Climate Sin Stocks: Stock Price Reactions to Global Climate Strikes*

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Abstract

The first Global Climate Strike on March 15, 2019 has represented a historical turn in climate activism. We investigate the cross-section of European stock price reactions to this event. Looking at a large sample of European firms, we find that the unanticipated success of this event caused a substantial stock price reaction on high-carbon intensity companies. These findings are likely driven by an update of investors' beliefs about the level of environmental social norms in the economy and the anticipation of future developments of climate regulation.

JEL Classification: Q01, G14, G40, G23
Keywords: Climate risks, stock returns, event study, environmental preferences, sustainable finance, investor attention

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1 Introduction

As extreme weather events become more frequent and severe, the risks of climate change for our societies become dramatically evident. In recent years, the demand for more far-reaching actions at the international level to limit CO2 emissions sparked an unprecedented wave of climate activism by young people. In this paper, we show that this new climate activism affects investors' behavior and the market values of high-polluting firms.

We investigate the cross-section of stock price reactions to the first ever Global Climate Strike, held on March 15, 2019. Under the slogan "FridaysForFuture", this coordinated wave of climate protests by students mobilized more than 1.4 million people in over 2,000 cities worldwide, receiving massive media coverage.[1] We argue that the success of Global Climate Strike, both in terms of participation and resonance, established a historical turning point in environmental activism, causing a shift in the general expectations in the economy about the environmental preferences of newest generations. In addition to its potential relevance for financial markets, the first Global Climate Strike is particularly interesting for our empirical purposes also because it was organized by, and addressed to, young people in the 14-19 age group, who are unlikely to be active participants in the stock markets. Hence, it can be considered quasi-exogenous to finance.[2]

Our analyses aim at testing whether investors reacted to the first Global Climate Strike by penalizing high-carbon intensity firms. To do that, we investigate the CAPM-adjusted cumulative abnormal returns from the day before the climate strike through three days

[1]According to data released on the official website of Fridays for Future: `https://www.fridaysforfuture.org/`.

[2]For details on the demographic characteristics and motivations of strike participants across Europe, see Wahlström et al. (2019).

afterwards (the period of highest saliency of the event) on a broad sample of European stocks. Our analyses are based on two complementary measures of corporate carbon intensity. First, we consider data on carbon emissions from Eurostat available for 64 different sectors and 27 countries. Although these data provide information only at the sector-country level, they allow us to analyze the effect of carbon emissions on the cross-section of returns for more than 4,000 stocks.

The second measure of carbon intensity is based on firm-level data carbon data by Sustainalytics. Sustainalytics is a major provider of ESG research, whose scores are often used in academic finance research. This measure is available for around 1,500 European firms, which allows us to analyze the relation between carbon intensity and stock prices at a more granular level.

Our evidence indicates that around the timing of the first Global Climate Strike, firms with higher carbon intensity experienced significantly negative abnormal returns. For instance, when using the measure from Eurostat, a one standard deviation increase in carbon intensity is associated with 25 basis points *lower* cumulative abnormal returns in the 5-day window around the event. Similar results are obtained when using the carbon intensities based on Sustainalytics data. These results are confirmed in alternative specifications and robustness checks.

A central question is "Why did a wave of climate protests by student stir such an effects on financial markets?". A first possible channel is the update of investors' beliefs about the level of environmental preferences in the economy. More pronounced environmental preferences imply higher future demand for "green" products, reducing the cash flows of more polluting firms. Furthermore, as the movement explicitly call political leaders to increase the regulatory efforts on climate change, our results are also likely to be driven by investors' anticipation of the future tightening of environmental regulation and deployment of new legislative initiatives. A related interpretation is also that the climate strikes contributed to renew investors' attention to already-existing corporate risks related to climate change. We provide suggestive evidence on a strategic explanation of investors' behavior by exploiting cross-country heterogeneities in terms of environmental social norms and environmental policy stringency. We find that the negative stock price reaction for more polluting companies is more pronounced in countries with ex-ante *lower* levels of average environmental preferences and *lower* levels of environmental policy stringency.

Finally, we conduct an out-of-sample panel regression exercise looking at the daily stock returns through June 30, 2019. We exploit an interesting cross-country differential timing of attention to the young climate activist Greta Thunberg, caused by her intense campaigning activity and travelling across Europe. Our analysis shows that a higher daily attention to climate activism is associated with a higher (negative) pricing of corporate carbon emissions on financial markets, in line with our results on the effects of the first Global Climate Strike.

Our paper is related to several strands of literature. First, it contributes to the literature studying investors' behavior with respect to corporate climate externalities, and how this behavior affect firm valuations. Chava (2014) and Matsumura, Prakash, and Vera-Muñoz (2014) find that financial markets penalize firms with more negative environmental externalities.[3] The firm-value price of carbon emissions, however, is also known to be influenced

[3] In a similar fashion, Tang and Zhang (2019) shows that following a green bond issuance (fixed income securities issued for environmental or climate-related projects), stock prices of these issuers have a positive reaction and domestic institutional investors, mainly investment advisers and pension funds, increase their share of ownership. Similarly, Flammer (2018) finds a positive stock market reaction to green bond issuance and an increase in holdings by long-term and environment-conscious investors.

by various factors, including the saliency of extreme weather events (e.g., Choi, Gao, and Jiang, 2019, Pankratz, Bauer, and Derwall, 2019) and the political uncertainty surrounding environmental regulation (e.g., Ilhan, Sautner, and Vilkov, 2019 and Ramelli, Wagner, Zeckhauser, and Ziegler, 2019). Our paper contributes to this debate by providing novel evidence that the markets' pricing of carbon intensity reacts to environmental activism.

Second, we contribute to the literature on the effect of social norms in financial markets. There is now extensive evidence that investors behavior is motivated also by non-pecuniary motives, and that a large fraction of retail investors prefer socially responsible investments, sometimes even irrespectively of risk and return considerations (e.g., Ceccarelli, Ramelli, and Wagner, 2019, Barber, Morse, and Yasuda, 2019, Hartzmark and Sussman, 2019, Riedl and Smeets, 2017). A growing number of institutional investors also integrate sustainability considerations – particularly with respect to climate change – in their investment decisions (e.g., Dyck, Lins, Roth, and Wagner, 2019, Krueger, Sautner, and Starks, 2019).[4]

However, the existence of this type of preferences does not necessarily imply an effect on firm valuations and, more specifically, on stock prices. In fact, other investors in the market may have symmetric tastes or sufficient ability to arbitrage-out any deviation of stock prices from fundamentals (Fama and French, 2007). In order to impact firm valuations, individual preferences need to become social norms,[5] and influence the trading behavior of

[4]According to Global Sustainable Investment Alliance (2019), as of 2018, the assets managed according to socially responsible criteria accounted for around 30 trillion USD globally. According to the NGO `350.org`, as of the same year, around 1,000 institutions with combined assets of around 8 trillion USD committed to divest from fossil fuels.

[5]Social norms are known to be important drivers of human behavior in several economic and non-economic settings. It should be stressed here that social norms are not just the mere collection of individual preferences. Bicchieri (2005) argues that social norms are shaped by two main elements: the individual expectations about how other people will behave (empirical expectations) and the individual expectations about what other people think is the right thing that ought to be done (normative expectations). The social nature of these expectations creates multiple equilibria, such that even small changes in the setting can lead to large changes in aggregate behavior.

marginal investors. Hong and Kacperczyk (2009) show that firms in the U.S. involved in the production of alcohol, tobacco and gambling have higher expected returns than comparable stocks, implying a higher cost of capital. They provide evidence of social norm effects on investments for these stocks, which are identified as "sin" stocks. Have the stocks of energy and other carbon-intensive firms become "climate sin stocks"? Bolton and Kacperczyk (2019) and Hsu, Li, and Tsou (2019) provide initial evidence that high carbon emissions are associated with higher expected returns, presumably because of their higher exposure to environmental regulatory risk and their under-weighting by institutional investors. Our paper contributes to this literature by showing that shifts in environmental social norms, at least among the population, directly impact the market valuation of high-carbon companies.

Finally, our paper is also related to the broader literature relating firm environmental performance to financing costs. Several studies indicate that companies with good environmental performance, or better environmental risk management practices, enjoy a lower cost of equity (Ghoul, Guedhami, Kwok, and Mishra, 2011; Cheng, Ioannou, and Serafeim, 2014; Sharfman and Fernando, 2008). On the debt market, Baker, Bergstresser, Serafeim, and Wurgler (2018) indicate that municipal green bonds are issued at a premium compared to ordinary bonds.[6] Kleimeier and Viehs (2018) document that loan spreads are positively related to borrowers' carbon emissions, and that more favourable lending conditions are accorded to borrowers voluntarily disclosing their emissions than to those non-disclosing them. Delis, de Greiff, and Ongena (2019) find that after the Paris Climate Agreement, banks started charging higher loan rates to firms with higher fossil fuel reserves. Our results warn

[6]However, the benefits of green bonds for corporate issuers is more ambiguous (see, e.g., Zerbib, 2019; Karpf and Mandel, 2018).

higher-polluting companies that their financing costs might further increase in the future as a result of a further intensification of environmental activism in the economy.

