxy of the firm's ability to access external capital on the credit markets. We retrieve corporate long-term S&P credit ratings from Bloomberg, and we classify them into three groups: *Low credit rating* < "BBB-" (non-investment grade); *Middle credit* = "BBB", "BBB+", "BBB-"; *High credit rating* = "A","A+","A-","AA", "AAA","AA-","AA+".

Table A4 in the Appendix shows the number of firms × quarters with above- and below-median environmental scores in each of the three credit rating groups. Not surprisingly, we observe a positive correlation between environmental responsibility and credit ratings, consistent with the evidence in Seltzer et al. (2021). For instance, we find that firms with a high environmental score have a likelihood of 34% also to have a high credit rating, versus only 16% among firms with low environmental score.[24]

Table 11 shows the heterogeneity of the effects of green sentiment on firm behavior along the credit rating. We obtain two intriguing results.

First, in Panel A, we find that the effect of green sentiment on capital investment is concentrated in firms with low and medium credit ratings. No significant effect is observed for high-credit-rated companies. This result is consistent with the idea that less equity-dependent firms are less influenced by stock prices in making investment decisions (Baker et al., 2003).

[23]For instance, the model in Landier and Lovo (2020) suggests that for ESG funds to force companies to internalize externalities partially, it is necessary to have significant frictions in financial markets.

[24]Indeed, the environmental score even correlates positively with the likelihood of having the credit rating available in the first place, causing Table A4 to show relatively more firms with an above-median environmental score.

Our results indicate that these firms are less likely to be influenced by green sentiment.

Second, in Panel B, we observe that the effect of green sentiment on cash holdings is primarily driven by the sub-samples of low- (and to a less extent high-rated firms), consistent with the idea that cash holdings are more valuable for financially constrained firms (Denis and Sibilkov, 2010). Conceivably, these firms take advantage of green sentiment to increase their precautionary buffers.

[Table 11 here]

5 Conclusion

In the recent decade, environmental considerations have gained a central-stage role in shaping the debate in global financial markets, a trend set to continue for many years. How do changes in investors' appetite for green assets influence the allocation of capital in the economy and the behavior of firms? This question is a key policy issue, as many policy-makers and regulators expect the re-direction of capital market financing towards green firms to have a decisive impact in reducing carbon emissions (e.g., Lagarde, 2021).

Studying the effects of investors' environmental preferences on economic outcomes is an empirical challenge due to the entanglement of fundamental and non-fundamental factors in driving firm value. This paper proposes a new method to estimate non-fundamental demand shocks for green financial assets. The method exploits the unique arbitrage mechanism of ETFs' primary market that the existing literature shows to be influenced by non-fundamental demand shocks due to differences in the ownership structure of ETFs compared to the underlying securities (Ben-David et al., 2017; Brown et al., 2021). Specifically, using a comprehensive sample of US ETFs from January 2010 through June 2020, we estimate the monthly excess flows into ETFs with explicit environment-friendly features (green ETFs) relative to other comparable conventional ETFs. The time series of these abnormal green flows- the Green Sentiment Index- quantifies the direction and magnitude of changes in investors' appetite for green financial assets not priced in the value of the underlying securities.

After establishing the difference between our index and other climate-related measures used in the literature, we study the effects of green sentiment on the pricing of corporate environmental responsibility in the stock market and on corporate decisions. We establish two key results using a sample of US firms from January 2010 to June 2020.

First, we show that a higher green sentiment is associated with a stock-price out-performance of environmentally responsible firms. A one-standard-deviation higher green sentiment in month t is followed by approximately 27 basis points higher returns in $t+1$ for a one-standard-deviation higher environmental score. The estimated out-performance considering returns through in $t+6$ is 53 basis points. A series of tests confirm that this effect does not reflect fundamental information: Green sentiment predicts stock prices both before and after the signature of the Paris Agreement, a structural break in climate transition risks; its stock-price effects are independent of variations in climate risk, as proxied by the negative climate news index used in EGKLS; finally, although they both have similar stock-price effects, EGKLS's index leads to positive revisions in analysts' earnings forecasts for environmentally responsible firms, while our green sentiment index does not.

Second, we document that increasing green sentiment also affects corporate decisions. In quarters with a higher green sentiment, environmentally responsible firms make higher capital investments (particularly firms with low and medium credit ratings) and accumulate more cash holdings (particularly firms with low and high credit ratings). The role of financial constraints in mediating the impact of (green) sentiment on corporate behavior is in line with previous works on the real effects of financial markets (e.g., Baker et al., 2003; Campello and Graham, 2013) and the theoretical literature on responsible investing. It is reasonable to expect that companies are more likely to do ‘‘good’’ when they are less financially constrained (Cohn and Wardlaw, 2016; Hong et al., 2012; Martin et al., 2021). In this sense, by (further) increasing the financial strength of environmentally responsible firms, green sentiment allows them to increase their environment-friendly investments further. At the same time, we should also be aware that green sentiment may inadvertently divert resources away from firms that are not currently considered green but have high green innovation potential (Cohen et al., 2020).

How to encourage firms to contribute to the development of technologies useful to decarbonize our economies is a key question of our times.[25] While the effects of governmental policies (such as carbon pricing) and the role of public finance are more researched and understood (e.g., Aghion et al., 2016; Gollier, 2021), the role of financial markets in stimulating firms to make more investments in green projects and technologies deserves investigation. Our results suggest that green sentiment can decrease the relative cost of capital of more environmentally-responsible firms and increase their investment capacity. How exactly firms use these extra resources is a critical issue that we leave for future research.

[25] Almost half of the emission reductions that are needed to reach the climate-neutrality goal by 2050 are expected to come from technologies that still need to be developed (International Energy Agency, 2021).

References

Aghion, Philippe, Antoine Dechezleprêtre, David Hemous, Ralf Martin, and John Van Reenen, 2016, Carbon taxes, path dependency, and directed technical change: Evidence from the auto industry, *Journal of Political Economy* 124, 1--51.

Albuquerque, Rui, Yrjo Koskinen, Shuai Yang, and Chendi Zhang, 2020, Resiliency of environmental and social stocks: An analysis of the exogenous COVID-19 market crash, *The Review of Corporate Finance Studies* 9, 593--621.

