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Investor Attention to the Fossil Fuel Divestment Movement and Stock Returns

Imane El Ouadghiri, Mathieu Gomes, Jonathan Peillex, Guillaume Pijourlet

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Abstract

This study investigates whether investor attention to the fossil fuel divestment (FFD) movement is related to the stock returns of firms involved in extracting fossil fuels. We consider three complementary indicators of investor attention to the FFD movement: (1) the US weekly Google Search Volume Index on the topic “fossil fuel divestment,” (2) the US weekly media coverage of fossil fuel divestment, and (3) the number of weekly visits to the “fossil fuel divestment” page on Wikipedia. Based on a sample of weekly returns on 1,850 US firms over the period 2012-2020, our econometric estimations report a positive relationship between investor attention to FFD and excess stock returns for US fossil fuel-related firms. Therefore, contrary to what the FFD campaigners might expect, the stigmatization of the fossil fuel industry does not drive down the stock returns on fossil fuel-related firms.

Keywords: fossil fuel divestment, stock returns, investor attention, fossil fuel-related firms

JEL: G11, G15, Q41, Q54

1. Introduction

The fossil fuel divestment (FFD) movement aims to urge investors—particularly institutional investors—to divest their holdings of investment in firms that extract coal, gas, and oil. As nearly two-thirds of carbon dioxide (CO₂) emissions come from the burning of fossil fuels,¹ the proponents of this social movement posit that reducing capital flows to the fossil fuel sector could help address climate change (Belfiori, 2021).

The FFD movement was born at US universities in 2010 and has become increasingly popular over time. For instance, the number of institutions (including pension funds, large banks, faith-based organizations, and philanthropic foundations) committed to divestment from fossil fuel assets rose from 50 in 2013 to 1,225 in 2020, representing more than \$14 trillion in assets.² Historically, the FFD movement has grown faster than any other previous divestment movements including those against the tobacco industry and apartheid policies in South Africa (e.g., Vaughan, 2014).

While many prominent financial institutions have made public statements about embracing the FFD movement, in reality, few of them are actively divesting assets related to the fossil fuel industry. For instance, according to a recent report from several climate organizations, 33 out of the 60 World's largest banks have increased their supply of financial capital to the fossil fuel industry between 2016 and 2020 (Kirsch et al., 2021). In the same vein, the CEO of BlackRock, one of the world's largest investment firms, stated in 2020 that he was taking measures to “*exit investments that present a high sustainability-related risk, such as thermal coal producers and*

¹ IPCC (2014). Mitigation of climate change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, 1454, <https://www.ipcc.ch/report/ar5/wg3/>.

² <https://www.statista.com/statistics/1090801/value-fossil-fuel-divestments-worldwide/>, accessed July 7, 2021.

launch new investment products that screen fossil fuels”.³ However, one year after this statement, BlackRock is still massively investing in firms producing coal for a total of \$85bn assets under management (Cuvelier et al., 2021).

In fact, even though the real amounts divested from fossil fuel companies are still moderate, the FFD movement might have side effects such as the stigmatization of the fossil fuel industry (Ferns et al., 2021). As a symbolic tool of stigmatization, the FFD movement might pressure fossil fuel–related firms to reduce their carbon emissions and the government to enact new policy changes and regulations against the extraction of fossil fuel–based energy sources (e.g., Byrd and Cooperman, 2017). This may drive a large number of investors to revise downwards their estimates of future net cash flows and, in turn, reduce their assessment of the intrinsic value of stigmatized firms. Another potential consequence of this social movement is the reduction of investor demand for fossil fuel–related stocks that might drive down their stock prices.

Notwithstanding the expansion of the FFD movement worldwide, we still have limited knowledge of their potential implications for fossil fuel–related stocks. In particular, we do not know whether the FFD movement, as a stigmatization process, affects returns on fossil fuel stocks. In this study, we shed light on this question by examining how investor attention to the FFD phenomenon might affect the prices of fossil fuel–related stocks.

Existing research on FFD is relatively scarce, and the majority of the available papers investigate the financial consequences of applying a FFD strategy—a portfolio strategy that simply excludes fossil fuel–related stocks—from the investor’s point of view (e.g., Henriques and Sadorsky, 2017; Trinks et al., 2018; Plantinga and Scholtens, 2021). These studies document a marginal difference in risk-adjusted returns between portfolios with and without

³ <https://www.blackrock.com/corporate/investor-relations/blackrock-client-letter>,

fossil fuel–related stocks. However, just because a screening strategy –which consists in excluding fossil fuel stocks from the portfolio– has no significant impact on the financial performance of that portfolio does not mean that fossil fuel stocks have not been affected by the FFD movement. As such, these studies do not advance our understanding of the financial effects of the FFD movement from the perspective of the fossil fuel companies. In particular, they do not explicitly explore whether and to what extent the FFD movement affects the stock returns of fossil fuel companies. Thus, our paper contributes to this strand of literature by being the first to explicitly investigate the potential consequence of this social movement on the stock prices of companies targeted by this movement.

As with all social movements, it is arguable that the strength of the FFD movement depends, at least in part, on the investor attention it generates. Therefore, to address our main question, we empirically assess the effect of investor attention to FFD on the weekly excess stock returns for US firms that supply coal, gas, or oil in comparison with US non–fossil fuel firms. In line with the literature on investor attention (e.g., Cziraki et al., 2021; Focke et al., 2020), we use three complementary indicators of investor attention to the FFD movement: (1) the US weekly Google Search Volume Index on the topic “fossil fuel divestment,” (2) the US weekly media coverage of FFD, and (3) the number of weekly visits to the Wikipedia page on “fossil fuel divestment.”

Contrary to what might be potentially expected by the FFD campaigners, our econometric estimations report a positive relationship between investor attention to FFD and the excess returns of US fossil fuel–related stocks. This positive effect is remarkably robust even after we control for firm-level and energy-level variables as well as for widely accepted risk factors, such as market, size, value, and momentum. This finding also holds when we consider alternative investor attention proxies and alternative empirical approaches including difference-in-differences analyses.

We advance one possible mechanism that would explain the positive effect of investor attention to the FFD movement on the returns of fossil fuel–related stocks. Specifically, we show that increased attention to the FFD movement leads investors to follow fossil fuel–related stocks more closely. Therefore, profit-motivated traders might view fossil fuel–related stocks as structurally undervalued and find it financially beneficial to allocate resources to those stocks. In line with this explanation, our sample data reveal indications of that potential undervaluation. Indeed, we find that, on average, fossil fuel–related US stocks did worse than US non–fossil fuel stocks in terms of their mean returns and standard deviation of returns, and they have lower average price-to-book ratios over the period 2012-2020.⁴ These results are consistent with the idea that the fossil fuel industry is an industry neglected by a portion of stock market participants as is the case for sin industries (e.g., gambling, tobacco, or alcohol). As such, previous studies on sin industries (e.g., Hong and Kacperczyk, 2009; Fabozzi et al., 2008) reveal for instance that sin stocks are undervalued and experience higher returns than comparables. They explain this result by societal norms leading an important portion of investors to neglect sin stocks, making them cheaper than other stocks, and thus depressed relative to their fundamental values.

Our study makes several important contributions to the literature. First, we contribute to the narrow literature on the effect of social movements, such as activist protests (e.g., King and Soule, 2007) and divestment campaigns in reaction to apartheid policies in South Africa (e.g., Wright and Ferris, 1997), on the market value of targeted firms. We analyze a novel social

⁴ Another explanation that is not specifically and empirically tested in the article could have been the following: The attention to stigmatization campaigns of fossil fuel firms may increase their exposure to reputational as well as litigation risk, leading to higher expected returns because of the positive association between returns and risk.

movement—the movement to divest from fossil fuels—and reveal that it positively influences the returns of fossil fuel–related stocks.

Second, fossil fuel–related stocks, to a certain extent, are comparable to “sin” stocks, i.e., those related to gambling, tobacco, or alcohol. This type of stock might be stigmatized because of potential reluctance by investors to finance companies that promote human vices or that make profits by exacerbating climate risk. Therefore, our research expands the literature that examines the financial performance of assets neglected by some stock market participants (e.g., Fabozzi et al., 2008; Hong and Kacperczyk, 2009; Colonnello et al., 2019).