The paper proceeds as follows. Section 2 introduces our main empirical strategy and hypothesis. Section 3 describes the data. Section 4 presents the main results. Section 5 discusses the potential channels of the main findings. Section 6 shows the results of the panel regression exercise exploiting daily variations in attention to the "FridaysForFutures" movement. Finally, Section 7 concludes.

2 Empirical strategy

We assume that the excess return $R_{i,t}$ of company $i = 1, ..., n$, at date $t = 1, 2, ...T$ satisfies the following linear factor model:

$$R_{i,t} = a_i + b_i' f_t + \varepsilon_{i,t}, \tag{1}$$

where a_i is the constant coefficient, f_t is a vector of K observable factors, b_i' is the vector containing the corresponding k factor loadings and $\varepsilon_{i,t}$ is the error term. To study the stock-price reactions to the first Global Climate Strike, we compute abnormal return $AR_{i,t}$ as:

$$AR_{i,t} = R_{i,t} - (\hat{a}_i + \hat{b}_i' f_t), \tag{2}$$

where $\hat{a}_i$ and $\hat{b}_i$ are estimated from OLS regression on Equation (1) using daily stock excess returns data from January 2, 2018 through December 31, 2018. Defining abnormal returns by adjusting for the Jensen's alpha, allows us to focus directly on the effect of the event under study, net of the systematic under- or out-performance of specific stocks.

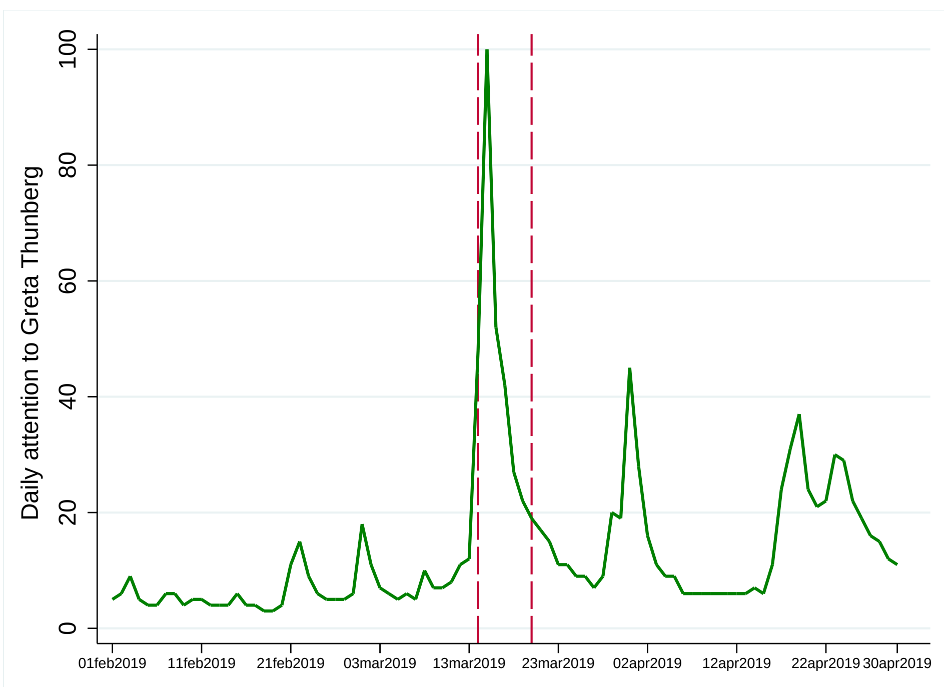
Our baseline model is the CAPM (Sharpe, 1964), i.e., the market model with $K = 1$ and $f_t = r_{m,t}$, where $r_{m,t}$ is the excess return on the value-weighted market portfolio over the risk free rate. Indeed, the advantages from employing multifactor models for event studies are limited (see, e.g., Campbell et al., 1997). However, in Section 4.1, for comparison reasons, we also collect results for the four-factor model (hereafter, labeled as 4F) proposed in Carhart (1997), with $f_t = (r_{m,t}, r_{smb,t}, r_{hml,t}, r_{mom,t})'$, where $r_{smb,t}$ and $r_{hml,t}$ are the returns on zero-investment factor-mimicking portfolios for size and book-to-market, respectively, and $r_{mom,t}$ is the momentum factor, i.e., the equal-weight average of the returns for the winner portfolios minus the average of the returns for the loser portfolios (see Fama and French, 1993).

For our empirical purposes, the choice of the event window is of particular importance. On the one hand, we need to balance the necessity to keep the event window as short as possible to limit the concerns on potential confounding events; on the other hand, we need an event window allowing enough time for markets to realize the success of the first Global Climate Strike, and integrate into prices information outside the traditional realm of finance.

In order to define the event window, Figure 2 shows the daily global Search Value Index (SVI) from Google Trends for the topic Greta Thunberg, the charismatic climate activist, icon of the "FridaysForFuture" movement. As it can be seen, the attention to young climate activism spikes around March 14, 2019 and remains at relative high levels up to March 20, 2019. Figure 2 provides valuable information for our empirical strategy. First, it suggests that, although the date and goals of the first Global Climate Strike were known in advance, its success in terms of participation and ex-post public attention was largely unanticipated, hence supporting the relevance of the event under study. Second, Figure 2 suggests that an appropriate event window for our empirical analyses is from the day before the Global Climate Strike (Thursday, March 14, 2019) up to thee trading days after the strike (Wednesday, March 20, 2019), i.e., the days of relative high public attention to Greta Thunberg.

Thus, we compute the cumulative abnormal returns over a 5-day window ranging from 1 day before through 3 days after the event ([-1,+3]), i.,e. $CAR_i(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{i,t}$ computed between 14th March (t_1) and 20th March (t_2).

Figure 1. Google search index on Greta Thunberg.
This figure shows the daily global Google Trends Search Value Index (SVI) for the topic "Greta Thunberg" from February 1, 2019 through April 30, 2019 (including non-trading days). The index varies from 0 to 100 and represents search interest relative to the highest point on the chart. The two vertical dashed lines indicate our chosen estimation windows of 5 trading days, ranging from Thursday, March 14 through the end of Wednesday, March 20, 2019.



To investigate how carbon intensity measure affects the cumulative abnormal return computed for the specified event window, we study the following cross-sectional specification:

$$CAR_i(t_1, t_2) = \alpha + \beta CI_i + X_i'\gamma + e_i, \tag{3}$$

where CI_i is the carbon intensity measure, X_i is a vector of accounting variables (e.g., leverage, market capitalization, profitability).[7]

Our hypothesis is that the relationship between stock market reaction and carbon intensity is negative. In other words, we expect companies with high carbon intensity – i.e., those involved in more polluting economic activities – to significantly under-perform in reaction to the Global Climate Strike. The null hypothesis is that investors do not consider the Global Climate Strike as a significant event in terms of shift of environmental preferences and/or anticipation of tighter regulation in the future and, hence, in our event window, do not price firms differently based on their carbon emissions.

Looking only at one single event poses the challenge of controlling for the potential cross-sectional correlation of returns. To account for potentially not-independently distributed errors, we test the statistical significance of estimates $\hat{a}_i$ and $\hat{b}_i$ from Equation (1) using – in addition to conventional t-statistics – adjusted t-statistics based on the empirical distribution of coefficient estimates, following the approach in Cohn et al. (2016).[8] All our findings hold irrespectively of whether we assess statistical significance based on conventional or adjusted t-statistics.[9]

[7] For easier notation, the measure of carbon intensity CI_i is defined for each company i. However, in Section 3.2, we also introduce carbon intensity measures defined at country-industry level. In that case, the specification in Equation (3), becomes $CAR_i(t_1, t_2) = \alpha + \beta CI_{c,j} + X_i'\gamma + e_i$, where $CI_{c,j}$ is the carbon intensity measure of country c and industry j in which the company i belongs.

[8] Specifically, we estimate Equation (1) over a short non-event period ranging from January 2, 2019 through February 28, 2019 (41 trading days). We then run the same cross-sectional regressions using the event period returns. Finally, we compute the adjusted t-statistics by subtracting the average time-series coefficients over the non-event period from the estimated event coefficients, and then dividing this difference by the standard deviation of the time-series coefficients over the non-event period.

[9] In Section 4.1, we show that our results are highly statistically significant also using adjusted t-statistics.

3 Data and summary statistics

In this section, we introduce the data involved in our empirical application. First, we provide information on stock returns and accounting variables. Then, we present carbon intensity data. Finally, we comment the descriptive statistics of our datasets.