Almeida, Heitor, Murillo Campello, Igor Cunha, and Michael S. Weisbach, 2014, Corporate liquidity management: A conceptual framework and survey, *Annual Review of Financial Economics* 6, 135--162.

Anderson, Anders, and David T. Robinson, 2020, Knowledge, fear and beliefs: Understanding household demand for green investments, Working Paper.

Baker, Malcolm, Jeremy C. Stein, and Jeffrey Wurgler, 2003, When does the market matter? Stock prices and the investment of equity-dependent firms, *The Quarterly Journal of Economics* 118, 969--1005.

Baker, Malcolm, and Jeffrey Wurgler, 2000, The equity share in new issues and aggregate stock returns, *The Journal of Finance* 55, 2219--2257.

Baker, Malcolm, and Jeffrey Wurgler, 2006, Investor sentiment and the cross-section of stock returns, *The Journal of Finance* 61, 1645--1680.

Baker, Malcolm, Jeffrey Wurgler, and Yu Yuan, 2012, Global, local, and contagious investor sentiment, *Journal of Financial Economics* 104, 272--287.

Bakke, Tor-Erik, and Toni M. Whited, 2010, Which firms follow the market? An analysis of corporate investment decisions, *The Review of Financial Studies* 23, 1941--1980.

Bansal, Ravi, Di Andrew Wu, and Amir Yaron, 2018, Is socially responsible investing a luxury good?, Working Paper.

Bartram, Söhnke M, Kewei Hou, and Sehoon Kim, 2020, Real effects of climate policy: Financial constraints and spillovers, *Journal of Financial Economics* Forthcoming.

Bates, Thomas W., Kathleen M. Kahle, and René M. Stulz, 2009, Why do US firms hold so much more cash than they used to?, *The Journal of Finance* 64, 1985--2021.

Battiston, Stefano, Irene Monasterolo, Keywan Riahi, and Bas J. van Ruijven, 2021, Accounting for finance is key for climate mitigation pathways, *Science* 372, 918--920.

Ben-David, Itzhak, Francesco Franzoni, Kim Byungwook, and Rabih Moussawi, 2021, Competition for attention in the ETF space, Working Paper.

Ben-David, Itzhak, Francesco Franzoni, and Rabih Moussawi, 2017, Exchange-traded funds, *Annual Review of Financial Economics* 9, 169--189.

Ben-David, Itzhak, Francesco Franzoni, and Rabih Moussawi, 2018, Do ETFs increase volatility?, *The Journal of Finance* 73, 2471--2535.

Ben-Rephael, Azi, Xi Dong, Massimo Massa, and Changyun Zhou, 2019, Foreign sentiment, Working Paper.

Ben-Rephael, Azi, Shmuel Kandel, and Avi Wohl, 2012, Measuring investor sentiment with mutual fund flows, *Journal of Financial Economics* 104, 363--382.

Berg, F., J. Koelbel, and R. Rigobon, 2020, Aggregate confusion: The divergence of ESG ratings, Working paper.

Bessec, Marie, and Julien Fouquau, 2020, Green sentiment in financial markets: A global warning, Working Paper.

Bessembinder, Hendrik, Michael J. Cooper, and Feng Zhang, 2019, Characteristic-based benchmark returns and corporate events, *The Review of Financial Studies* 32, 75--125.

Bingler, Julia Anna, Mathias Kraus, and Markus Leippold, 2021, Cheap talk and cherry-picking: What climatebert has to say on corporate climate risk disclosures, Working Paper.

Bolton, Patrick, Hui Chen, and Neng Wang, 2013, Market timing, investment, and risk management, *Journal of Financial Economics* 109, 40--62.

Bolton, Patrick, and Marcin T. Kacperczyk, 2021a, Do investors care about carbon risk?, *Journal of Financial Economics* Forthcoming.

Bolton, Patrick, and Marcin T. Kacperczyk, 2021b, Global pricing of carbon-transition risk, Working Paper.

Bond, Philip, Alex Edmans, and Itay Goldstein, 2012, The real effects of financial markets, *Annual Review of Financial Economics* 4, 339--360.

Brown, David C., Shaun William Davies, and Matthew C. Ringgenberg, 2021, ETF arbitrage, non-fundamental demand, and return predictability, *Review of Finance* 25, 937--972.

Brown, Lawrence D., and Michael S. Rozeff, 1978, The superiority of analyst forecasts as measures of expectations: Evidence from earnings, *The Journal of Finance* 33, 1--16.

Campello, Murillo, and John R. Graham, 2013, Do stock prices influence corporate decisions? Evidence from the technology bubble, *Journal of Financial Economics* 107, 89--110.

Ceccarelli, Marco, Stefano Ramelli, and Alexander F. Wagner, 2021, Low-carbon mutual funds, Working paper.

Choi, Darwin, Zhenyu Gao, and Wenxi Jiang, 2020, Attention to global warming, *The Review of Financial Studies* 33, 1112--1145.

Cohen, Lauren, Umit G. Gurun, and Quoc H. Nguyen, 2020, The ESG-innovation disconnect: Evidence from green patenting, Working Paper.

Cohn, Jonathan B., and Malcolm I. Wardlaw, 2016, Financing constraints and workplace safety, *The Journal of Finance* 71, 2017--2058.

Da, Zhi, Joseph Engelberg, and Pengjie Gao, 2015, The sum of all FEARS investor sentiment and asset prices, *The Review of Financial Studies* 28, 1--32.

Davies, Shaun, 2020, Speculation sentiment, *Journal of Financial and Quantitative Analysis* Forthcoming.

De Angelis, Tiziano, Peter Tankov, and Olivier David Zerbib, 2020, Environmental impact investing, Working Paper.

Delis, Manthos D., Kathrin de Greiff, and Steven Ongena, 2019, Being stranded with fossil fuel reserves? Climate policy risk and the pricing of bank loans, Working Paper.

Denis, David J, and Valeriy Sibilkov, 2010, Financial constraints, investment, and the value of cash holdings, *The Review of Financial Studies* 23, 247--269.

Dessaint, Olivier, Thierry Foucault, Laurent Frésard, and Adrien Matray, 2019, Noisy stock prices and corporate investment, *The Review of Financial Studies* 32, 2625--2672.