Third, our empirical analyses reveal that investor attention to the FFD movement has become an important driver of the financial performance of fossil fuel–related stocks. This result adds to the literature on fossil fuel industry stocks that examines the determinants of their financial performance. In particular, this body of literature points out the importance of changes in energy prices (e.g., Arouri, 2011; Broadstock et al., 2016; Dhaoui et al., 2020; Rahman and Serletis, 2019) as well as in social and environmental performance (Brzezczński et al., 2019) in explaining the returns and volatility of energy–related stocks.

Finally, we extend the emerging literature that analyzes how investor attention to environmental issues, such as natural disasters (e.g., Kollias and Papadamou, 2016), climate change (e.g., El Quadghiri et al., 2021), global warming (e.g., Choi et al., 2020), and climate–related policy events (e.g., Monasterolo and De Angelis, 2020), influence returns on sustainable stocks.

The paper proceeds as follows. Section 2 presents the data and summary statistics. Section 3 describes the methodology. Section 4 provides and discusses the empirical results. Section 5 concludes the article.

2. Data

We use various sources to examine the influence of investor attention to FFD on the stock returns of US firms that supply coal, gas, or oil in comparison with US non-fossil fuel firms. In this section, we describe the datasets we use and the variables we consider in our econometric analyses.

2.1. Investor Attention to the Fossil Fuel Divestment Movement

We use the US weekly Google Search Volume Index (GSVI) on the topic “fossil fuel divestment” as the first proxy for investor attention to the FFD movement. We consider topics and not search terms because it allows us to capture searches with misspellings and different searches with the same meaning (e.g., Choi et al., 2020). In fact, Google offers free access to the search volume history on any topic or keyword in a given geographic area with the Google Trends tool.⁵ The main advantage of the GSVI is that every day billions of queries are searched on Google. Consequently, the volume of these queries might accurately reflect public attention (e.g., Da et al., 2011). Technically, the GSVI is expressed in relative values, i.e., the number of searches on a term or topic divided by the total number of searches in that region during the sample period being examined. These data are normalized between 0 and 100, where 0 is assigned when the relative number of searches is very low or null, and 100 is the peak of search intensity during the specified sample period and region.

The main limitation of using the GSVI is that it only takes into account the attention of people who actively search for information on Google. Nonetheless, people who do not search for information on FFD using this search engine are not necessarily unfamiliar with this social

⁵ <https://trends.google.com/trends/?geo=US/>.

movement. For example, they may have received information about FFD from traditional media.⁶

Therefore, we also use media coverage (MC) on “fossil fuel divestment” as a complementary indicator for investor attention to this social movement. Specifically, we measure the media coverage of FFD by the weekly number of articles related to this movement published in the United States. Following Fang and Peress (2009) and El Ouadghiri and Peillex (2018), we examine four US newspapers: the *New York Times*, the *Wall Street Journal*, the *Washington Post*, and *USA Today*. These four national newspapers are characterized by a wide circulation and strong influence on the investor community (e.g., Fang and Peress, 2009). In accordance with Guriev and Melnikov (2016), we retrieve these data from Factiva. Our media coverage data comprise 151 newspaper articles related to FFD, published between 2012 and 2020.

Figure 1 depicts the evolution of the GSVI (blue line) and media coverage (gray line) for FFD in the United States over the period 2012-2020. The GSVI for FFD starts to increase in mid-2012, whereas the first news articles on this topic appear at the end of 2012. As seen in the figure, the values for GSVI and media coverage are particularly high from 2014 to 2016, which indicates that these two data series might illustrate a trend. These two indicators for public attention to FFD mostly demonstrate similar movement. Moreover, most of their peaks coincide with announcements of divestment commitments by well-known institutions, which reveals the suitability of using the GSVI and media coverage as proxies for public awareness of the FFD movement. For instance, the big peak in April 2013 (Event 1) can be attributed to the

⁶ One could argue that another risk is that people may seek information on FFD using search engines other than Google. However, this is a relatively minor concern given Google’s largely dominant market share as it accounts for roughly 80% of the global breakdown of search engine users across desktop/laptop and mobile devices (<https://netmarketshare.com>).

announcement by the San Francisco Employees' Retirement System (SFERS) that it would henceforth exclude fossil fuel producers from its portfolio,⁷ and that of April 2014 (Event 2) can be explained by the publication of an open letter by a hundred professors at Harvard University arguing for FFD.⁸ In the same vein, the two highest values in February and April 2015 (Events 3 and 4, respectively) can be explained by protests (including marches and a blockade of buildings on campus) by Harvard alumni to urge universities to divest their stakes in fossil fuels.⁹ Finally, the peak in February 2020 (Event 5) coincides with the official decision by Georgetown University to divest from publicly listed fossil fuel companies.¹⁰ These five events are used in Section 4.2.4. "Difference-in-Differences (DiD) Analysis" as quasi-natural experiments capturing intense variations in investor attention to the FFD movement.

Insert Figure 1 Around Here

Following Da et al. (2011) and Cziraki et al. (2021), we transform the GSVI and the media coverage of FFD into abnormal measures to neutralize the trend followed by these two indicators. Thus, we consider the natural logarithm of the ratio of one plus the GSVI during the week to its average during the previous eight weeks (AGSVI). We follow the same transformation process for media coverage to obtain the AMC.¹¹ In order to examine the

⁷ https://www.huffpost.com/entry/san-francisco-fossil-fuel-divestment_n_3158012/.

⁸ <https://www.theguardian.com/environment/2014/apr/10/harvard-faculty-letter-divest-fossil-fuels-oil/>.

⁹ <https://www.msnbc.com/msnbc/fossil-fuel-divestment-protests-hit-colleges-nationwide-msna576456/> and <https://www.thecrimson.com/article/2015/3/30/faust-disapproves-divest-occupation/>.

¹⁰ <https://www.georgetown.edu/news/fossil-fuels-divestment-continues-georgetown-commitment-to-sustainability/>.

¹¹ As an additional robustness check, we also consider twelve prior weeks to estimate our main independent variables. When we use this alternative estimation window, the estimation results we obtain are qualitatively similar to those presented in the paper.

stationarity of our data, we have applied the usual unit root tests for panel datasets (i.e., the Breitung (2001), the Levin–Lin–Chu (2002), and the Im–Pesaran–Shin (2003) test) for the main explanatory variables. These tests provide no evidence of a unit root in these series, suggesting that our econometric analysis is not subject to spurious regression issues.¹²

2.2. Stock and Firm Information

We use the excess weekly returns of US fossil fuel stocks (treated group) and US non–fossil fuel stocks (control group) as dependent variables. To construct these dependent variables, we start by retrieving the weekly individual stock prices of all US stocks in the Russell 3000 index from the Bloomberg terminal. This US equity index includes the 3,000 largest US companies, representing approximately 90 percent of total US equity market capitalization (Da et al., 2011).

We use the Standard Industry Classification (SIC) codes to differentiate fossil fuel–related stocks from non–fossil fuel stocks. In accordance with Trinks et al. (2018), we consider a company involved in the extraction, production, or commercialization of fossil fuel energy if it is assigned at least one of these SIC codes: 12 (coal mining), 3532 (mining machinery), 13 (oil and gas extraction), 291 (petroleum refining), 3533 (oil and gas field machinery and equipment), 46 (pipelines, except natural gas), and 492 (gas production and distribution).

We then omit firms for which at least one observation is missing, which leads us to remove 1,150 stocks. Our final sample consists of 815,850 weekly observations on 1,850 unique US firms, including 88 fossil fuel–related firms and 1,762 non–fossil fuel firms. The sample period is from January 1, 2012, when the FFD movement began to gain media attention, to June 19, 2020. The majority of US fossil fuel–related firms are involved in oil and gas extraction (41%). Among the remaining fossil fuel–related firms, 23% specialize in gas production and

¹² The corresponding results are not reported due to brevity, but are available upon request.

distribution, 15% in petroleum refining, 8% in mining machinery, 8% in oil and gas field machinery and equipment, and 6% in coal mining. In Table 1, the first rows of Panels B and C list some statistics on the variable for excess stock returns (i.e., the dependent variable). On average, it appears that the weekly excess returns are lower for US fossil fuel-related stocks than for US non-fossil fuel stocks in the period 2012-2020 (i.e., -0.177 versus 0.114, respectively). In terms of the standard deviation of the weekly excess returns, US fossil fuel-related stocks are also riskier than US non-fossil fuel stocks (i.e., 6.902 versus 5.564, respectively). Taken together, these results indicate that, on average, US fossil fuel-related stocks underperform US non-fossil fuel stocks over the sample period.