3.1 Stock returns and accounting variables

We obtain daily stock prices from January 2, 2018 through June 30, 2019 for all listed firms head-quartered in Europe (EU 28, Switzerland and Norway) from Compustat Security Daily. Following Chaieb, Langlois, and Scaillet (2018), we keep only common shares (tpci ="0") listed on major stock exchanges.[10] In cases of dual listings, we keep only the firm's security with the highest market capitalization, remaining with approximately 5,800 securities traded as of March 14, 2019.

To compute stock returns, we closely follow the procedure outlined in Chaieb, Langlois, and Scaillet (2018). We convert all prices in USD using the appropriate Compustat currency conversion tables and daily conversion rates. We also adjust prices for dividends through the daily multiplication factor and the price adjustment factors provided by Compustat.

We obtain data on European market, size, value, and momentum factors, in addition to the risk-free asset, from Ken French's website. The risk-free rate is the U.S. one month T-bill rate. For each stock i, we estimate the vector of factor loadings b_i in Equation (1), using daily stock excess returns from January 2, 2018 through December 31, 2018 (estimation period). Then, we compute abnormal returns $AR_{i,t}$ for the period from January 1, 2019 to

[10]The list of major exchanges is reported in Table A1. It includes the exchanges with the highest number of equities per country, except for France (Paris and NYSE Euronext), Germany (Deutsche Boerse and Xetra), and Switzerland (Zurich and Swiss Exchange) where two exchanges are selected.

June 30, 2019 as defined in Equation (2). To ensure that our estimates are not affected by numerical instability, we compute abnormal returns only for stocks with at least 127 daily observations available during the estimation period. As shown in Table A2 in the Appendix, around 90% of firms have at least 230 daily observations.

In order to estimate Equation (3), we also collect standard accounting data from Compustat Global, i.e., market value of equity, profitability (ROA), and market leverage. Accounting data refers to fiscal year 2018, except for an approximately 10% of firms for which we use 2017 data as their fiscal year 2018 ended after March 15, 2019. We convert all accounting data in USD using the Compustat currency conversion tables and 12-month average exchange rate. Market capitalization is computed as the share price as of March 13, 2019 times the number of shares outstanding on the same day.

3.2 Carbon intensity measures

We consider two measures of carbon intensity, one at the sector-country level and the other at the firm level. These two measures offer complementary advantages. The first one allows us to conduct cross-sectional analyses on a larger sample (virtually the entire market), while the second one is suited to exploit the within-sector variation in climate performance.

At the country-industry level, data on carbon intensity are retrieved from Eurostat Air emissions accounts (AEA).[11] AEA are compiled at national level but follow the accounting structures and principles of the System of Environmental-Economic Accounting, producing internationally comparable and coherent statistics on the environment and its relationship with the economy. Greenhouse gases (GHG) include CO2 plus other air pollutants expressed

[11] They are part of the European environmental economic accounts (Regulation (EU) No 691/2011).

in CO2 equivalents. Data are published at annual frequency, broken down by country and economic activity. The industry classification of economic activities is based on NACE Rev. 2 with details for 64 emitting industries.[12] Based on Eurostat data, we define the variable *Carbon intensity (country-industry)*, computed as the ratio between total GHG and the firms' value added (the unit of measure is kilotons of CO2 emissions equivalent per millions of USD). As alternative measure, we also consider the carbon intensity from Eurostat defined as the ratio between GHG and value of output. We use the data from the last available Eurostat release before the Global Climate Strike, which refers to year 2017.

The second carbon intensity measure involved in our analysis is derived by firm-level carbon data provided by Sustainalytics. Sustainalytics is a major ESG research provider whose scores are often used in finance research, including, e.g., in Engle et al. (2019). We define the variable *Carbon intensity (firm)* as a firm's total Scope 1 and Scope 2 CO2 emission equivalents in 2017 (the latest available information on corporate carbon emissions), divided by its market capitalization as of the day before the first Global Climate Strike. Using the market value of equity to normalize GHG emissions emphasizes the amount of a firm's negative climate externalities relative to its current overall value for shareholders (see, e.g., Hoffmann and Busch, 2008).[13]

[12]Since 1970 NACE, derived from the French Nomenclature statistique des Activités économiques dans la Communauté Européenne, is the official industry classification used in the European Union. NACE Rev. 2 is a revised classification adopted at the end of 2006. The 64 industries are the most granular level to which the GHG data are available. Alternative datasets provide information at country level, without a breakdown at industry level (e.g., Germanwatch, Worldbank).

[13]According to the GHG Protocol, there are three types of emission categories, Scope 1, 2 and 3. Scope 1 refers to all direct emissions from the activities of a company. Scope 2 considers indirect emissions are created during the production flow. Scope 3 includes emissions that are a consequence of the operations of a company, but are not under its direct control.

3.3 Summary statistics

We merge the abnormal returns from Equation (3) and firm's accounting information with the carbon intensity data from Eurostat. We end up with a main sample of 4,108 stocks. Then, in a similar way, we merge firms' financial and accounting information with the emissions data at the firm level obtained from Sustainalitycs. The corresponding main sample includes 1,529 companies. Of these, 707 firms voluntary disclose their CO2 emissions. The CO2 emissions of the remaining non-reporting companies are estimated by Sustainalytics based on firm-specific information.

Table 1 provides the distribution of the companies by country of domicile. About half of the companies are domiciled in the United Kingdom, France and Germany. Table 2 shows the distribution of the companies by the 11 Global Industry Classification Standard (GICS) sectors.[14] About half of the companies of the sample belongs in three sectors, i.e., industrial, information technology and consumer discretionary.

Table 3 in Panel A and B reports descriptive statistics on stock returns of the Eurostat and Sustainalytics samples, respectively. Focusing on the factor loadings, small stocks outperform large stocks and value stocks outperform growth stocks during our sample period. Table 4 shows the summary statistics for the explanatory variables. In Panel A, the average carbon intensity is around 0.32, but the distribution is highly skewed with a low number of observations having very high values. A similar distribution is observed in Panel B.

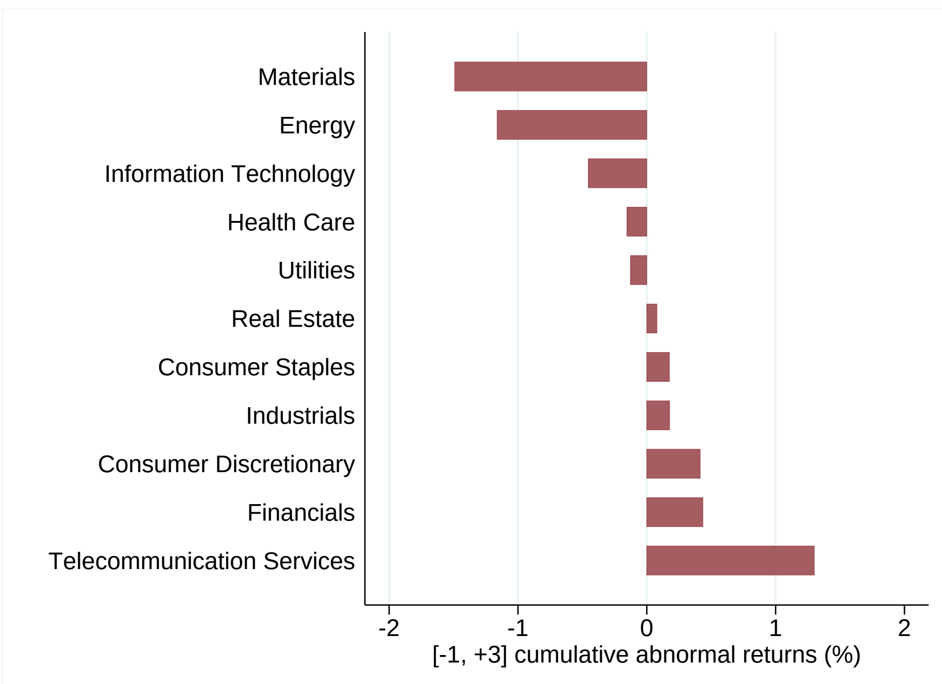
In order to investigate the heterogeneity of *Carbon intensity (country-industry)*, in Figures 5 and 6 we plot its distribution by countries and sectors, respectively. In the Panel A of Figure 5, we observe a quite similar median of carbon intensity across countries. However,

[14] Henceforth, we consider the GICS industry classification because our reference data source is Compustat.

we notice a different spreads of data. For example, the distribution of CI_i in Finland is tight due to the commitment of the country to reach carbon neutrality target by 2035. Looking at Figure 6, the distribution of CI_i for utilities, energy and materials sectors are shifted to the right with respect to the distributions of the low-carbon intensity sectors. A similar pattern can be also observed for the Sustainalytics sample.