Dittmar, Amy, Jan Mahrt-Smith, and Henri Servaes, 2003, International corporate governance and corporate cash holdings, *Journal of Financial and Quantitative Analysis* 38, 111--133.

Engle, Robert F., Stefano Giglio, Bryan Kelly, Heebum Lee, and Johannes Stroebel, 2020, Hedging climate change news, *The Review of Financial Studies* 33, 1184--1216.

Faccini, Renato, Rastin Matin, and George S. Skiadopoulos, 2021, Dissecting climate risks: Are they reflected in stock prices?, Working Paper.

Fama, Eugene F., and Kenneth R. French, 2007, Disagreement, tastes, and asset prices, *Journal of Financial Economics* 83, 667--689.

Fama, Eugene F, and James D. MacBeth, 1967, Risk, return, and equilibrium empirical tests, *Journal of Political Economy* 81, 607–--36.

Garel, Alexandre, and Arthur Petit-Romec, 2021, Investor rewards to environmental responsibility: Evidence from the COVID-19 crisis, *Journal of Corporate Finance* 68, 101948.

Gibson, R., P. Krueger, and P.S. Schmidt, 2020, ESG rating disagreement and stock returns, Working paper.

Glosten, Lawrence, Suresh Nallareddy, and Yuan Zou, 2021, ETF activity and informational efficiency of underlying securities, *Management Science* 67, 22--47.

Gollier, Christian, 2021, The welfare cost of ignoring the beta, Working Paper.

Gollier, Christian, and Sébastien Pouget, 2014, The "washing machine": Investment strategies and corporate behavior with socially responsible investors, TSE Working Paper.

Gourdel, Régis, Irene Monasterolo, Nepomuk Dunz, Andrea Mazzocchetti, and Laura Parisi, 2021, Assessing the double materiality of climate risks in the eu economy and banking sector, *Available at SSRN 3939895* .

Hau, Harald, and Sandy Lai, 2013, Real effects of stock underpricing, *Journal of Financial Economics* 108, 392--408.

Heinkel, Robert, Alan Kraus, and Josef Zechner, 2001, The effect of green investment on corporate behavior, *Journal of Financial and Quantitative Analysis* 36, 431--449.

Henderson, Brian J., Narasimhan Jegadeesh, and Michael S. Weisbach, 2006, World markets for raising new capital, *Journal of Financial Economics* 82, 63--101.

Hong, Harrison, and Marcin Kacperczyk, 2009, The price of sin: The effects of social norms on markets, *Journal of Financial Economics* 93, 15--36.

Hong, Harrison, Jeffrey D. Kubik, and Jose A. Scheinkman, 2012, Financial constraints on corporate goodness, Working Paper.

Huynh, Thanh, and Ying Xia, 2020, Climate change news risk and corporate bond returns, *Journal of Financial and Quantitative Analysis* Forthcoming.

Ilhan, Emirhan, Zacharias Sautner, and Grigory Vilkov, 2021, Carbon tail risk, *The Review of Financial Studies* 3, 1540--1571.

International Energy Agency, IEA, 2021, Net zero by 2050: A roadmap for the global energy sector, Available at `www.iea.org`.

Investment Company Institute, ICI, 2021, Investment company fact book, Available at `www.ici.org`.

Kelly, Bryan T, Seth Pruitt, and Yinan Su, 2019, Characteristics are covariances: A unified model of risk and return, *Journal of Financial Economics* 134, 501--524.

Kim, Woojin, and Michael S. Weisbach, 2008, Motivations for public equity offers: An international perspective, *Journal of Financial Economics* 87, 281--307.

Kothari, Sagar P., Eric So, and Rodrigo Verdi, 2016, Analysts' forecasts and asset pricing: A survey, *Annual Review of Financial Economics* 8, 197--219.

Krüger, Philipp, 2015, Corporate goodness and shareholder wealth, *Journal of Financial Economics* 115, 304--329.

Krüger, Philipp, Zacharias Sautner, and Laura T Starks, 2020, The Importance of Climate Risks for Institutional Investors, *The Review of Financial Studies* 33, 1067--1111.

Lagarde, Christine, 2021, Towards a green capital market in europe, Speech at the European Commission's High Level Conference on the Proposal for a Corporate Sustainbility Reporting Directive, May 6, available at: https://www.ecb.europa.eu/press/key/date/2021/html/ecb.sp210506~4ec98730ee.en.html.

Landier, Augustin, and Stefano Lovo, 2020, ESG investing: How to optimize impact?, Working Paper.

Landier, Augustin, and David Thesmar, 2020, Earnings expectations in the COVID crisis, *Review of Corporate Finance Studies* 4, 598--617.

Lemmon, Michael, and Evgenia Portniaguina, 2006, Consumer confidence and asset prices: Some empirical evidence, *The Review of Financial Studies* 19, 1499--1529.

Lettau, Martin, and Ananth Madhavan, 2018, Exchange-traded funds 101 for economists, *Journal of Economic Perspectives* 32, 135--54.

Li, Qing, Hongyu Shan, Yuehua Tang, and Vincent Yao, 2020, Corporate climate risk: Measurements and responses, Working Paper.

Lins, Karl V., Henri Servaes, and Ane Tamayo, 2017, Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis, *The Journal of Finance* 72, 1785--1824.

Luo, H. Arthur, and Ronald J. Balvers, 2017, Social screens and systematic investor boycott risk, *Journal of Financial and Quantitative Analysis* 52, 365--399.

Luo, Yuanzhi, 2005, Do insiders learn from outsiders? Evidence from mergers and acquisitions, *The Journal of Finance* 60, 1951--1982.

Martin, Ralf, Ralph De Haas, Mirabelle Muuls, and Helena Schweiger, 2021, Managerial and financial barriers to the net-zero transition, Working Paper.

Morck, Randall, Andrei Shleifer, Robert W. Vishny, Matthew Shapiro, and James M. Poterba, 1990, The stock market and investment: Is the market a sideshow?, *Brookings Papers on Economic Activity* 1990, 157--215.

Morningstar, 2020, Global sustainable fund flows: Q4 2020 in review, available at: https://www.morningstar.com/lp/global-esg-flows.