2.3. Control Variables

In line with the extant literature (e.g., Da et al., 2011; Cziraki et al., 2021), we use various firm-level control variables that have been shown to influence stock returns. Specifically, our models include firm size, measured by the natural logarithm of market capitalization (SIZE), the natural logarithm of return on assets (ROA), the cumulative return on the stock over the previous 52 weeks (RET), the conditional weekly volatility estimated with a GARCH (1,1) model (VOL), the Amihud illiquidity ratio (2002) (ILLIQ) measured by the natural logarithm of the ratio of the absolute value of the weekly return on the stock to its trading volume during the same week, analyst coverage measured by the natural logarithm of the number of analysts covering the stock (AC), and, finally, the natural logarithm of the percentage of institutional ownership (INST). All variables are collected from the Bloomberg terminal.

Second, in accordance with the literature on energy stocks (e.g., Broadstock et al., 2016; Rahman and Serletis, 2019), we also consider the weekly changes in fossil fuel prices as additional control variables. To calculate changes in coal ($\Delta COAL$), gas (ΔGAS), and oil (ΔOIL) prices, we use the weekly spot price for ICE Newcastle coal (e.g., Alim et al., 2018) and the

weekly spot price for Henry Hub gas (e.g., Arora and Lieskovsky, 2014) and Brent crude oil (e.g., Guesmi et al., 2018; Abdel-Latif et al., 2020), respectively.

Finally, following Scholtens and Wang (2008) and Mohanty and Nandha (2011), we incorporate the four traditional risk factors (Carhart, 1997) into our econometric estimation.¹³ We extract weekly excess returns on the US market (RM-RF), the size factor (SMB), the value factor (HML), and the momentum factor (MOM) from the Kenneth R. French data library. RM-RF is the weekly value-weight return of all CRSP firms in the US market and listed on the NYSE, AMEX, or NASDAQ minus the weekly Treasury bill rate. SMB is the average return on “small” US portfolios minus the average return on “big” US portfolios. HML is the average return on US “value” portfolios minus the average return on US “growth” portfolios, and MOM is the difference between the average return for US “winner” portfolios and the average return on US “loser” portfolios. Table 2 provides the definitions of all the variables used in our empirical analysis.

Insert Table 1 Around Here

Insert Table 2 Around Here

Table 1 also reports the summary statistics for the main independent variables (see Panel A), firm-level controls (Panels B and C), and market-level controls (Panel D). As can be seen in Panels B and C in Table 1, the 88 US fossil fuel–related firms and the 1,762 US non–fossil fuel firms are very similar in terms of all firm-level variables. For instance, the average value of SIZE, ROA, AC, and INST is 8.12, 0.48, 2.65, and 4.35 for fossil fuel–related firms and 7.59,

¹³ Instead of a Carhart four-factor model, we also base our econometric estimations on an extended version of the Fama-French three-factor model and an extended version of the CAPM model. The results are almost identical to those reported in the article.

1.06, 2.15, and 4.36 for non-fossil fuel firms, respectively. This reveals that non-fossil fuel firms on the Russell 3000 index can be considered a suitable control sample for fossil fuel-related firms.

3. Methodology

We assess the effect of investor attention to FFD on the weekly excess returns of US fossil fuel-related stocks (treatment group) in comparison with US non-fossil fuel stocks (control group) using pooled panel models with interaction effects. This method enables us to control for fluctuations in US stock prices when the attention to FFD varies, and fluctuations in the stock prices for US fossil fuel-related firms that are not necessarily related to changes in investor attention to FFD.

As such, our first econometric model investigates the impact of the weekly Google search volume on “fossil fuel divestment” on the weekly excess returns on US stocks after controlling for the two confounding trends described above. It takes the following form:

$$R_{it} - R_{ft} = \alpha_0 + \beta_1 FF_{it} + \beta_2 AGSVI_t + \beta_3 FF_{it} * AGSVI_t + Y'X_{it} + \theta_t + \mu_i + \varepsilon_{it} \quad (1)$$

where the dependent variable $R_{it} - R_{ft}$ is the weekly excess return on stock i in week t . In this column vector, we pool the weekly excess returns on 1,850 US stocks (i.e., 88 US fossil fuel-related stocks and 1,762 US non-fossil fuel firms) over the sample period January 2012 to June 2020. FF_{it} is a dummy variable coded as one if stock i is a fossil fuel-related stock, and zero otherwise.¹⁴ $AGSVI_t$ is the abnormal Google search volume index on “fossil fuel divestment”

¹⁴ To prevent any collinearity issues between the time-invariant dummy variable FF_{it} and fixed effects, we perform three robustness checks. First, we remove the term FF_{it} from the equations, Second, we re-estimate the equations excluding fixed effects and finally we re-estimate the equations including random effects. The estimation results

in week t . The interaction variable $FF_{it} * AGSVI_t$ is the main variable of interest. β_3 captures the influence of $AGSVI_t$ on changes in excess returns on the 88 US fossil fuel–related stocks. X is a vector of control variables, which includes variables at the firm level, the weekly changes in fossil fuel prices, and the four traditional risk factors (Carhart, 1997). θ_t denotes year-fixed effects, and μ_i expresses industry-fixed effects on the basis of the first two digits of the SIC code. We use year-fixed effects on US stock returns to control for factors that change every year and are common to all firms in a given year (e.g., the COVID-19 pandemic).¹⁵ Finally, ε_{it} is the error term.

In the same spirit, our second pooled-panel model with interaction effects allows us to compare the impact of weekly media coverage of FFD on 88 US fossil fuel–related firms with the corresponding effect on 1,762 US non–fossil fuel firms. This model is as follows:

$$R_{it} - R_{ft} = \alpha_0 + \beta_1 FF_{it} + \beta_2 AMC_t + \beta_3 FF_{it} * AMC_t + Y' X_{it} + \theta_t + \mu_i + \varepsilon_{it} \quad (2)$$

where AMC_t is abnormal media coverage of FFD in week t . The estimator β_3 of the interaction term $FF_{it} * AMC_t$ indicates the effect of media coverage on the FFD phenomenon on excess returns on US fossil fuel–related stocks in comparison with US non–fossil fuel firms. All other variables are the same as in Equation (1).

4. Results

4.1. Main results

remain very similar to those presented in the article. The estimation results are not displayed here due to space limitations, but are available upon request.

¹⁵ In fact, we reproduced all the empirical analyses by excluding the COVID-19 period and the results remain almost identical to those reported in the paper.

4.1.1. Effect of investor attention to the FFD movement

In this section, we present the results of the pooled-panel regressions to examine the continuous effect of investor attention to FFD on weekly excess returns on 88 US fossil fuel–related stocks, considering a control group of 1,762 US non–fossil fuel firms.

Insert Table 3 Around Here

Models 1-2 in Table 3 assess the influence of the AGSVI for “fossil fuel divestment” on excess stock returns. In Model 1, we first show the regression results for the explanatory variables of interest (AGSVI) only. The parameter estimates for the interaction term between the dummy variable FF and AGSVI are positive and statistically different from zero at the 5 percent level ($\beta_3 = 0.061$). In Model 2, we augment this baseline model by including firm- and market-level control variables (i.e., the full model described in Eq. (1)). The estimated coefficient associated with the interaction variable FF*AGSVI is still positive and statistically significant at the 5 percent level ($\beta_3 = 0.047$). These first estimation results suggest that excess returns on US fossil fuel–related stocks are positively related to the intensity of search queries on Google on the FFD movement.