Finally, in Figure 2 we show the average 5-days cumulative abnormal returns by GICS sectors. As it can be seen, the average abnormal returns vary considerably between sectors. In particular, in our event window, firms in the energy and material sectors appear to have significantly underperformed the market.

Figure 2. Sector-level stock price reactions.
The figure shows the average 5-day CAPM-adjusted cumulative abnormal returns by 11 GICS sectors for the 4,108 firms in the Eurostat sample.



4 Main results

In this section, we investigate the relationship between stock market reaction and carbon intensity providing cross-sectional evidence based on Equation (3).

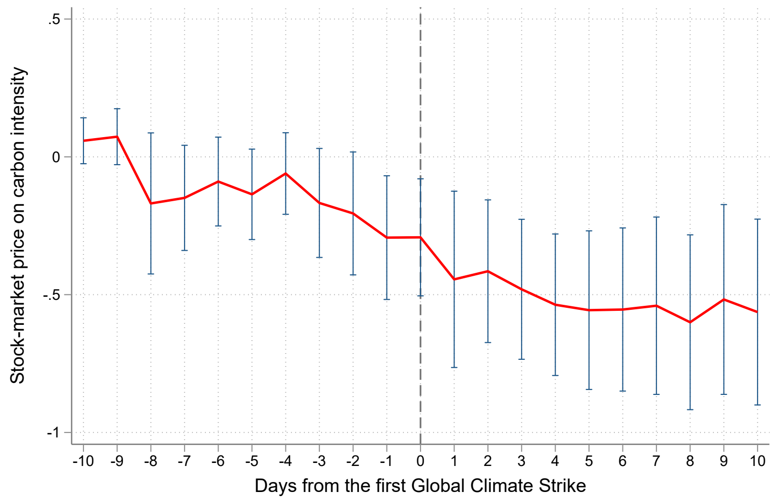
Table 5 refers to the Eurostat sample for which the carbon intensity measure is defined at country-industry level. In specification 1, without any controls, the coefficient on carbon intensity is negative and highly statistically significant. Including firm controls (specification 2), the coefficient of interest is even slightly larger. A one standard deviation increase in the carbon intensity decreases the adjusted cumulative abnormal returns by a 25 basis points, a bit higher than 5% of a standard deviation of the raw returns. Among the firm control variables, only one coefficient on firms' size is statistically significantly different from zero. It should be noticed that this is coherent with the fact that we are analyzing abnormal returns, net of a stock's alpha and correlation with the market. Accounting information are unlikely to influence abnormal returns, because they are already priced-in by the market. Finally, in specification 3, we include also industry and country fixed effects. As expected, the coefficient of interest is still negative but no more statistically significant. Indeed, as this variable is defined at the country-sector level, adding country and sector FE absorb most of its variation and, hence, significantly reduces the identification power of the regression.

Symmetrically, Table 6 provides analysis on the Sustainalytics sample. In all three specifications, the coefficients on the firm-level carbon intensity is always negative and statistically significantly. Focusing on specification 3, controlling for firm characteristics and sector fixed effect, a one standard deviation increase in the carbon intensity decreases the adjusted cumulative abnormal returns by a 40 basis points.

To further support our results, Figure 3 shows the evolution of the estimated coefficients on *Carbon intensity (firm)* from 10 days before the first Global Climate Strike (March 1, 2019) through 10 days after it (March 27, 2019). Most specifically, the coefficients are obtained by regressing the CAPM-adjusted cumulative abnormal returns, from March 1, 2019 up to each day (controlling for sector and firm characteristics). As shown, up to the day before our event of interest, the price of carbon intensity implied by market valuations is not statistically different from zero. We observe a negative trend starting on day -3 – presumably due to a natural anticipation of the event – suggesting that our results represent only a lower bound of the market reactions to the first Global Climate Strike. The value penalty of carbon intensity is statistical significant on the day before the event, and further increases on the day *after* the event. Interestingly, the negative coefficient remains statistically significant even after 10 days, without any apparent reversal in the short run.

Finally, Figure A1 in the Appendix displays the evolution of the estimated coefficients on Carbon intensity (firm) using daily returns from January 2 through January 31, 2019. Throughout this (pre-event) period, the coefficients on carbon intensity are always close to zero and statistically insignificant. This placebo test confirms that the downward trend observed in Figure 3 does not just reflect a pre-existing trend in the pricing of climate risks, but is attributable to the effect of the first global climate strike.

Figure 3. Global Climate Strike and stock-market carbon price.
The figure shows the evolution of the regression estimates of the effect of *Carbon intensity (firm)* on CAPM-adjusted cumulative abnormal returns from 10 days before through 10 days after the Global Climate Strike on March 15, 2019, controlling for sector and firm characteristics. The cumulation of returns starts on March 1, 2019 (day -10). The graph also plots the 95% confidence intervals around estimates.



Overall, the results presented in this section indicate that the success of the first Global Climate Strike negative impacted the market valuation of high-carbon intensity firms, those more exposed to climate change mitigation and adaptation risks.

4.1 Robustness checks

In this section, we provide several robustness checks to ensure the reliability of our main results along four dimensions: i) the computation of t-statistics, ii) the definition of the dependent variable, iii) the proxy for carbon intensity, and iv) excluding financial companies. Results are presented in Tables 7, 8, 9, and 10, both for the Eurostat sample (Panels A) and the Sustainalytics sample (Panels B).

In Table 7, we present our baseline results by assessing statistical significance based on adjusted t-statistics, as described in Section 2. For both samples and all specifications, the results remain statistically significant as for the model estimated using conventional t-statistics (for comparison, see Tables 5 and 6).

In Table 8, we estimate Equation (3) using the cumulative raw returns (CR) and the Carhart-adjusted cumulative abnormal returns (4F-CAR) as dependent variables. All previous results are confirmed, both when considering carbon intensity at the industry-country level (Panel A) and at the firm level (Panel B).

In Table 9, we use alternative definition of carbon intensity. In particular, Panel A shows the results when using the country-sector-specific carbon intensity from Eurostat defined as GHG emissions over output value. In Panel B, we restrict the Sustainalytics sample to firms that actually self-reported their CO2 emissions, to make sure our results are not driven by Sustainalytics's estimation methodology for non-reporting companies. The results of these alternative specifications are in line with those presented in Tables 5 and 6.

Finally, as an additional check, in Table 10, we replicate our analysis excluding financial firms from the sample (i.e., companies for which GICS equal to 40). Indeed, Scope 1 and Scope 2 GHG emissions for financial firms offer only a rough approximation of their actual exposure to climate policy risks, which mainly originate from their investment portfolios and financial exposures. The results are in line with the previous evidence.

5 Environmental social norms and policy stringency

This section investigates the potential channels driving the negative impact of the Global Climate Strike to the stock prices of high-carbon intensity firms. We focus on two possible factors: (i) the role of environmental social norms, and (ii) the level of stringency of climate regulation.

To measure country-level climate-conscious preferences, we exploit the 2016-2017 survey on public attitudes to climate change included in the Round 8 of the European Social Survey (ESS), which was the first systematic comparison of public attitudes to energy and climate change between European countries.[15] We retrieve responded-level data on personal norms to reduce climate change.[16] We aggregate data at the country level by applying the appropriate weights provided by ESS. We then split the sample between firms domiciled in countries in the top tercile of environmental norms (i.e., Finland, France, Germany, Norway, Sweden, and Switzerland), and firms head-quartered in other countries (i.e., Austria, Belgium, Czech Republic, Hungary, Italy, Netherlands, Portugal, Slovenia, Spain, and the United Kingdom), obtained two similarly-sized sub-samples.

To proxy for cross-country differences in the level of climate policy stringency, we exploit the OECD Environmental Policy Stringency Index (EPS) developed by Botta and Koźluk (2014). The OECD Environmental Policy Stringency Index (EPS) is a country-specific and

[15]Fieldwork for the ESS Round 8 took place between August 2016 and December 2017. The full dataset consists of 44,387 respondents from 23 countries. For an overview of the survey results on the topic of climate change see ESS (2018).

[16]The variable that we exploit is *ccrdprs*. This indicator is based on the response to the question "To what extent do you feel a personal responsibility to try to reduce climate change?" from 0 (not at all) to 10 (a great deal). According the ESS, this variable captures the extent to which an individual feels personally responsible to contribute to the solution of environmental problems. Personal norms require a certain level of awareness about the existence of a problem (climate change) and the feeling of moral obligation to contribute to solve it. For more methodological details, see ESS (2016).

internationally-comparable measure of the stringency of environmental policy. Stringency is defined as the degree to which environmental policies put an explicit or implicit price on polluting or environmentally harmful behavior. The index ranges from 0 (not stringent) to 6 (highest degree of stringency), and covers 28 OECD and 6 BRIICS countries for the period 1990-2012. The index is based on the degree of stringency of 14 environmental policy instruments, primarily related to climate and air pollution. We use the EPS score to split the sample between firms domiciled in countries in the top tercile of environmental policy stringency (i.e., Denmark, Finland, France, Italy, Netherlands, Switzerland, and the United Kingdom), and firms domiciled in other countries.