Oehmke, Martin, and Marcus M. Opp, 2020, A theory of socially responsible investment, Working Paper.

Pagano, Marco, Antonio Sánchez Serrano, and Josef Zechner, 2019, Can ETFs contribute to systemic risk?, Working Paper.

Pankratz, Nora M.C., and Christoph M. Schiller, 2019, Climate change and adaptation in global supply-chain networks, Working Paper.

Pastor, Lubos, Robert F. Stambaugh, and Lucian A. Taylor, 2021, Dissecting green returns, Working Paper.

Pástor, Ľuboš, Robert F. Stambaugh, and Lucian A. Taylor, 2020, Sustainable investing in equilibrium, *Journal of Financial Economics* Forthcoming.

Pástor, Ľuboš, and M. Blair Vorsatz, 2020, Mutual fund performance and flows during the COVID-19 crisis, *The Review of Asset Pricing Studies* 10, 791--833.

Pedersen, Lasse Heje, Shaun Fitzgibbons, and Lukasz Pomorski, 2020, Responsible investing: The ESG-efficient frontier, *Journal of Financial Economics* Forthcoming.

Petersen, Mitchell A., 2009, Estimating standard errors in finance panel data sets: Comparing approaches, *The Review of Financial Studies* 22, 435--480.

Qiu, Lily, and Ivo Welch, 2004, Investor sentiment measures, Working Paper.

Ramelli, Stefano, Alexander F. Wagner, Richard J. Zeckhauser, and Alexandre Ziegler, 2021, Investor rewards to climate responsibility: Stock-price responses to the opposite shocks of the 2016 and 2020 U.S. elections, *Review of Corporate Financial Studies* Forthcoming.

Santi, Caterina, 2020, Investors' climate sentiment and financial markets, Working Paper.

Sautner, Zacharias, Laurence van Lent, Grigory Vilkov, and Ruishen Zhang, 2020, Firm-level climate change exposure, Working Paper.

Seltzer, Lee, Laura T. Starks, and Qifei Zhu, 2021, Climate regulatory risks and corporate bonds, Working Paper.

Stambaugh, Robert F., 2014, Presidential address: Investment noise and trends, *The Journal of Finance* 69, 1415--1453.

Stambaugh, Robert F., Jianfeng Yu, and Yu Yuan, 2012, The short of it: Investor sentiment and anomalies, *Journal of Financial Economics* 104, 288--302.

Thompson, Samuel B., 2011, Simple formulas for standard errors that cluster by both firm and time, *Journal of Financial Economics* 99, 1--10.

Van der Beck, Philippe, 2021, Flow-driven esg returns, Working Paper.

Wang, Jesse, and Kjell Nyborg, 2020, The effect of stock liquidity on cash holdings: The repurchase motive, *Journal of Financial Economics* Forthcoming.

Zerbib, Olivier David, 2020, A sustainable Capital Asset Pricing Model (S-CAPM): Evidence from green investing and sin stock exclusion, Working Paper.

Tables

Table 1: Descriptive statistics of ETF variables
This table shows the descriptive statistics of the 1,195 US-domicile equity ETFs present in our sample from January 2010 to June 2020. *AUM* is the end-of-month market capitalization in billions USD, *Shares outstanding* is the number of shares outstanding at the end of the month (in millions USD), *Flows* is the monthly percentage growth in the number of shares outstanding. *NAV* is the net asset value. *Return* is the ETF's annualized monthly return. *Volatility* is the monthly realized volatility calculated on daily returns. *Age* is the number of years since the ETF's inception. *Institutional ownership* is the percentage of the ETF's market capitalization held by institutional investors. *Net expense ratio* is the net expense ratio in basis points. *Levered ETF* is a dummy variable indicating leveraged ETF. *Creation fee* is the fee charged by the ETF sponsor to Authorized Participants to create or redeem shares (per order and in USD). The sample period is January 2010 through June 2020. All data are obtained from Bloomberg, except *Age*, *Net expense ratio*, *Levered ETF*, and *Creation fees* from the ETF Global database.

	p5	p25	mean	p50	p75	p95	sd	N
AUM	0.01	0.05	2.26	0.20	0.89	9.42	10.62	81,929
Shares outstanding	0.25	1.50	31.19	4.85	19.10	144.30	94.38	81,929
Flows (%)	-9.29	-0.89	2.05	0.00	3.29	17.83	10.59	81,929
NAV	16.91	26.84	52.24	38.58	62.19	130.25	45.32	81,929
Return	-1.07	-0.25	0.06	0.11	0.41	1.03	0.68	81,929
Volatility	0.07	0.11	0.17	0.15	0.20	0.31	0.08	81,929
Age	0.88	2.90	7.10	6.34	10.54	16.27	4.88	67,322
Institutional Ownership (%)	10.24	29.00	49.03	45.17	66.62	100.00	26.33	80,846
Net expense ratio	8.40	25.00	45.67	44.00	60.00	80.00	42.56	65,917
Levered ETF	0.00	0.00	0.00	0.00	0.00	0.00	0.06	67,286
Creation fee	250.00	500.00	1,588.26	500.00	1,500.00	7,000.00	2,768.64	64,749

Table 2: List of Green ETFs
This table shows the list of green equity ETFs, their Bloomberg identification ticker, their average net expense ratio (in basis points), their inception and de-listing years, and their designation as ‘‘sustainable’’ by Morningstar.