Models 3-4 in Table 3 estimate the impact of AMC to FFD on excess stock returns. Model 3 corresponds to the baseline model whereas Model 4 is the full model, including all control variables. In these two specifications, the estimated coefficients for the interaction variable FF*AMC are also significantly positive (i.e., $\beta_3 = 0.071$ and $\beta_3 = 0.067$, according to Models 3 and 4, respectively). This second set of results reveals that returns on US fossil fuel–related stocks are also positively associated with media coverage of the FFD movement. Therefore, the observed positive link between investor attention to FFD and excess returns on fossil fuel–related stocks is confirmed when we consider this alternative indicator to measure investor attention to FFD.

Regarding the results for control variables, Models 2 and 4 in Table 3 show that the estimated parameters for firm-level variables are statistically significant. In line with the financial literature (e.g., Da et al., 2011; Cziraki et al., 2021), firm size, return on assets (ROA), the previous cumulative stock returns (RET), conditional volatility (VOL), the illiquidity ratio (ILLIQ), and the percentage of institutional ownership (INST) are positively related to excess stock returns, whereas analyst coverage (AC) has a negative impact on stock returns. Moreover, in accordance with the literature on the energy–stock prices nexus (e.g., Driesprong et al., 2008), we find a negative relationship between changes in fossil fuel prices (ΔCOAL , ΔGAS , and ΔOIL) and stock returns. We also observe that returns on US stocks are significantly exposed to each of the risk factors (i.e., RM-RF, SMB, HML, and MOM). Thus, in line with Brzeszczyński (2019), we base our analysis on an extension of the Carhart four-factor model to explain the excess returns on US stocks. In addition, the negative coefficients on the variable FF indicate that, on average, US fossil fuel–related stocks underperformed US non–fossil fuel–related stocks over the period 2012–2020. This corroborates the findings in the first row of Panels B and C in Table 1 in which, on average, fossil fuel–related stocks have lower weekly returns and higher volatility than non–fossil fuel stocks. Finally, Table 3 reveals that, on average, excess returns on US stocks are significantly higher when AGSVI or AMC for the FFD phenomenon increases. Note that these findings hold when we lag all independent variables of Eqs. (1) and (2). Moreover, when we winsorize all variables in our models at cut points of 1% and 99% to reduce the potential influence of outliers, the estimation results are almost identical to those reported in the paper.

4.1.2. Effect of Extreme Investor Attention to FFD

Previously, we examined the effect of investor attention to FFD on stock returns. In this section, instead of considering the level of attention, we focus on extreme investor attention to FFD.

Extreme investor attention to FFD is measured with two dummy variables: DAGSVI and DAMC. DAGSVI (or DAMC) takes a value of one if AGSVI (or AMC) exceeds the average of the weekly values of AGSVI (or AMC) plus one standard deviation. In other terms, when DAGSVI and DAMC take a value of one, it means a sudden positive change has occurred in investor attention to FFD. Consequently, these transformations enable us to examine the effect of the right tail of the variables' distribution on excess returns on fossil fuel-related stocks.

Table 4 reports the results of the panel regressions that aim to assess the impact of extreme investor attention to FFD on weekly excess returns on US stocks. Table 4 is very similar to Table 3. The only differences are that AGSVI and AMC are replaced by DAGSVI and DAMC, respectively. The estimated parameters for the interaction variable FF*DAGSVI in Models 1 and 2 indicate that shocks in search queries on Google for the FFD movement positively affect excess returns on fossil fuel-related stocks (i.e., $\beta_3 = 0.19$ and $\beta_3 = 0.144$, according to Models 1 and 2, respectively). As these coefficients are larger in magnitude than those observed in Models 1 and 2 in Table 3, as expected, DAGSVI seems to have a higher impact on returns on fossil fuel-related stocks than AGSVI.

Similarly, the coefficients for the interaction term FF*DAMC in Models 2 and 3 reveal that shocks to media coverage of the FFD movement also exert a significant impact on excess returns on fossil fuel-related stocks (i.e., $\beta_3 = 0.382$ and $\beta_3 = 0.305$, according to Models 1 and 2, respectively). The results for control variables are very similar to those observed in Table 3.

Insert Table 4 Around Here

As an additional analysis, we also measure DAGSVI (and DAMC) from GSVI and MC expressed in categorical variables (i.e., Ben-Rephael et al., 2017). Specifically, GSVI (and MC) on week t takes zero if its value is in the lowest 80% of GSVI (MC) values over the previous 8 weeks. Alternatively, it takes 1, 2, 3, or 4 if its value is between 80% and 90%, 90% and 94%,

94% and 96%, or greater than 96% of the previous 8 weeks GSVI (MC) values, respectively. Then, in accordance with Ben-Rephael et al. (2017), DAGSVI and DAMC take the value of one if the score is 3 or 4, and zero otherwise. This alternative method to measure extreme attention to the FFD movement leads to similar estimation results to those reported in Table 4.¹⁶

4.1.3. Exploring the Potential Mechanism

We now investigate the potential channel through which the FFD movement positively influences excess returns on fossil fuel-related stocks. As mentioned earlier, US fossil fuel-related stocks, on average, had lower returns and higher volatility than US non-fossil fuel stocks over the period 2012-2020. Moreover, on average, the price-to-book ratio was 3.94 for US fossil fuel-related stocks compared with 12.45 for their non-fossil fuel counterparts over the same period. These results indicate that US fossil fuel-related stocks tend to be valued less than their non fossil-fuel counterparts.

Therefore, it is conceivable that the FFD movement leads investors to pay more attention to fossil fuel-related stocks. By scrutinizing fossil fuel-related stocks more closely, opportunistic investors might realize their potential undervaluation and thus purchase those securities to take advantage of higher expected returns.

To test whether investor attention to FFD positively affects investor attention to fossil fuel-related firms, we re-estimate Eqs. (1) and (2) by replacing the dependent variable $R_{it} - R_{ft}$ with investor attention to a specific firm. In accordance with recent empirical studies in finance (e.g., Ben-Rephael et al., 2017; Cziraki et al., 2021), investor attention to stock i on week t is measured from the number of times that Bloomberg terminal users, who are mostly financial

¹⁶ The estimation results are not displayed here due to space limitations, but are available upon request.

practitioners, read and search for news about a particular stock. The weekly attention ratings from Bloomberg ranged between 0 and 4. A higher rating means higher investor attention to a particular stock during the current week. Our dependent variable, i.e., the abnormal investor attention is measured using a dummy variable that receives a value of one if Bloomberg's score is 3 or 4, and zero otherwise.¹⁷ The results are reported in Table 5.

In Models 1 and 2, we find that the coefficients on the interaction term FF*AGSVI are positive and statistically significant at the 1 percent level (i.e., $\beta_3 = 0.051$ and $\beta_3 = 0.060$ according to Models 1 and 2, respectively), suggesting that the intensity of search queries on Google for the FFD movement is positively related to abnormal investor attention to fossil fuel-related stocks. Similarly, in Models 3 and 4, the estimated parameters on the interaction term FF*AMC are also positive and statistically significant (i.e., $\beta_3 = 0.085$ and $\beta_3 = 0.081$ according to Models 3 and 4, respectively). This indicates that an increase in the media coverage of the FFD movement positively affects abnormal investor attention to fossil fuel-related stocks. Collectively, our findings suggest that an increase in investor attention to FFD leads investors to pay more attention to fossil fuel-related stocks. In this way, profit-motivated investors will realize that fossil fuel-related stocks are undervalued and bid for them, thereby raising demand for those stocks and ultimately increasing their excess returns.

Insert Table 5 Around Here

4.2. Robustness Checks

4.2.1. Wikipedia as a Proxy for Investor Attention to the FFD Movement

¹⁷ For an in-depth discussion of this measure, see Ben-Rephael et al. (2017).

Previously, our measures of investor attention to the FFD movement were based on GSVI and media coverage of this phenomenon. In accordance with Focke et al. (2020), we posit that the most similar alternative measure of the weekly GSVI is probably the number of times a specific Wikipedia page is visited per week. Therefore, as a first sensitivity analysis, we consider the number of weekly visits to the Wikipedia page on “fossil fuel divestment” (WIKI), instead of the weekly GSVI.