Table 11 reports the standardized scores (mean zero and unit standard deviation) on the two dimensions – environmental social norms and environmental policy stringency – by countries covered by our analyses.[17]

Table 12 presents the results of cross-sectional regression in Equation (3) exploiting the two ex-ante country-level dimensions across countries. Panel A reports the results for the sub-sample of firms located in countries with low level of environmental social norms (specification 1) and the sub-sample of firms in countries with high level of environmental social norms (specification 2). Although the coefficients on carbon intensity in the two sub-samples are not statistically different from each others, the results indicate that the effect of the Global Climate Strike on high carbon-intensity firms is more precise in countries having lower, rather than higher, ex-ante environmental social norms.

In Panel B, we report the results of our main regressions by splitting the sample in

[17] The two dimensions have a correlation of 0.45, statistically significant at 1% level. Indeed, environmental social norms shape environmental regulation through the democratic process. At the same time, environmental regulation may in turn contribute to shape environmental social norms through the expressive function of law (Sunstein, 1996).

firms located in countries with low (specification 1) and high levels of environmental policy stringency (specification 2). Also in this case, the coefficients on carbon intensity in the two specifications are not statistically different from each others, but the market penalization for high-polluting firms appears statistically significant only for the sub-sample of firms located in countries where the ex-ante environmental regulation is considered less advanced.

Although the analyses in this section do not allow to draw any definitive conclusions about the drivers of investors' behavior, they provide suggestive evidence that the market penalty on high-carbon firms around the timing of the first Global Climate Strike can not be entirely explained by ex-ante environmental preferences or existing regulation. Indeed, these results suggest that the impact of the Global Climate Strike is stronger precisely in countries with relatively laxer ex-ante environmental regulation, where firms will need higher efforts to comply with *future* tightening of climate adaptation and mitigation policies. For instance, companies operating in the same sector but in different countries, may face major costs in the long-period to comply with new European-wide regulation, for instance the technical screening criteria identified in the EU Taxonomy for sustainable activities.[18] Similarly, investors might foreseen that adaptation strategies could be more financially costly in countries with weaker environmental social norms.

6 The Greta Thunberg effect

In this section, we explore the stock market effects of daily variations in attention to climate activism from the first Global Climate Strike through the end of June 2019.

[18]See the report by the Technical Expert Group on Sustainable Finance introducing the EU Taxonomy.

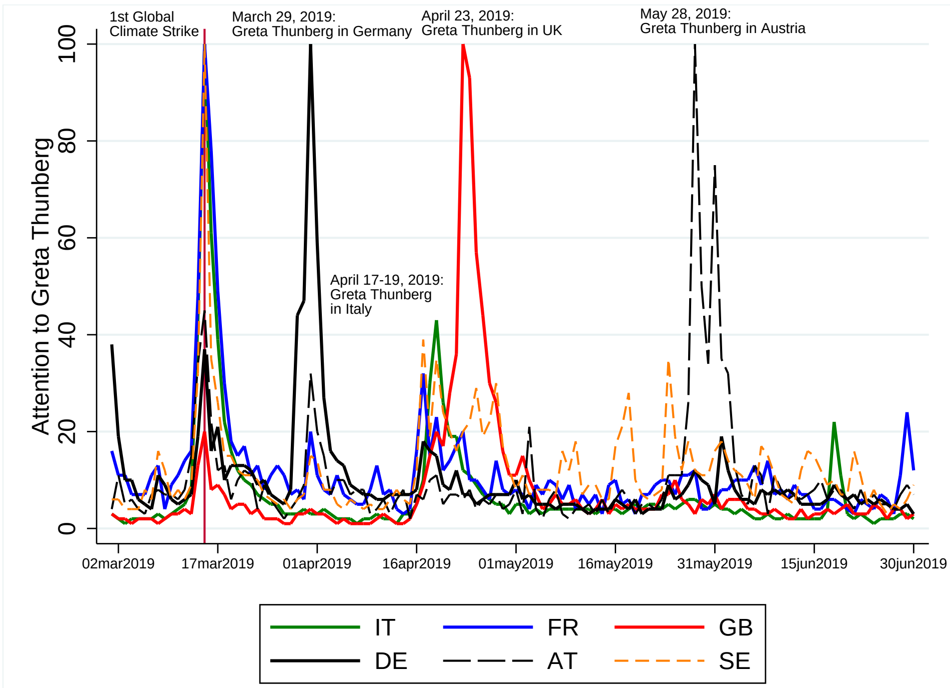
One of the peculiarities of the "FridaysForFuture" movement is to have a clear icon, the young activist Greta Thunberg. After the success of the Global Climate Strike on March 15, Greta Thunberg started an intensive travelling across Europe to lead various climate protests and met politician in several countries. In particular, on April 6, 2019, she gave a speech at the European parliament in Strasbourg; on April 17-19, she visited Rome, meeting the Pope and addressing the Italian parliament; on April 21-23, she was in London, joining the Extinction Rebellion protest and giving a speech at the UK parliament; on May 28, she was in Vienna giving a speech at the Austrian World Summit.[19] Greta Thunberg's international agenda caused an interesting heterogeneity in the level of attention to young climate activism across European countries.

Figure 6 shows the daily Google search activity to the topic "Greta Thunberg" from March 1 to June 30, 2019 for six European countries officially visited by the young activist in the same period.[20] Interestingly, the country-specific measures of daily attention spike exactly when the young activist is visiting the country, reflecting a higher increase in media coverage and general interest.

[19] See, e.g., The Guardian, "Greta Thunberg's train journey through Europe highlights no-fly movement", April 26, 2019.

[20] For an application of Google SVIs in a multi-country setting see Choi, Gao, and Jiang (2019).

Figure 4. Country-specific attention to Greta Thunberg.
The figure shows the daily country-specific Google Trends Search Value Index (SVI) for the topic "Greta Thunberg" from March 1, 2019 to June 30, 2019 (including non-trading days) for Italy, France, the United Kindgdom, Germany, Austria and Sweden. For each country, the index varies from 0 to 100 and represents search interest relative to the highest point on the chart.



To investigate the relationship between market returns and the attention on Greta Thunberg, we estimate the following model for daily abnormal returns $AR_{i,t}$ computed from March 20 (the first trading day outside our main event window) through June 30, 2019:

$$AR_{i,t} = \alpha + \beta_1 CI_i \times SVIGreta_{c,t} + \beta_2 CI_i + \beta_3 SVIGreta_{c,t} + X_i'\gamma + \epsilon_{i,t}, \qquad (4)$$

where $SVIGreta_{c,t}$ is the Google search value index (SVI) for the topics "Greta Thunberg" defined for each country c at date t. β_1 is the parameter measuring the interaction between carbon intensity level and the attention for Greta Thunberg.[21]

The results are reported in Table 13. The regressions also include country, sector, and day fixed effects. Looking at specification 1, the estimated interaction term of interest is negative and highly statistically significant. A peak of attention to "Greta Thunberg" ($SVIGreta = 100$) is associated with a 10 basis points under-performance per additional unit of carbon intensity (ktCOeq per millions USD of market value), which corresponds to around one half of the effect we estimated looking at the 5-day abnormal returns around the first Global Climate Strike. Even more economically significant results are obtained when using a measure of attention at the global level (specification 2), instead of a country-specific one, presumably because of the trading activities of investors on international markets.

Overall, these findings suggest that a higher level of attention to young climate activism is associated with a stronger penalization of carbon intensity on financial markets.

7 Conclusion

In recent years, the increasing concerns for the future effects of global warming have given rise to an unprecedented wave of environmental activism by young people.

In this paper, we study whether and how this call for bolder climate actions is influencing financial markets. By analyzing the stock prices of a large sample of European firms around the occurrence of the first Global Climate Strike in March 2019, we provide evidence of a loss in value of stocks of firms operating in high-polluting activities. The effect is likely

[21] Our approach of exploiting the international mobility of Greta Thunberg shares the same spirit of Lin et al. (2019), showing that when the the Dalai Lama visit non-Chinese countries are followed by a reduction in the host country's trade with China in following quarters. We thank Steven Ongena for having pointed this paper to us.

resulting from an update of investors' expectations about the environmental preferences in the economy and the future tightening of climate regulation.[22]

Our results are relevant for corporates, investors, and policy-makers. First, high-carbon intensity firms should anticipate that, as the degree of climate activism intensifies, their cost of capital is likely to increase further (see, e.g., in Heinkel, Kraus, and Zechner, 2001). Second, our results warn investors of the fact that the timing in the "stranding" of high-polluting assets is marked not only by the passing of new regulations, but also by perhaps more unpredictable shifts in environmental norms in the population. Not surprisingly, on July 2, 2019, the secretary general of the Organization of the Petroleum Exporting Countries (OPEC) declared that the growing mass mobilisation against high-polluting sectors is "perhaps the greatest threat" to the fossil fuel industry.[23]

Finally, our paper is also interesting in the context of current regulatory initiatives and future legislation aimed at stimulating businesses and investors to account for climate risks. For instance, the European Commission is setting in place a number of measures to making financial flows more consistent with a low-carbon economy, including the development of a EU-wide classification system (Taxonomy) for sustainable economic activities. Our results suggest that the upcoming climate-policy actions are likely to have significant stock market effects.