Ticker	ETF name	Net expense ratio (bp)	Inception - delisting	Morningstar sustainable?
ICLN	iShares Global Clean Energy	48	2008 -	yes
TAN	Invesco Solar	70	2008 -	yes
SPYX	SPDR S&P 500 Fossil Fuel Reserves Free	20	2015 -	yes
CRBN	iShares MSCI ACWI Low Carbon Target	20	2014 -	yes
PBW	Invesco WilderHill Clean Energy	70	2005 -	yes
QCLN	First Trust NASDAQ Clean Edge Green Energy	60	2007 -	yes
PZD	Invesco Cleantech	68	2006 -	yes
ACES	ALPS Clean Energy	65	2018 -	yes
SMOG	VanEck Vectors Low Carbon Energy	63	2007 -	yes
FAN	First Trust Global Wind Energy	60	2008 -	yes
ETHO	Etho Climate Leadership US	47	2015 -	yes
PBD	Invesco Global Clean Energy	75	2007 -	yes
LOWC	SPDR MSCI ACWI Low Carbon Target	20	2014 -	yes
YLCO	Global X YieldCo&Renewable Engy Income	65	2015 -	no
EVX	VanEck Vectors Environmental Services	55	2006 -	yes
CNRG	SPDR Kensho Clean Power	45	2018 -	yes
VEGN	US Vegan Climate	60	2019 -	yes
CHGX	Change Finance US LargeCap FossilFuel Free	49	2017 -	yes
PUW	Invesco WilderHill Progressive Energy	70	2006 - 2019	yes
HECO	Strategy Shares EcoLogical Strategy	95	2012 -	yes
RENW	Pickens Morningstar Renewable Energy Response	65	2019 -	yes
ECLN	First Trust EIP Carbon Impact	95	2019 -	yes

Table 3: Pairwise correlation between indexes

The number of observations is in parentheses. *Green sentiment* is our green-ETF-based sentiment measures computed as in Equation 1 and standardized to have mean 0 and unit standard deviation. *Negative climate news* is the standardized negative climate news index used in Engle et al. (2020). *Google climate SVI* is the monthly Google search volume intensity in the US for the topic ‘‘climate change’’, also used in Choi et al. (2020) and Ilhan et al. (2021). ***, **, and * indicate that the correlation significantly differs from zero at the 1%, 5%, and 10% levels, respectively.

	1.	2.	3.
1. Green sentiment	1		
	(125)		
2. Negative climate news	-0.25***	1	
	(101)	(101)	
3. Google climate SVI	0.29***	0.08	1
	(125)	(125)	(101)

Table 4: Descriptive statistics of firm-level characteristics

This table shows descriptive statistics of the firm-level variables used in the analyses from January 2010 to June 2020. The sample comprises firms in major US stock exchanges included in Compustat and with available environmental scores from Sustainalytics. *Returns* (adjusted for stock splits and dividends) are computed based on monthly stock prices retrieved from the Compustat North America database. *Cumulative returns t+6* are the buy-and-hold returns over a 6-month look-ahead period. *Env score* is the standardized environmental score from Sustainalytics, while *Env score (kld)* is the standardized environmental score computed based on the MSCI KLD database. *Leverage* is the percentage of long-term debt plus debt in current liabilities over total assets (dltt + dlc) $\times$ 100/at). *Market beta* is the coefficient estimated computed by regressing monthly returns above the 1-month Treasury-bill rate on the excess market return using a 36-month moving window, with at least 24 months of non-missing returns. *Log(market cap)* is the log of the market capitalization at the end of the last fiscal year (ln(prcc f $\times$ csho)). *Book-to-market* is the book value of equity divided by market valuation (ceq/(prcc f $\times$ csho)). *Profitability* is income before extraordinary items over total assets (ib $\times$ 100/at). *Momentum* is the average individual stock return from month t-12 to t-2. *Green ETF ownership* is the percentage of common stocks owned by Green ETFs derived from the CRSP mutual funds database, set to zero for missing observations. *Capex/PPE* is the percentage of quarterly capital investments scaled by lagged Property, Plant, and Equipment (capexq $\times$ 100/L1.ppentq). *Cash/Assets* is the percentage of quarterly cash holdings over total assets (chq $\times$100/atq). *R&D/Assets* it the percentage of quarterly R&D expenses over total assets (xrdq $\times$100/atq).

	p5	p25	mean	p50	p75	p95	sd	N
Firm-level characteristics (monthly observations)								
Return	-12.88	-3.55	0.98	1.12	5.54	14.36	8.92	95,248
Cumulative return t+6	-28.64	-6.18	6.38	6.33	18.35	40.89	21.74	87,756
Env score	-1.32	-0.78	0.04	-0.14	0.73	1.90	1.01	95,248
Env score (kld)	-0.39	-0.39	0.49	-0.39	1.17	3.21	1.33	84,995
Leverage	0.00	13.34	28.95	26.82	40.60	64.10	21.62	95,248
Market beta	0.21	0.71	1.12	1.07	1.47	2.18	0.61	95,248
Log(market cap)	7.43	8.26	9.12	8.97	9.84	11.41	1.21	95,248
Book-to-market	0.03	0.20	0.45	0.37	0.62	1.13	0.41	95,248
Profitability	-3.24	1.55	4.98	4.38	8.28	16.16	7.41	95,248
Momentum	-2.83	-0.13	1.08	1.18	2.41	4.63	2.35	95,248
Green ETF ownership	0.00	0.00	0.01	0.00	0.00	0.01	0.06	95,248
Firm-level characteristics (quarterly observations)								
Capex/PPE	-10.35	0.95	4.15	3.96	7.80	19.03	9.19	25,055
Cash/Assets	0.35	2.31	9.00	6.11	12.62	27.46	9.35	32,599
R&D/Assets	0.00	0.00	1.29	0.64	1.90	4.70	1.89	15,277

Table 5: Green sentiment and the pricing of corporate environmental responsibility