Analogous to the transformation of GSVI used to obtain AGSVI, we normalize WIKI to obtain AWIKI. As presented in Table 2, AWIKI is the natural logarithm of the ratio of one plus WIKI during the week to its average during the previous eight weeks. Models 1 and 2 in Table 6 assess the impact of AWIKI on the excess returns on US stocks from July 1, 2015 (the week in which the “fossil fuel divestment” Wikipedia page was created), to June 19, 2020. The results from Models 1 and 2 report significantly positive effects of the interaction $FF*AWIKI$ on the weekly excess returns on US fossil fuel–related stocks (i.e., $\beta_3 = 0.142$ and $\beta_3 = 0.136$, respectively). This indicates that excess returns on fossil fuel–related stocks are positively related to the number of visits to the Wikipedia page on “fossil fuel divestment.”

We also create a dummy variable DAWIKI to account for peaks in the number of visits to the “fossil fuel divestment” Wikipedia page. This dummy variable takes a value of one if AWIKI exceeds the average of the weekly AWIKI plus one standard deviation. Models 3 and 4 in Table 6 show the reaction of excess returns on fossil fuel–related stocks to extreme positive changes in the number of visits to the “fossil fuel divestment” Wikipedia page. The estimated coefficients for the interaction variable $FF*DAWIKI$ are positive and statistically significant (i.e., $\beta_3 = 0.218$ and $\beta_3 = 0.252$ according to Models 3 and 4, respectively). This suggests that excess returns on US fossil fuel–related stocks are positively linked to sudden positive changes in the intensity of visits to the “fossil fuel divestment” Wikipedia page. In sum, this first set of

robustness checks supports our main finding that investor attention and extreme investor attention to the FFD movement have a positive influence on excess returns on US fossil fuel-related stocks.

Insert Table 6 Around Here

4.2.2. Nearest-Neighbor Matching

In the empirical analyses above, we used all US non-fossil fuel firms in the Russell 3000 index (i.e., 1,762 non-fossil fuel firms for which data are available) as a control sample. As a second robustness check, we reproduce our main empirical estimations by considering a more limited sample. Specifically, we match each of the 88 US fossil fuel-related firms to a US non-fossil fuel firm (out of 1,762) using nearest-neighbor matching. The nearest neighbor is the US non-fossil fuel firm with the lowest Mahalanobis distance¹⁸ to the selected US fossil fuel-related firm across four matching criteria: firm size, ROA, analyst coverage, and the percentage of institutional ownership.¹⁹ This method allows us to reinforce the similarity between fossil fuel-related firms (treatment group) and non-fossil fuel firms (control group) (e.g., Flammer, 2015). Because each fossil fuel-related firm is matched to one non-fossil fuel firm, the final sample for this sensitivity analysis totals 176 firms (i.e., 88 fossil fuel-related firms vs. 88 non-fossil fuel matched firms).

Table 7 presents the means and means differences for the four firm-level matching characteristics for the two groups of firms. We observe that fossil fuel firms are very similar to

¹⁸ For further detail, see Mahalanobis (1936).

¹⁹ We use these four firm-level variables because they are more time invariant than financial market-related variables, such as volatility or the illiquidity ratio. All the matching variables are computed as average of the eight years covering our sample period.

non-fossil fuel matched firms in terms of firm size, ROA, analyst coverage, and the percentage of institutional ownership. This confirms that our matching procedure is efficient.

Table 8 reports the results of the panel regressions that examine the effect of investor attention to FFD on the weekly excess returns of US fossil fuel-related stocks considering a more restrained (matched) control sample. The construction of Table 8 is identical to Table 3. The estimated coefficients for the interaction variable FF*AGSVI from Models 1 and 2 and the interaction variable FF*AMC from Models 3 and 4 confirm that investor attention to the FFD movement positively affects the excess returns on US fossil fuel-related stocks in comparison with US non-fossil fuel firms (i.e., $\beta_3 = 0.136$; $\beta_3 = 0.062$; $\beta_3 = 0.067$; $\beta_3 = 0.092$, respectively).

We also duplicated the analysis in Table 4 using the 88 non-fossil fuel matched firms as a control sample instead of the 1,762 non-fossil fuel firms. The results are qualitatively similar to those in Table 4, i.e., the estimated parameters for the variables FF*DAGSVI and FF*DAMC are still positive and statistically significant. These results are not tabulated in the paper but are available from the authors upon request.

Insert Table 7 Around Here

Insert Table 8 Around Here

The mechanism we advance to explain the positive effect of investor attention to the FFD movement on the returns of fossil fuel-related stocks is that increased attention leads to upward revaluation because the fossil fuel stocks were undervalued. Therefore, it seems relevant to explicitly select control firms that have these same pre-existing conditions, i.e., that are also undervalued. Thus, we reproduce our previous analyses by considering a control group of 88 US non-fossil fuel firms using only the price-to-book ratios as matching criteria. Under this configuration, the average price-to-book ratio is 3.94 for fossil fuel firms and 3.95 for the non-

fossil fuel matched firms (against 6.51 in the previous analysis). The underlying results are reported in Table A.1 (Appendix) and confirm our main findings. Therefore, once we explicitly control for undervaluation, we still observe a positive relationship between investor attention to FFD and excess stock returns for US fossil fuel-related firms.

4.2.3. Difference-in-Differences (DiD) Analysis

As a further test to assess the influence of the FFD movement on the excess returns of fossil fuel-related firms in comparison to the excess returns of non-fossil fuel firms, we conduct a difference-in-differences (DiD) analysis. We consider the five major FFD events described in Section 2.1. and reported in Figure 1 as quasi-natural experiments designed to capture intense variations in investor attention to the FFD movement. An important condition for difference-in-differences analyses is the “parallel trends” assumption. The parallel trends assumption implies that the control group provides the counterfactual of the trend that the treated group would have followed had it not been exposed to the treatment (e.g., Jaeger et al., 2020). In our context, it is reasonable to think the parallel trends assumption holds for two main reasons. First, our treatment group and our control group are very similar in terms of all firm-level characteristics (see Table 1). Second, the correlation between the returns of fossil fuel stocks and the returns of non-fossil fuel stocks during the pre-treatment period was 0.83. The fact that our treatment and control groups are very similar across different variables in levels and that their returns followed quite similar movements during the pre-DiD period make more plausible the assumption that these two groups have parallel trends (e.g., Ryan et al., 2019).

The sample period we consider for these DiD regressions is the four weeks before and after the week of each FFD event; therefore, the variable $POST_{jt}$ takes a value of one for the four weeks after event j and zero otherwise. Because we consider five events, we estimate five DiD regression models. We expect the estimated parameters on the interaction terms $FF_{it} * POST_{jt}$

to be positive and significant, implying that events related to the FFD movement lead to increased excess stock returns on fossil fuel–related firms. Specifically, we estimate the following specification:

$$R_{it} - R_{ft} = \alpha_0 + \beta_1 FF_{it} + \beta_2 POST_{jt} + \beta_3 FF_{it} * POST_{jt} + Y'X_{it} + \theta_t + \mu_i + \varepsilon_{it} \quad (3)$$

The results from the DiD regressions are reported in Table 9. Each column presents the impact of a specific FFD event on excess returns on US stocks. In each econometric specification, we find that the coefficient on the interaction term $FF_{it} * POST_{jt}$ is positive and statistically significant at the 1 percent level (i.e., $\beta_3 = 1.288$ for Event 1; $\beta_3 = 1.454$ for Event 2; $\beta_3 = 1.722$ for Event 3; $\beta_3 = 2.452$ for Event 4; and $\beta_3 = 2.159$ for Event 5). This indicates that after an event related to the FFD movement, fossil fuel–related stocks experience a significant increase in excess returns.

Insert Table 9 Around Here

4.2.4. Isolating the Effect of FFD on Fossil Fuel–Related Firms

Our main estimation results are based on panel regressions with interaction effects to facilitate a comparison of the effects of investor attention to FFD on fossil fuel–related firms (treatment group) and on non–fossil fuel firms (control group). To isolate the financial effects of investor attention to FFD on fossil fuel–related firms alone, we also conduct pooled-panel regressions using the weekly excess returns on US fossil fuel–related firms as a dependent variable (i.e., without a control group). We report these results in Table A.2 (Appendix).