[22] Indeed, already in December 2019, the European Commission set out a European Green Deal for the EU28 countries to cut emissions by 50-55 percent against 1990 levels by 2030, strengthening the previous target mandates, and to reach net-zero emissions by 2050.

[23] See The Guardian, "Biggest compliment yet: Greta Thunberg welcomes oil chief's 'greatest threat' label", July 6, 2019.

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Tables

Table 1. Distribution of companies by country.
The table provides the percentage of the number of stocks for each country for the Eurostat sample (4, 108 stocks) and the Sustainalytics sample (1, 529 stocks).

Country	Country ISO code	Eurostat sample	Sustainalytics sample
United Kingdom	GB	23.32%	20.99%
France	FR	12.03%	10.27%
Germany	DE	10.81%	10.20%
Poland	PL	9.52%	2.75%
Sweden	SE	9.47%	16.22%
Italy	IT	5.40%	5.82%
Switzerland	CH	3.85%	6.67%
Spain	ES	3.53%	4.12%
Greece	GR	3.51%	1.57%
Finland	FI	3.07%	2.42%
Denmark	DK	2.73%	2.81%
Norway	NO	2.73%	4.45%
Netherlands	NL	2.24%	3.53%
Belgium	BE	2.17%	3.01%
Austria	AT	1.02%	1.77%
Romania	RO	0.83%	–
Ireland	IE	0.80%	1.05%
Portugal	PT	0.73%	0.85%
Hungary	HU	0.49%	0.26%
Bulgaria	BG	0.39%	–
Lithuania	LT	0.34%	–
Estonia	EE	0.32%	–
Cyprus	CY	0.24%	–
Czech Republic	CZ	0.17%	0.33%
Slovenia	SI	0.17%	–
Latvia	LV	0.12%	–
Slovakia	SK	0.02%	–
Luxembourg	LU	–	0.85 %
Total		100%	100%

Table 2. Distribution of stocks by GICS sectors.
The table provides the percentage of the number of stocks for each GICS sector for the Eurostat sample (4,108 stocks) and the Sustainalytics sample (1,529 stocks).

GICS	Eurostat sample	Sustainalytics sample
Industrials	21.03%	23.11%
Information Technology	14.00%	8.83%
Consumer Discretionary	13.02%	14.52%
Health Care	9.88%	9.22%
Telecommunication Services	7.52%	5.69%
Materials	7.47%	7.52%
Financials	7.45%	10.73%
Real Estate	6.96%	6.87%
Consumer Staples	5.40%	5.89%
Energy	4.43%	3.86%
Utilities	2.82%	3.73%
Total	100%	100%

Table 3. Summary statistics on stocks returns.
The table presents descriptive statistics on stocks returns of the Eurostat sample (Panel A) and of the Sustainalytics sample (Panel B). Throughout the paper, all returns are reported in percentage. CR and CAR indicated cumulative raw return and cumulative abnormal returns, respectively. CAPM-adjusted and 4F-adjusted returns are computed as defined in Equation (2). The table also reports descriptive statistics of the factor exposures computed on daily market excess return ($\hat{b}_m$), size ($\hat{b}_{smb}$), and value ($\hat{b}_{hml}$) factor returns, momentum return ($\hat{b}_{mom}$), and estimated constant ($\hat{a}$), from January 2, 2018 to December 31,2018.

	N	Mean	sd	p5	p25	p50	p75	p95
Panel A: Eurostat sample								
CAR (CAPM-adj.) from Mar 14 to Mar 20	4,108	-0.124	7.423	-8.381	-2.313	-0.228	1.961	8.673
CAR (4F-adj.) from Mar 14 to Mar 20	4,108	-0.007	9.274	-8.154	-2.087	-0.066	2.142	8.886
$\hat{b}_m$	4,108	0.819	1.156	0.182	0.509	0.779	1.091	1.610
$\hat{b}_{smb}$	4,108	0.911	9.396	-0.473	0.268	0.699	1.166	2.084
$\hat{b}_{hml}$	4,108	0.088	3.755	-1.020	-0.295	0.089	0.446	1.249
$\hat{b}_{mom}$	4,108	-0.014	2.546	-0.946	-0.349	-0.077	0.224	0.840
$\hat{a}$	4,108	0.070	2.619	-0.343	-0.098	-0.006	0.073	0.283
Panel B: Sustainalytics sample								
CAR (CAPM-adj.) from Mar 14 to Mar 20, 2019	1,529	0.413	4.063	-5.180	-1.222	0.257	2.013	5.583
CAR (4F-adj.) from Mar 14 to Mar 20, 2019	1,529	0.652	4.044	-4.580	-1.033	0.431	2.203	5.672
$\hat{b}_m$	1,529	1.058	0.370	0.514	0.806	1.029	1.268	1.693
$\hat{b}_{smb}$	1,529	0.587	0.683	-0.479	0.139	0.560	0.967	1.739
$\hat{b}_{hml}$	1,529	-0.053	0.682	-1.043	-0.440	-0.089	0.312	1.142
$\hat{b}_{mom}$	1,529	-0.059	0.506	-0.879	-0.334	-0.066	0.210	0.730
$\hat{a}$	1,529	-0.004	0.132	-0.200	-0.066	0.000	0.062	0.175

Table 4. Summary statistics on explanatory variables.
The table presents descriptive statistics of the carbon intensity and accounting variables in the Eurostat sample (Panel A) and the Sustainalytics sample (Panel B). *Carbon intensity (country-industry)* and *Carbon intensity (country-industry, output)* are reported as the ratio between greenhouse gasses and an industry's value added, or output (unit of measure kt of CO2 equivalents (ktCO2eq) per millions USD), respectively. *Carbon intensity (firm)* is computed as the total 2017 Scope 1 and 2 GHG emissions in kt of CO2 equivalents (ktCO2eq) obtained from the research provider Sustainalytics divided by market value of equity in million USD. In both sample, accounting variables refers to 2018 and are computed based on Compustat Global data as follows: Log market cap is the logarithm of firms' market capitalization in USD as of March 13, 2019; Leverage is defined as equity over total assets as; Profitability corresponds to the return on assets.

	N	Mean	sd	p5	p25	p50	p75	p95
Panel A: Eurostat sample								
Carbon intensity (country-industry)	4,108	0.323	0.903	0.001	0.008	0.030	0.093	2.130
Carbon intensity (country-industry, output)	4,108	0.111	0.287	0.001	0.005	0.013	0.037	0.657
Log market cap	4,108	19.016	2.424	15.283	17.232	18.907	20.723	23.162
Leverage	4,108	0.224	0.205	0.000	0.053	0.188	0.333	0.594
Profitability	4,108	-3.660	24.423	-49.309	-2.485	2.472	6.077	14.789
Panel B: Sustainalytics sample								
Carbon intensity (firm)	1,529	0.388	1.729	0.001	0.006	0.025	0.125	1.680
Log market cap	1,529	21.327	1.729	18.377	20.275	21.289	22.457	24.198
Leverage	1,529	0.239	0.173	0.000	0.107	0.223	0.347	0.535
Profitability	1,529	3.142	13.455	-8.953	1.245	3.841	7.397	16.709

Table 5. Main results – Eurostat sample.
The table reports estimation results of Equation (3) of the 5-day cumulative abnormal returns on the carbon intensity measure at industry-country level from Eurostat. Carbon intensity is computed as the kilotons of CO2 emission equivalents per gross value added in USD millions at the industry-country level. Specifications 2 and 3 also controls for basic firm characteristics (log market cap, leverage, and profitability). Specification 3 includes industry and country fixed effects. t-statistics based on robust standard errors are shown in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)
Dependent variable:	5-day CAR	5-day CAR	5-day CAR
Carbon intensity (country-industry)	-0.271***	-0.280***	-0.138
	(-3.035)	(-3.131)	(-1.187)
Log market cap		0.117**	0.128**
		(2.123)	(2.371)
Leverage		0.698	0.408
		(0.982)	(0.515)
Profitability		-0.002	-0.004
		(-0.237)	(-0.420)
Constant	-0.010	-2.417**	-2.616**
Observations	4,603	4,108	4,107
R-squared	0.001	0.003	0.020
Sector FE	No	No	Yes
Country FE	No	No	Yes