This table shows the results of OLS regressions of individual stock returns from January 2010 through June 2020 on the Green Sentiment Index based on ETF flows, firms' Environmental score, and the interaction of these two variables. The specification in column 1 regresses monthly returns, while the specifications in columns 2-7 regress cumulative returns up to 6 months ahead. The regressions also control for lagged firm characteristics and GICS industry group indicators. t-statistics based on standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate that the coefficient estimate significantly differs from zero at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Return in t	Cumulative return through:					
		t+1	t+2	t+3	t+4	t+5	t+6
Green sentiment × Env score	0.069**	0.273***	0.300***	0.448***	0.485***	0.371***	0.517***
	(2.37)	(5.31)	(4.37)	(5.66)	(5.22)	(3.38)	(4.10)
Env score	0.042	0.041	0.103	0.199	0.165	0.181	0.192
	(1.25)	(0.60)	(1.01)	(1.49)	(1.00)	(0.92)	(0.84)
Green sentiment	-1.169***	-2.268***	-2.416***	-2.407***	-2.661***	-2.336***	-2.057***
	(-36.11)	(-42.33)	(-36.16)	(-30.82)	(-28.94)	(-22.20)	(-17.77)
Leverage	0.003	0.004	0.004	-0.001	-0.000	0.001	0.001
	(1.48)	(1.18)	(0.78)	(-0.09)	(-0.00)	(0.06)	(0.10)
Market beta	0.245***	0.177	0.159	-0.208	-0.342	-0.544	-0.725*
	(3.48)	(1.36)	(0.86)	(-0.90)	(-1.19)	(-1.58)	(-1.79)
Log(marketcap)	0.002	0.008	-0.053	-0.162	-0.152	-0.193	-0.222
	(0.06)	(0.14)	(-0.62)	(-1.45)	(-1.10)	(-1.17)	(-1.16)
Book-to-market	-0.134	-0.405	-0.567	-0.685	-1.003*	-1.015	-0.971
	(-1.00)	(-1.54)	(-1.52)	(-1.49)	(-1.84)	(-1.58)	(-1.31)
Profitability	-0.003	-0.017	-0.030*	-0.048**	-0.070***	-0.090***	-0.112***
	(-0.59)	(-1.52)	(-1.80)	(-2.28)	(-2.73)	(-2.90)	(-3.07)
Momentum	-0.141***	-0.249***	-0.290***	-0.143**	-0.144**	-0.090	-0.027
	(-9.05)	(-8.41)	(-6.61)	(-2.57)	(-2.09)	(-1.10)	(-0.29)
Constant	0.859***	2.086***	3.731***	5.886***	7.093***	8.679***	10.158***
	(2.74)	(3.42)	(4.21)	(5.14)	(5.05)	(5.16)	(5.20)
Observations	95,248	93,972	92,704	91,444	90,199	88,969	87,756
R-squared	0.018	0.037	0.032	0.030	0.032	0.027	0.025

Table 6: Green sentiment and stock prices: Before and after the Paris Agreement
This table shows the results of OLS regressions of individual (cumulative) stock returns on the Green Sentiment Index, firms' Environmental score, and the interaction of these two variables. Panel A refers to the sample period from January 2010 through November 2015 (before the adoption of the Paris Agreement), while Panel B to the period from December 2015 through June 2020. The regressions also control for lagged firm characteristics (leverage, market beta, size, book-to-market, profitability, and momentum) and GICS industry group indicators. t-statistics based on standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate that the coefficient estimate significantly differs from zero at the 1%, 5%, and 10% levels, respectively.

Panel A: Before December 2015							
Dependent variable:	Return in t	Cumulative return through:					
		t+1	t+2	t+3	t+4	t+5	t+6
Green sentiment × Env score	0.093**	0.428***	0.342***	0.628***	0.642***	0.506***	0.628***
	(2.25)	(7.08)	(4.49)	(7.10)	(6.69)	(4.93)	(5.68)
Observations	49,054	48,879	48,699	48,518	48,337	48,160	47,995
R-squared	0.021	0.033	0.033	0.036	0.043	0.033	0.037
Panel B: After December 2015							
Green sentiment × Env score	0.181***	0.476***	0.578***	0.445***	0.516***	0.422**	0.335*
	(3.42)	(5.12)	(5.24)	(3.70)	(3.36)	(2.53)	(1.74)
Observations	46,193	45,092	44,004	42,925	41,861	40,808	39,760
R-squared	0.027	0.068	0.055	0.044	0.048	0.044	0.047
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: Green sentiment and stock prices: Accounting for negative climate news
This table shows the results of OLS regressions of individual stock returns from January 2010 through May 2018 on *Green sentiment* and the negative climate news index used in Engle et al. (2020) interacted with the firm's environmental score. The regressions also control for the direct effects of these variables, as well as lagged firm characteristics (leverage, market beta, size, book-to-market, profitability, and momentum) and GICS industry group indicators. The structure of the columns follows the one in Table 5. t-statistics based on standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate that the coefficient estimate significantly differs from zero at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Return in t	Cumulative return through:					
		t+1	t+2	t+3	t+4	t+5	t+6
Green sentiment ×	0.066*	0.490***	0.449***	0.686***	0.688***	0.609***	0.691***
Env score	(1.66)	(8.81)	(7.00)	(9.14)	(8.67)	(6.44)	(6.31)
Negative climate news ×	0.045*	0.209***	0.276***	0.356***	0.331***	0.320***	0.351***
Env score	(1.76)	(4.74)	(4.61)	(4.75)	(3.43)	(2.91)	(2.74)
Env score	0.105***	0.251***	0.354***	0.487***	0.533***	0.574***	0.607**
	(3.00)	(3.69)	(3.48)	(3.53)	(3.08)	(2.76)	(2.49)
Green sentiment	-1.301***	-1.488***	-1.551***	-1.598***	-2.205***	-1.647***	-1.763***
	(-30.34)	(-26.27)	(-23.89)	(-21.61)	(-26.33)	(-17.03)	(-16.64)
Negative climate news	-0.312***	-0.362***	-0.674***	-0.574***	-0.904***	-0.997***	-1.289***
	(-10.70)	(-7.28)	(-10.06)	(-7.03)	(-8.89)	(-8.47)	(-9.35)
Observations	73,280	72,986	72,691	72,397	72,111	71,833	71,563
R-squared	0.021	0.019	0.016	0.016	0.022	0.018	0.021
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: Green sentiment and analysts' forecast revisions

This table shows the results of OLS regressions of mean monthly earnings forecast revisions (Δ *EPS forecast*) at the 1-, 2-, and 3-year-ahead horizons on the Green Sentiment Index and the negative climate news index used in Engle et al. (2020) interacted with the firm's environmental score. Δ *EPS forecast* is computed as the percentage change in mean EPS forecasts, excluding observations with negative baseline forecasts and extreme values (as, e.g., in Landier and Thesmar, 2020). The regressions control for lagged firm characteristics (leverage, market beta, size, book-to-market, profitability, and momentum) and GICS industry group indicators. t-statistics based on standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate that the coefficient estimate significantly differs from zero at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
Dependent variable:		Δ EPS forecast	
Horizon:	1-year ahead	2-year ahead	3-year ahead
Green sentiment × Env score	-0.025	-0.003	0.044
	(-0.65)	(-0.12)	(1.35)
Negative climate news × Env score	0.031	0.066***	0.061**
	(1.01)	(2.79)	(2.43)
Env score	-0.117	-0.067	-0.071
	(-1.58)	(-1.18)	(-1.41)
Observations	61,055	62,102	58,608
R-squared	0.026	0.045	0.035
Firm controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes

Table 9: Green sentiment and direct price pressure from green ETFs

This table shows the results of OLS regressions of individual stock returns from January 2010 through June 2020 on *Green sentiment* interacted with both the firm's environmental score and the percentage of common stocks held by green ETFs *Green ETF ownership*. The regressions also control for the direct effects of these variables, as well as lagged firm characteristics (leverage, market beta, size, book-to-market, profitability, and momentum) and GICS industry group indicators. The structure of the columns follows the one in Table 5. t-statistics based on standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate that the coefficient estimate significantly differs from zero at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Return in t	Cumulative return through:					
		t+1	t+2	t+3	t+4	t+5	t+6
Green sentiment ×	0.069**	0.273***	0.292***	0.445***	0.500***	0.403***	0.533***
Env score	(2.41)	(5.33)	(4.28)	(5.59)	(5.39)	(3.65)	(4.19)
Green sentiment ×	-0.287	0.003	0.153	-0.687	-0.773	-0.907	-0.905
Green ETF ownership	(-0.60)	(0.01)	(0.16)	(-0.56)	(-0.44)	(-0.42)	(-0.33)
Env score	0.044	0.042	0.112	0.207	0.176	0.201	0.211
	(1.29)	(0.61)	(1.10)	(1.56)	(1.07)	(1.03)	(0.92)
Green sentiment	-1.150***	-2.160***	-2.246***	-2.266***	-2.561***	-2.094***	-1.939***
	(-36.21)	(-40.56)	(-33.85)	(-28.88)	(-27.98)	(-19.93)	(-16.75)
Green ETF ownership	-2.014***	-3.988***	-6.184***	-8.413***	-10.024***	-11.873***	-14.615***
	(-4.86)	(-4.44)	(-4.63)	(-5.03)	(-4.63)	(-4.53)	(-4.43)
Observations	95,248	93,972	92,704	91,444	90,199	88,969	87,756
R-squared	0.019	0.035	0.030	0.029	0.033	0.026	0.026
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 10: Effects of green sentiment on real corporate decisions

This table shows the results of OLS regressions of quarterly corporate investment decisions (column 1) and cash accumulation (column 2) on the quarterly average green sentiment, the Environmental score, and the interaction of these two variables. All models also control for lagged firm characteristics, as well as industry and date fixed effects. *Capex/PPE* is the percentage of capital investments scaled by Property, Plant, and Equipment. *Cash/Assets* is the percentage of cash holdings over total assets. *R&D/Assets* is the percentage of R&D expenses over total assets. t-statistics based on standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate that the coefficient estimate significantly differs from zero at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Capex/PPE	Cash/Assets	R&D/Assets
Green sentiment (q) × Env score	0.257***	0.316***	-0.007
	(3.03)	(3.05)	(-0.41)
Env score	-0.322***	-0.079	-0.081
	(-3.91)	(-0.39)	(-1.28)
Green sentiment (q)	-1.303***	-0.113	0.040*
	(-14.34)	(-1.08)	(1.77)
Leverage	-0.009	-0.083***	-0.016***
	(-1.31)	(-6.04)	(-5.75)
Market beta	-0.024	0.637**	0.156*
	(-0.17)	(2.12)	(1.72)
Log(marketcap)	0.072	-0.822***	-0.015
	(0.96)	(-4.40)	(-0.23)
Book-to-market	-1.531***	-4.559***	-1.300***
	(-6.26)	(-6.63)	(-4.10)
Profitability	-0.021	0.038	-0.057***
	(-1.57)	(0.83)	(-5.28)
Momentum	-0.095***	0.098**	0.015
	(-3.91)	(2.51)	(1.43)
Constant	4.661***	19.839***	2.477***
	(5.93)	(9.66)	(3.61)
Observations	23,656	30,018	14,136
R-squared	0.035	0.281	0.475
Industry FE	Yes	Yes	Yes

Table 11: Green sentiment, corporate investments, and credit ratings

This table shows the results of OLS regressions of quarterly Capex/PPE (Panel A) and Cash/Assets (Panel B) on the quarterly green sentiment, the Environmental score, and the interaction of these two variables. The sample is divided into firms with Low (column 1), Middle (column 2), and High (column 3) credit ratings. All regressions also control for firm quarterly lagged controls (leverage, size, profitability, book-to-market, market beta, and momentum), as well as industry and date fixed effects. The quarter fixed effect absorbs the direct coefficient on the green index. t-statistics based on robust standard errors in parentheses. ***, **, and * indicate that the coefficient estimate significantly differs from zero at the 1%, 5%, and 10% levels, respectively.

	Low credit rating	Medium credit rating	High credit rating
Panel A: Dependent variable: Capex/PPE			
Green sentiment (q) × Env score	0.555***	0.365**	-0.009
	(2.66)	(2.35)	(-0.05)
Env score	-0.107	-0.173	-0.070
	(-0.54)	(-1.24)	(-0.54)
Green sentiment (q)	-1.525***	-1.453***	-1.004***
	(-7.89)	(-8.83)	(-4.86)
Observations	4,469	7,643	4,389
R-squared	0.047	0.042	0.027
Panel B: Dependent variable: Cash/Assets			
Green sentiment (q) × Env score	0.578***	0.036	0.252
	(2.93)	(0.30)	(1.62)
Env score	0.257	0.520*	-0.020
	(0.77)	(1.92)	(-0.06)
Green sentiment (q)	-0.241	-0.170	-0.176
	(-1.36)	(-1.21)	(-1.07)
Observations	5,526	10,003	5,338
R-squared	0.263	0.362	0.371
Firm controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes

Appendix

Table A1: Green sentiment and stock prices, robustness I: Double-clustering standard errors