In Models 1-4 in Table A.2, the estimated coefficients for AGSVI and AMC are positive and statistically different from zero at the 1 percent significance level. This confirms that the intensity of search queries on Google as well as the media coverage of the FFD movement are positively related to the weekly excess returns of US fossil fuel–related firms. This additional

analysis strongly supports our previous estimation results as it shows that, from a purely financial perspective, investor attention to the FFD movement does not impair the returns of fossil fuel–related firms. Moreover, the magnitude of coefficients on the variables AGSVI and AMC suggest that these variables have an economically significant impact. Indeed, the coefficients suggest that a 1% (100%) increase in AGSVI is associated with a 0.181% (18.1%) increase in excess returns for fossil fuel stocks, *ceteris paribus*. Regarding the media coverage measure, if AMC increases by 1% (100%), we would expect the excess returns of fossil fuel stocks to increase by 0.097% (9.7%), *ceteris paribus*.

Similarly, the effects of investor attention to FFD on the returns of non-fossil fuel stocks only are reported in Table A.3 (Appendix). In Models 1-4, the estimated coefficients for AGSVI and AMC are not statistically significant. As expected, this shows that investor attention to the FFD does not influence the returns of non-fossil fuel firms.

5. Conclusion

In this paper, we empirically explore whether investor attention to the FFD movement is related to the stock returns of companies that extract coal, gas, and oil. Based on a sample of weekly returns on 1,850 US firms over the period 2012-2020, our econometric analyses reveal a positive association between investor attention intensity to this social movement and excess stock returns on US fossil fuel–related firms. A comprehensive set of sensitivity analyses including the use of alternative investor attention proxies, alternative sample specifications, and the use of a quasi-natural experiment, confirms that investor attention to the FFD movement is a relevant driver of returns for fossil fuel–related stocks.

Thus, the mechanism through which the stigmatization of fossil fuel–related stocks—as one of the potential consequences of the FFD movement—could impair their returns because of increased pressure to sell them does not seem conclusive. By contrast, as observed in empirical

studies on “sin stocks” (e.g., Hong and Kacperczyk, 2009), the stigmatization process tends to increase the returns of fossil fuel-related stocks. One potential explanation of this key finding is that the FFD movement draws attention to the undervaluation of fossil fuel–related stocks, which makes them attractive to profit-motivated investors. Our empirical investigation of the potential channels supports this explanation by revealing that fossil fuel stocks are structurally undervalued and that, at the same time, the FFD movement leads to greater investor attention to these securities.

We are convinced that these results are relevant for profit-motivated traders, climate change–conscious investors, and FFD campaigners. Profit-motivated traders might find it financially profitable to invest in fossil fuel–related stocks and divest from non–fossil fuel firms when attention to the FFD movement is abnormally high (and the opposite when attention is abnormally low). Climate change–conscious investors—who are inclined to exclude fossil fuel–related stocks from their investment universe—should be aware that when attention to the FFD movement increases, this exclusion strategy is likely to reduce their portfolio returns. Finally, FFD activists—who are doing their best to reveal the negative environmental effects of fossil fuel firms’ activities—should realize that, from a purely financial perspective, their efforts contribute to increase the returns of fossil fuel firms.

Our study, which is the first to examine the effect of investor attention to the FFD movement on the returns on fossil fuel–related stocks, opens several promising avenues for future research. Indeed, while we show that the stigmatization caused by the FFD movement exerts a positive influence on the stock returns of targeted companies, we can hardly conclude that this movement is not a persuasive mechanism against the extraction and the exploitation of coal, gas, and oil reserves. Indeed, the FFD movement, or the stigmatization it causes, could be

potentially effective in increasing other financial as well as nonfinancial constraints on fossil fuel-related holdings.

First, future research could examine the impact of the FFD movement on the cost of bank loans to fossil fuel-related companies. In other terms, does the FFD movement increase the cost of bank financing for fossil fuel-related companies? Second, it would be worth investigating whether this social movement has a positive influence on the environmental (or even social) behavior of fossil fuel-related firms. As such, one could argue that, because of stigmatization campaigns to harm their reputation, fossil fuel-related companies might react by improving their environmental practices. Exploring these issues could provide better understanding of the corporate effects of social movements in general, in particular those of the FFD movement.

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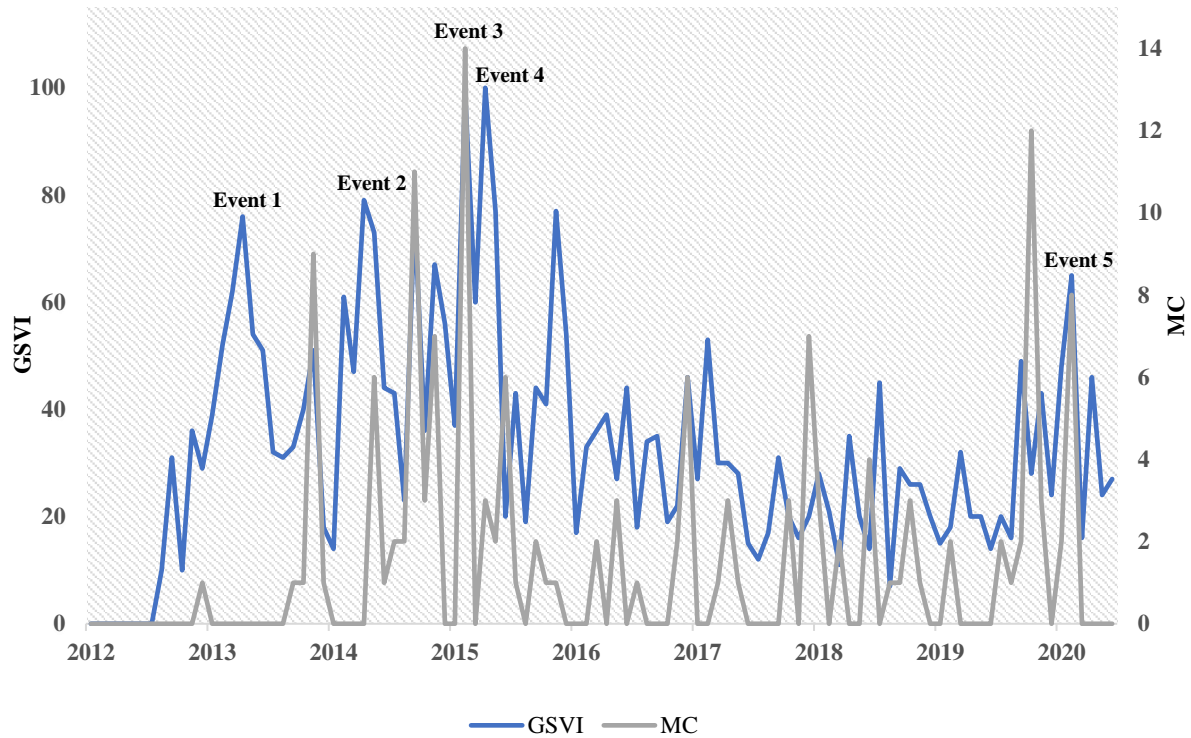
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Figure 1

Evolution of the GSVI and media coverage related to fossil fuel divestment in the US



Source: Google Trends and Factiva.

Event 1 (April 2013): the announcement by the San Francisco Employees' Retirement System (SFERS) that it would henceforth exclude fossil fuel producers from its portfolio.

Event 2 (April 2014): the publication of an open letter by a hundred professors at Harvard University arguing for FFD.

Event 3 and Event 4 (February and April 2015, respectively): protests by Harvard alumni to urge universities to divest their stakes in fossil fuels.

Event 5 (February 2020): the official decision by Georgetown University to divest from publicly listed fossil fuel companies.