Table 6. Main results – Sustainalytics sample.
The table reports estimation results of Equation (3) of 5-day CAPM-adjusted cumulative returns on the firm-level carbon intensity measure from Sustainalytics, defined as kt of CO2 emission equivalents divided by the market value of equity in millions USD. Specifications 2 and 3 also controls for basic firm characteristics (log market cap, leverage, and profitability). Specification 3 includes industry and country fixed effects. t-statistics based on robust standard errors are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)
Dependent variable:	5-day CAR	5-day CAR	5-day CAR
Carbon intensity (firm)	-0.232***	-0.238***	-0.203***
	(-4.866)	(-4.870)	(-3.059)
Log market cap		0.046	0.009
		(0.524)	(0.083)
Leverage		0.366	0.272
		(0.546)	(0.366)
Profitability		-0.003	-0.003
		(-0.229)	(-0.229)
Constant	0.476***	-0.558	0.730
	(4.710)	(-0.293)	(0.294)
Observations	1,629	1,529	1,529
R-squared	0.009	0.011	0.055
Sector FE	No	No	Yes
Country FE	No	No	Yes

Table 7. Robustness I: Adjusted t-statistics.
The table reports estimation results of Equation (3) of the 5-day CAPM-adjusted cumulative returns on carbon intensity measures. Panel A and B refer to the Eurostat and Sustainalytics samples, respectively. Specifications 2 and 3 also controls for basic firm characteristics (log market cap, leverage, and profitability). Specification 3 includes industry and country fixed effects. t-statistics in brackets are adjusted for the empirical distribution of coefficients in a pre-event period from Jan 2 through Feb 28, 2019, following the approach in Cohn et al. (2016). ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

Panel A: Eurostat sample			
	(1)	(2)	(3)
Dependent variable:	5-day CAR	5-day CAR	5-day CAR
Carbon intensity (country-industry)	-0.271***	-0.280***	-0.138
	(-3.531)	(-4.872)	(-1.312)
Observations	4,603	4,108	4,107
R-squared	0.001	0.003	0.020
Panel B: Sustainalytics sample			
	(1)	(2)	(3)
Dependent variable:	5-day CAR	5-day CAR	5-day CAR
Carbon intensity (firm)	-0.243***	-0.260***	-0.232**
	(-2.892)	(-3.081)	(-2.408)
Observations	1,629	1,529	1,529
R-squared	0.010	0.013	0.048
Firm controls	No	Yes	Yes
Sector FE	No	No	Yes
Country FE	No	No	Yes

Table 8. Robustness II: Alternative returns as dependent variable.
The table reports estimation results of Equation (3) of the 5-day raw returns (CR) and of the 5-day Cahart-adjusted cumulative returns (4F-CAR) on carbon intensity measures. Panel A and B refer to the Eurostat and Sustainalytics samples, respectively. Specifications 2 and 3 also controls for basic firm characteristics (log market cap, leverage, and profitability). Specification 3 includes industry and country fixed effects. t-statistics based on robust standard errors are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

Panel A: Eurostat sample			
	(1)	(2)	(3)
Dependent variable:	5-day CR	5-day CR	5-day CR
Carbon intensity (country-industry)	-0.224***	-0.271***	-0.201*
	(-2.858)	(-3.524)	(-1.881)
Observations	4,603	4,108	4,107
R-squared	0.001	0.009	0.029
	(1)	(2)	(3)
Dependent variable:	5-day 4F-CAR	5-day 4F-CAR	5-day 4F-CAR
Carbon intensity (country-industry)	-0.354***	-0.369***	-0.162
	(-3.009)	(-2.962)	(-1.288)
Observations	4,603	4,108	4,107
R-squared	0.001	0.003	0.019
Panel B: Sustainalytics sample			
	(1)	(2)	(3)
Dependent variable:	5-day CR	5-day CR	5-day CR
Carbon intensity (firm)	-0.233***	-0.225***	-0.186***
	(-4.683)	(-4.507)	(-2.798)
Observations	1,633	1,533	1,533
R-squared	0.009	0.014	0.056
	(1)	(2)	(3)
Dependent variable:	5-day 4F-CAR	5-day 4F-CAR	5-day 4F-CAR
Carbon intensity (firm)	-0.243***	-0.260***	-0.232***
	(-4.973)	(-5.109)	(-3.445)
Observations	1,629	1,529	1,529
R-squared	0.010	0.013	0.048
Firm controls	No	Yes	Yes
Sector FE	No	No	Yes
Country FE	No	No	Yes

Table 9. Robustness III: Alternative carbon intensity definitions.
The table reports estimation results of Equation (3) of 5-day cumulative abnormal returns. Specifications 2 and 3 control for 2018 firm accounting data (market leverage, log market cap, and profitability). Specification 3 includes industry and country fixed effects. In Panel A, carbon intensity is obtained from Eurostat and is computed as CO2 emission equivalents in kilotons of output in million USD at the industry-country level. In Panel B, we replicate our main regressions with the Sustainalytics sample, using only the sub-sample of reporting firms. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. *t*-statistics based on robust standard errors are shown in parentheses.

Panel A: Carbon intensity from Eurostat, normalized by output			
	(1)	(2)	(3)
Dependent variable:	5-day CAR	5-day CAR	5-day CAR
Carbon intensity (country-industry, output)	-0.916***	-0.948***	-0.413
	(-2.681)	(-2.740)	(-0.955)
Observations	4,603	4,108	4,107
R-squared	0.001	0.003	0.020
Panel B: Carbon intensity from Sustainalytics, reporting firms			
	(1)	(2)	(3)
Dependent variable:	5-day CAR	5-day CAR	5-day CAR
Carbon intensity (firm)	-0.339***	-0.320***	-0.275***
	(-7.850)	(-7.476)	(-4.901)
Observations	747	707	707
R-squared	0.035	0.043	0.105
Firm controls	No	Yes	Yes
Sector FE	No	No	Yes
Country FE	No	No	Yes

Table 10. Robustness IV: Excluding financial firms.
The table reports estimation results of Equation (3) of 5-day cumulative abnormal returns, excluding financial firms. Regressions in Panel A use the sample and carbon intensity measure from Eurostat, while regressions in Panel B use the sample and carbon intensity measure from Sustainalytics. Specifications 2 and 3 control for basic firm characteristics (leverage, size, and profitability). Specification 3 includes industry and country fixed effects. *t*-statistics based on robust standard errors are shown in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

Panel A: Eurostat sample			
	(1)	(2)	(3)
Dependent variable:	5-day CAR	5-day CAR	5-day CAR
Carbon intensity (country-industry)	-0.250***	-0.280***	-0.143
	(-2.768)	(-3.095)	(-1.206)
Observations	4,057	3,802	3,801
R-squared	0.001	0.003	0.020
Panel B: Sustainalytics sample			
	(1)	(2)	(3)
Dependent variable:	5-day CAR	5-day CAR	5-day CAR
Carbon intensity (firm)	-0.223***	-0.218***	-0.179***
	(-4.598)	(-4.495)	(-2.997)
Observations	1,409	1,365	1,365
R-squared	0.010	0.013	0.050
Firm controls	No	Yes	Yes
Sector FE	No	No	Yes
Country FE	No	No	Yes

Table 11. Environmental social norms and policy stringency by country.
This table shows the average environmental social norms and environmental policy stringency for countries included in our analyses and for which the scores are available. We standardized both measures to have mean zero and unit standard deviation.

Country	Environmental social norms (z-score)	Environmental policy stringency (z-score)
AT	0.213	0.004
BE	0.120	-0.791
CH	1.147	0.578
CZ	-2.740	-0.930
DE	0.867	0.315
DK	.	1.505
ES	0.146	-1.206
FI	0.769	0.806
FR	1.199	1.062
GB	0.163	1.477
GR	.	-1.345
HU	-1.766	-0.515
IE	-0.052	-1.483
IT	-0.641	0.564
NL	-0.038	1.131
NO	0.415	0.523
PT	-0.341	-0.612
PR	-0.133	-1.345
SE	0.672	0.260
Total	0.000	0.000

Table 12. Channels: Environmental social norms and policy stringency.
The table reports estimation results of Equation (3) of 5-day cumulative abnormal returns on Sustainalytics sample. In Panel A, specification 1 (2) refers to countries with low (high) environmental social norms. Similarly, in Panel B specification 1 (2) refers to countries with low (high) environmental policy stringency. All specifications includes firm controls, sector and country fixed effects. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. *t*-statistics based on robust standard errors are shown in parentheses.