This table shows the results of OLS regressions of individual stock returns from January 2010 through June 2020 on the (standardized) Green Sentiment Index, the firm's environmental score, and the interaction of these two variables. The regressions also control for lagged firm and stock characteristics (leverage, market beta, size, book-to-market, profitability, and momentum), as well as GICS industry group indicators. The structure of the columns follows the one in Table 5. t-statistics based on standard errors double-clustered at the firm and month levels are reported in parentheses. ***, **, and * indicate that the coefficient estimate significantly differs from zero at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	Return in t	Cumulative return through:					
		t+1	t+2	t+3	t+4	t+5	t+6
Green sentiment × Env score	0.068	0.272*	0.290**	0.440***	0.495**	0.397**	0.527**
	(0.88)	(1.67)	(2.41)	(2.75)	(2.47)	(2.00)	(2.10)
Env score	0.039	0.033	0.098	0.189	0.153	0.175	0.179
	(0.47)	(0.26)	(0.59)	(1.02)	(0.68)	(0.67)	(0.63)
Green sentiment	-1.153***	-2.163**	-2.248***	-2.275***	-2.572***	-2.106**	-1.952*
	(-2.88)	(-2.59)	(-2.67)	(-2.93)	(-3.37)	(-2.48)	(-1.93)
Leverage	0.003	0.004	0.004	-0.001	0.000	0.000	0.001
	(0.44)	(0.59)	(0.44)	(-0.07)	(0.00)	(0.02)	(0.08)
Market beta	0.245	0.178	0.158	-0.210	-0.345	-0.544	-0.729
	(0.96)	(0.53)	(0.37)	(-0.49)	(-0.71)	(-1.01)	(-1.25)
Log(market cap)	0.006	0.011	-0.056	-0.163	-0.152	-0.201	-0.222
	(0.06)	(0.08)	(-0.32)	(-0.86)	(-0.68)	(-0.79)	(-0.79)
Book-to-market	-0.133	-0.405	-0.565	-0.682	-1.000	-1.011	-0.965
	(-0.51)	(-1.02)	(-1.04)	(-1.01)	(-1.24)	(-1.05)	(-0.86)
Profitability	-0.003	-0.017	-0.030	-0.048*	-0.070**	-0.090**	-0.112***
	(-0.27)	(-0.95)	(-1.30)	(-1.89)	(-2.35)	(-2.52)	(-2.69)
Momentum	-0.145	-0.255*	-0.292	-0.146	-0.147	-0.089	-0.027
	(-1.37)	(-1.73)	(-1.50)	(-0.81)	(-0.80)	(-0.40)	(-0.12)
Constant	0.857	2.131	3.824**	5.967***	7.168***	8.812***	10.216***
	(0.81)	(1.50)	(2.28)	(3.28)	(3.36)	(3.52)	(3.67)
Observations	95,248	93,972	92,704	91,444	90,199	88,969	87,756
R-squared	0.018	0.035	0.030	0.028	0.032	0.025	0.024
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A2: Green sentiment and stock prices, robustness II: Adding month fixed effects

This table shows the results of OLS regressions of individual stock returns from January 2010 through June 2020 on the (standardized) Green Sentiment Index, the firm's environmental score, and the interaction of these two variables. The regressions also control for lagged firm characteristics (leverage, market beta, size, book-to-market, profitability, and momentum), as well as GICS industry group and month fixed effects. The structure of the columns follows the one in Table 5. t-statistics based on standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate that the coefficient estimate significantly differs from zero at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	Return in t	Cumulative return through:					
		t+1	t+2	t+3	t+4	t+5	t+6
Green sentiment × Env score	0.028	0.165***	0.190***	0.210***	0.250***	0.249**	0.307**
	(0.96)	(3.44)	(3.01)	(2.68)	(2.68)	(2.26)	(2.42)
Env score	-0.048	-0.098	-0.111	-0.112	-0.122	-0.109	-0.105
	(-1.65)	(-1.60)	(-1.21)	(-0.91)	(-0.78)	(-0.58)	(-0.47)
Observations	95,248	93,972	92,704	91,444	90,199	88,969	87,756
R-squared	0.292	0.273	0.257	0.235	0.221	0.214	0.202
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A3: Green sentiment and stock prices, robustness III: Alternative environmental score

This table shows the results of OLS regressions of individual stock returns from January 2010 through June 2020 on the ETF-flows-based Green Sentiment Index, the firm's standardized environmental score based on the MSCI KLD database, and the interaction of these two variables. The regressions also control for lagged firm characteristics (leverage, market beta, size, book-to-market, profitability, and momentum) and GICS industry group fixed effect indicators. The structure of the columns follows the one in Table 5. t-statistics based on standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate that the coefficient estimate significantly differs from zero at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Return in t	Cumulative return through:					
		t+1	t+2	t+3	t+4	t+5	t+6
Green sentiment ×	0.063***	0.065*	0.075*	0.108**	0.169***	0.209***	0.326***
Env score (kld)	(3.52)	(1.91)	(1.72)	(2.14)	(2.79)	(3.06)	(4.27)
Env score (kld)	-0.047**	-0.107***	-0.182***	-0.227***	-0.265***	-0.254**	-0.254*
	(-2.30)	(-2.60)	(-3.07)	(-2.96)	(-2.79)	(-2.22)	(-1.91)
Green sentiment	-1.211***	-2.486***	-2.530***	-2.628***	-2.885***	-2.495***	-2.410***
	(-52.92)	(-64.40)	(-51.49)	(-44.84)	(-41.51)	(-31.27)	(-27.25)
Observations	232,622	228,156	223,806	219,560	215,394	211,315	207,340
R-squared	0.014	0.031	0.025	0.023	0.025	0.019	0.018
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A4: Sample distribution by environmental score and credit rating

This 2-by-3 matrix shows the number of firm×quarter observations with environmental score below or above the median in three groups of credit ratings: *Low credit rating* < ''BBB-''; *Medium credit credit* = ''BBB'', ''BBB+'', ''BBB-''; and *High credit rating* = ''A'',''A+'',''A-'',''AA'', ''AAA'',''AA-'',''AA+''. The split along the median of the environmental score is performed unconditionally of the availability of the credit rating.

	Credit rating			
Env score	Low	Medium	High	Total
Below or equal median	4,267	5,481	1,887	11,635
Above median	2,693	6,290	4,653	13,636
Total	6,960	11,771	6,540	25,271