Table 1
Summary statistics

	Mean	Median	SD	Min.	Max.
<i>Panel A: Main independent variables</i>					
MA	0.342	0.000	1.087	0.000	12.00
GSVI	27.861	24.000	18.551	0.000	100.0
AMC	0.704	0.287	0.917	-0.628	3.951
AGSVI	-0.172	-0.037	0.932	-3.960	1.752
<i>Panel B: Variables at the firm level (88 US fossil fuel-related firms)</i>					
RI-RF	-0.177	0.000	6.902	-135.6	169.7
SIZE	8.120	8.107	1.851	0.874	13.007
ROA	0.480	1.278	1.904	-5.186	5.041
RET	1.640	4.176	13.562	-161.7	157.0
VOL	0.059	0.051	0.038	0.013	1.030
ILLIQ	-17.506	-17.766	2.639	-26.090	0.000
AC	2.646	2.890	0.838	0.000	3.871
INST	4.354	4.513	0.547	0.478	5.136
<i>Panel C: Variables at the firm level (1,762 US non-fossil fuel firms)</i>					
RI-RF	0.114	0.211	5.564	-192.4	306.6
SIZE	7.585	7.529	1.811	0.342	14.231
ROA	1.061	1.485	1.665	-7.473	5.729
RET	1.932	4.504	12.961	-207.2	311.7
VOL	0.048	0.041	0.029	1.6e-5	2.174
ILLIQ	-16.813	-17.015	2.739	-29.342	0.000
AC	2.148	2.197	0.841	0.000	4.174
INST	4.360	4.513	0.501	0.001	5.303
<i>Panel D: Control variables at the market level</i>					
Δ COAL	-0.172	-0.064	2.992	-17.57	15.67
Δ GAS	-0.153	-0.408	7.459	-27.93	41.40
Δ OIL	-0.223	-0.090	5.071	-29.07	31.35
RM-RF	0.253	0.370	2.182	-14.57	12.35
SMB	-0.028	0.040	1.138	-5.920	6.050
HML	-0.098	-0.140	1.514	-8.600	9.940
MOM	0.074	0.173	1.815	-15.68	6.373

Notes: This table reports the summary statistics for the main independent variables, the variables for the 88 US fossil fuel firms (treatment group) as well as for the 1,762 US non-fossil fuel firms (control group), and control variables at the market level. A company is considered involved in the fossil fuel industry when it is assigned at least one of the following SIC codes: 12 (coal mining), 3532 (mining machinery), 13 (oil and gas extraction), 291 (petroleum refining), 3533 (oil and gas field machinery and equipment), 46 (pipelines, except natural gas), and 492 (gas production and distribution). The sample period is January 2012-June 2020.

Table 2
Variable definitions

Independent variables

GSVI	The weekly Google Search Volume Index on the topic “fossil fuel divestment” in the US. Source: Google Trends.
AGSVI	The natural log of the ratio of one plus GSVI during the week to its average during the previous eight weeks.
DAGSVI	Dummy variable coded as one if AGSVI exceeds the average of the weekly values of AGSVI plus one standard deviation.
MC	Media coverage of fossil fuel divestment movement, measured by the number of weekly articles published in four US newspapers (<i>The New York Times</i> , <i>The Wall Street Journal</i> , <i>The Washington Post</i> , <i>USA Today</i>). Source: Factiva.
AMC	The natural log of the ratio of one plus MC during the week to its average during the previous eight weeks.
DAMC	Dummy variable coded as one if AMC exceeds the average of the weekly values of AMC plus one standard deviation.
WIKI	The weekly number of visits to the Wikipedia page on “fossil fuel divestment.” Source: pageviews.toolforge.org
AWIKI	The natural log of the ratio of one plus WIKI during the week to its average during the previous eight weeks.
DAWIKI	Dummy variable coded as one if AWIKI exceeds the average of the weekly values of AWIKI plus one standard deviation.
FF	Dummy variable coded as one if the firm is involved in the extraction, production, or commercialization of fossil fuel-based energy sources.

Control variables at the firm level

SIZE	Firm size measured by the natural log of its market capitalization. Source: Bloomberg.
ROA	The natural log of return on assets. Source: Bloomberg.
RET	The cumulative return of the stock over the previous 52 weeks. Source: Bloomberg.
VOL	The conditional weekly volatility of the firm estimated from a GARCH (1,1) model.
ILLIQ	The Amihud illiquidity ratio (2002) measured by the natural log of the ratio of the absolute value of the weekly return on the stock to its trading volume during the same week.
AC	The analyst coverage measured the natural log of the number of analysts covering the stock. Source: Bloomberg.
INST	The natural log of the percentage of firm’s equity owned by institutional investors. Source: Bloomberg.

Control variables at the market level

ΔCOAL	Weekly changes in spot prices of the ICE Newcastle coal price. Source: Bloomberg.
ΔGAS	Weekly changes in spot prices of Henry Hub gas. Source: Bloomberg.

ΔOIL	Weekly changes in spot prices of the Brent crude oil. Source: Bloomberg.
RM-RF	The weekly value-weight return of all CRSP firms in the US market and listed on the NYSE, AMEX, or NASDAQ minus the weekly Treasury bill rate. Source: Kenneth R. French data library.
SMB	The average return on “small” US portfolios minus the average return on “big” US portfolios. Source: Kenneth R. French data library.
HML	The average return on US “value” portfolios minus the average return on US “growth” portfolios. Source: Kenneth R. French data library.
MOM	The difference between the average return for US “winner” portfolios and the average return on US “loser” portfolios. Source: Kenneth R. French data library.

Table 3

Investor attention to fossil fuel divestment and weekly excess returns on US stocks

	AGSVI		AMC	
	Model 1	Model 2	Model 3	Model 4
C	0.295** (0.01)	2.716*** (0.00)	0.276** (0.02)	2.688*** (0.00)
FF	-0.151*** (0.00)	-0.071*** (0.00)	-0.222*** (0.00)	-0.127*** (0.00)
AGSVI	0.111*** (0.00)	0.191*** (0.00)	—	—
FF*AGSVI	0.061** (0.03)	0.047** (0.03)	—	—
AMC	—	—	0.004 (0.51)	0.029*** (0.00)
FF*AMC	—	—	0.071** (0.02)	0.067*** (0.00)
SIZE	—	0.113*** (0.00)	—	0.112*** (0.00)
ROA	—	0.034*** (0.00)	—	0.034*** (0.00)
RET	—	0.422*** (0.00)	—	0.424*** (0.00)
VOL	—	8.733*** (0.00)	—	8.435*** (0.00)
ILLIQ	—	0.043*** (0.00)	—	0.038*** (0.00)
AC	—	-0.076*** (0.00)	—	-0.086*** (0.00)
INST	—	0.062*** (0.00)	—	0.058*** (0.00)
ΔCOAL	—	-0.076*** (0.00)	—	-0.089*** (0.00)
ΔGAS	—	-0.039*** (0.00)	—	-0.036*** (0.00)
ΔOIL	—	-0.029*** (0.00)	—	-0.033*** (0.00)
RM-RF	—	0.832*** (0.00)	—	0.826*** (0.00)
SMB	—	0.296*** (0.00)	—	0.282*** (0.00)
HML	—	0.187*** (0.00)	—	0.168*** (0.00)
MOM	—	-0.170*** (0.00)	—	-0.159*** (0.00)
R ²	0.004	0.520	0.003	0.523
N	743,700	701,842	743,700	701,842

Notes: This table reports estimated parameters for Eqs. (1) and (2) derived from pooled-panel models with interaction effects. It presents the effects of the weekly US investor attention to fossil fuel divestment on weekly excess returns on 88 US fossil fuel-related stocks in comparison with a control group of 1,762 US non-fossil fuel firms. FF is a dummy variable coded as one when the given stock is a fossil fuel stock. A company is considered involved in the fossil fuel industry when it is assigned at least one of the following SIC codes: 12 (coal mining), 3532 (mining machinery), 13 (oil and gas extraction), 291 (petroleum refining), 3533 (oil and gas field machinery and equipment), 46 (pipelines, except natural gas), and 492 (gas production and distribution). In Models 1 and 2, investor attention to fossil fuel divestment is measured by AGSVI. In Models 3 and 4, investor attention to fossil fuel divestment is measured by AMC. All the independent variables are defined in Table 2. In each econometric specification, we include year- as well as industry-fixed effects. Standard errors are clustered at the firm level. The sample period is January 2012-June 2020. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$. — means that the parameters are not estimated.