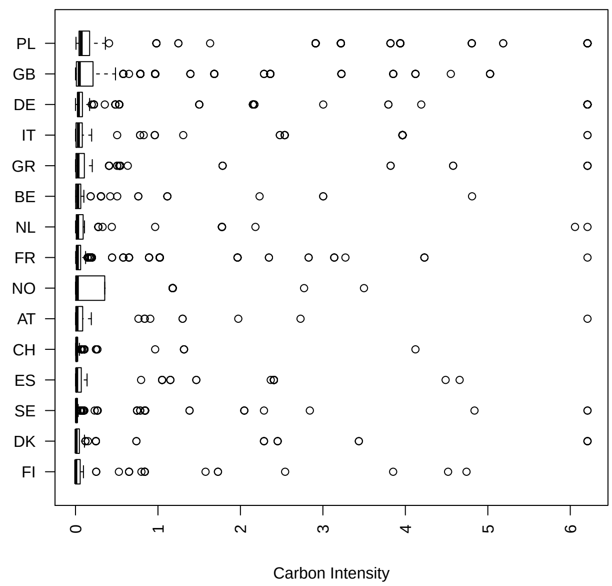
	(1)	(2)
Dependent variable:	5-day CAR	5-day CAR
Panel A: Environmental social norms		
	Low	High
Carbon intensity (firm)	-0.328***	-0.164
	(-3.773)	(-1.151)
Observations	680	768
R-squared	0.089	0.059
Panel B: Environmental policy stringency		
	Low	High
Carbon intensity (firm)	-0.239***	-0.165
	(-3.211)	(-1.075)
Observations	712	803
R-squared	0.062	0.060
Firm controls	Yes	Yes
Sector FE	Yes	Yes
Country FE	Yes	Yes

Table 13. Carbon intensity and the Greta Thunberg effect.
The table reports estimation results of Equation (3) of daily CAPM-adjusted returns from March 20, 2019 to June 30, 2019 (69 trading days) on the interaction between the firm-level carbon intensity from Sustainalytics and the Google search value index (SVI) for the topics "Greta Thunberg" (SVI Greta), and on the direct effects of both variables. Specification 1 uses the SVI at country-level, while specification 2 uses the SVI at global level. The regressions also control for firm characteristics (size, leverage, and profitability) and sector fixed effects. *t*-statistics based on robust standard errors are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

	(1)	(2)
Dependent variable:	AR	AR
Carbon intensity (firm) × SVI Greta (country)	-0.001***	
	(-3.367)	
Carbon intensity (firm) × SVI Greta (global)		-0.003***
		(-4.535)
Carbon intensity (firm)	0.001	0.022**
	(0.232)	(2.542)
SVI Greta (country)	0.005***	
	(6.317)	
SVI Greta (global)		-0.044***
		(-6.649)
Observations	102,751	102,751
R-squared	0.001	0.001
Firm controls	Yes	Yes
Country FE	Yes	Yes
Day FE	Yes	Yes
Sector FE	Yes	Yes

Figure 5. Distribution of Carbon intensity (country-industry) by countries, Eurostat sample.
Panel A shows the distributions of carbon intensity (country-industry) for each country with at least 1% of companies in the sample. In order to highlight the heterogeneity between data, Panel B shows the distributions focusing on a limited scale (from 0 to 1) of carbon intensity.

Panel A



Panel B

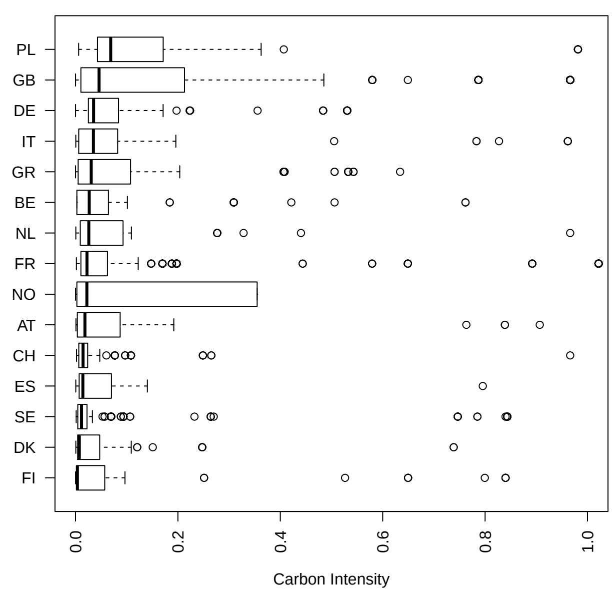
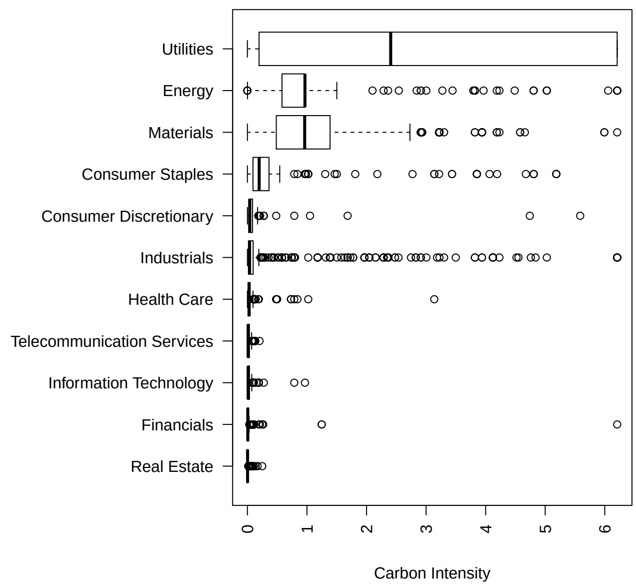
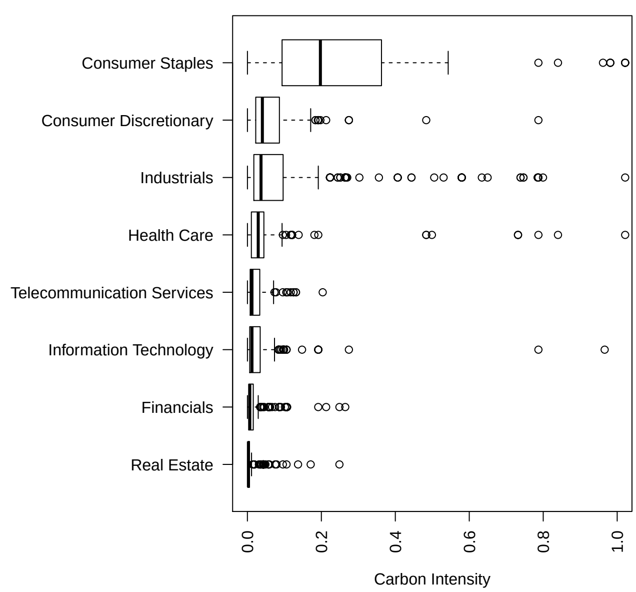


Figure 6. Distribution of carbon intensity (country-industry) by sectors, Eurostat sample.
Panel A shows the distributions of carbon intensity (country-industry) for each GICS sector. In order to highlight the heterogeneity between data, Panel B shows the distributions focusing on a limited scale (from 0 to 1) of carbon intensity.

Panel A



Panel B



Supplementary Appendix

Table A1. List of major stock exchanges.
The table provides the list of Stock Exchanges in which the stocks in our samples are listed.

Stock Exchange	Country	Country
London	United Kingdom	GB
NYSE Euronext Paris	France	FR
Paris	France	
Frankfurt	Germany	DE
IBIS	Germany	
Warsaw	Poland	PL
Stockholm	Sweden	SE
Milan	Italy	IT
Zurich	Switzerland	CH
SWX Swiss Exchange	Switzerland	
Madrid	Spain	ES
Athens	Greece	GR
Helsinki	Finland	FI
Copenhagen	Denmark	DK
Oslo	Norway	NO
Luxembourg City	Luxembourg	LU
NYSE Euronext Amsterdam	Netherlands	NL
NYSE Euronext Brussels	Belgium	BE
Vienna	Austria	AT
Bucharest	Romania	RO
Irish	Ireland	IE
Lisbon	Portugal	PT
Budapest	Hungary	HU
Sofia	Bulgaria	BG
Vilnius	Lithuania	LT
Tallinn	Estonia	EE
Nicosia	Cyprus	CY
Prague	Czech Republic	CZ
Ljubljana	Slovenia	SI
Riga	Latvia	LV
Bratislava	Slovakia	SK

Table A2. Distribution of the number of observations available for each company. The table reports the percentage number of stocks with respect to the their buckets of number of daily observations in 2018.

Number of daily obs.	Frequency
$127 \leq 140$	1.73%
$141 \leq 170$	2.93%
$171 \leq 200$	5.79%
$201 \leq 230$	10.53%
$231 \leq 258$	79.02%

Figure A1. Placebo test: Stock-market carbon price in January 2019. The figure shows the evolution of regression estimates of the effect of *Carbon intensity (firm)* on CAPM-adjusted cumulative abnormal returns from January 2 through January 31, 2019, controlling for sector and firm characteristics. The cumulation of returns starts on January 2, 2019 (day -51). The graph also plots the 95% confidence intervals around estimates.