Table 4

Extreme attention to fossil fuel divestment and weekly excess returns on US stocks

	DAGSVI		DAMC	
	Model 1	Model 2	Model 3	Model 4
C	0.230** (0.04)	1.629*** (0.00)	0.262** (0.02)	2.516*** (0.00)
FF	-0.174*** (0.00)	-0.155*** (0.00)	-0.238*** (0.00)	-0.131*** (0.00)
DAGSVI	0.249*** (0.00)	0.036*** (0.00)	—	—
FF*DAGSVI	0.190** (0.01)	0.144** (0.02)	—	—
DAMC	—	—	0.041*** (0.00)	0.836*** (0.00)
FF*DAMC	—	—	0.382*** (0.00)	0.305*** (0.00)
SIZE	—	0.167*** (0.00)	—	0.113*** (0.00)
ROA	—	0.080*** (0.00)	—	0.034*** (0.00)
RET	—	0.317*** (0.00)	—	0.427*** (0.00)
VOL	—	14.671*** (0.00)	—	8.624*** (0.00)
ILLIQ	—	0.042*** (0.00)	—	0.041*** (0.00)
AC	—	-0.149*** (0.00)	—	-0.081*** (0.00)
INST	—	0.098*** (0.00)	—	0.065*** (0.00)
Δ COAL	—	-0.065*** (0.00)	—	-0.088*** (0.00)
Δ GAS	—	-0.030*** (0.00)	—	-0.037*** (0.00)
Δ OIL	—	-0.031*** (0.00)	—	-0.036*** (0.00)
RM-RF	—	0.888*** (0.00)	—	0.818*** (0.00)
SMB	—	0.319*** (0.00)	—	0.297*** (0.00)
HML	—	0.238*** (0.00)	—	0.162*** (0.00)
MOM	—	-0.121*** (0.00)	—	-0.155*** (0.00)
R ²	0.003	0.527	0.003	0.525
N	743,700	701,842	743,700	701,842

Notes: This table presents the impacts of extreme investor attention to fossil fuel divestment on weekly excess returns on 88 US fossil fuel-related stocks in comparison with a control group of 1,762 US non-fossil fuel firms. It reports the estimated coefficients for Eqs. (1) and (2) by replacing AGSVI and AMC by DAGSVI and DAMC, respectively. The estimated parameters are derived from pooled-panel models with interaction effects. DAGSVI takes a value of one if AGSVI exceeds the average of the weekly values of AGSVI plus one standard deviation. Similarly, DAMC is coded as one if AMC exceeds the average of the weekly values of AMC plus one standard deviation. FF is a dummy variable coded as one when the given stock is a fossil fuel stock. A company is considered involved in fossil fuel industry when it is assigned at least one of the following SIC codes: 12 (coal mining), 3532 (mining machinery), 13 (oil and gas extraction), 291 (petroleum refining), 3533 (oil and gas field machinery and equipment), 46 (pipelines, except natural gas), and 492 (gas production and distribution). All the independent variables are defined in Table 2. In each econometric specification, we include year- as well as industry-fixed effects. Standard errors are clustered at the firm level. The sample period is January 2012-June 2020. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$. — means that the parameters are not estimated.

Table 5**Investor attention to fossil fuel divestment and abnormal investor attention to specific stocks**

	AGSVI		AMC	
	Model 1	Model 2	Model 3	Model 4
C	-14.501 (0.69)	-25.531 (0.99)	-22.982 (0.99)	-28.893 (0.99)
FF	0.207*** (0.00)	0.049* (0.08)	0.123*** (0.00)	-0.009 (0.76)
AGSVI	-0.001 (0.81)	-0.001 (0.70)	—	—
FF*AGSVI	0.051** (0.03)	0.060** (0.01)	—	—
AMC	—	—	0.002 (0.58)	0.005 (0.26)
FF*AMC	—	—	0.085*** (0.00)	0.081*** (0.00)
SIZE	—	0.176*** (0.00)	—	0.180*** (0.00)
ROA	—	-0.021*** (0.00)	—	-0.025*** (0.00)
RET	—	-0.006*** (0.00)	—	-0.006*** (0.00)
VOL	—	-0.144*** (0.53)	—	-0.544** (0.01)
ILLIQ	—	-0.019*** (0.00)	—	-0.020*** (0.00)
AC	—	0.432*** (0.00)	—	0.367*** (0.00)
INST	—	0.268*** (0.00)	—	0.282*** (0.00)
ΔCOAL	—	0.001 (0.62)	—	-0.001 (0.57)
ΔGAS	—	-0.001*** (0.00)	—	-0.001** (0.02)
ΔOIL	—	-0.003*** (0.00)	—	-0.004*** (0.00)
RM-RF	—	-0.008*** (0.00)	—	-0.006*** (0.00)
SMB	—	-0.026*** (0.00)	—	-0.025*** (0.00)
HML	—	-0.011*** (0.00)	—	-0.011*** (0.00)
MOM	—	-0.024*** (0.00)	—	-0.023*** (0.00)
R ²	0.155	0.233	0.073	0.149
N	776,270	734,447	776,270	734,447

Notes: This table reports estimated parameters derived from logistic pooled-panel regressions with interaction effects. It presents the effects of the weekly US investor attention to fossil fuel divestment on weekly abnormal investor attention to specific stocks. Weekly investor attention to specific stock is measured from the number of times that Bloomberg terminal users, who are mostly financial practitioners, read and search for news about a particular stock. Provided by Bloomberg, weekly attention ratings are between 0 and 4. A higher rating means higher investor attention to a particular stock in the current week. Then, the abnormal investor attention is measured using a dummy variable that receives a value of one if Bloomberg's score is 3 or 4, and zero otherwise. For an in-depth discussion of this measure, see Ben-Rephael et al. (2017). The sample includes 88 US fossil fuel-related stocks and a control group of 1,762 US non-fossil fuel firms. FF is a dummy variable coded as one when the given stock is a fossil fuel stock. In Models 1 and 2, investor attention to fossil fuel divestment is measured by AGSVI. In Models 3 and 4, investor attention to fossil fuel divestment is measured by AMC. All the independent variables are defined in Table 2. In each econometric specification, we include year- as well as industry-fixed effects. Standard errors are clustered at the firm level. The sample period is January 2012-June 2020. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$. — means that the parameters are not estimated.

Table 6
Wikipedia page on “fossil fuel divestment” and weekly excess returns on US stocks

	AWIKI		DAWIKI	
	Model 1	Model 2	Model 3	Model 4
C	0.346*** (0.00)	0.843*** (0.00)	-0.105*** (0.00)	-3.320*** (0.00)
FF	-0.223*** (0.00)	-0.171*** (0.00)	-0.252*** (0.00)	-0.166*** (0.00)
AWIKI	0.059*** (0.00)	0.315*** (0.00)	—	—
FF*AWIKI	0.142* (0.09)	0.136* (0.08)	—	—
DAWIKI	—	—	0.057** (0.03)	0.737*** (0.00)
FF*DAWIKI	—	—	0.218* (0.07)	0.252** (0.03)
SIZE	—	0.192*** (0.00)	—	0.303*** (0.00)
ROA	—	0.135*** (0.00)	—	0.058*** (0.00)
RET	—	0.343*** (0.00)	—	0.209*** (0.00)
VOL	—	22.011*** (0.00)	—	20.397*** (0.00)
ILLIQ	—	0.043*** (0.00)	—	0.048*** (0.00)
AC	—	-0.152*** (0.00)	—	-0.361*** (0.00)
INST	—	0.141*** (0.00)	—	0.260*** (0.00)
ΔCOAL	—	-0.071*** (0.00)	—	-0.014*** (0.00)
ΔGAS	—	-0.028*** (0.00)	—	-0.012*** (0.00)
ΔOIL	—	-0.006*** (0.00)	—	-0.005*** (0.00)
RM-RF	—	0.888*** (0.00)	—	0.912*** (0.00)
SMB	—	0.291*** (0.00)	—	0.459*** (0.00)
HML	—	0.192*** (0.00)	—	0.220*** (0.00)
MOM	—	-0.187*** (0.00)	—	-0.154*** (0.00)
R ²	0.001	0.533	0.002	0.407
N	464,350	441,677	464,350	441,677

Notes: This table presents the effects of investor attention and extreme investor attention to the topic “fossil fuel divestment” on weekly returns on 88 US fossil fuel–related stocks in comparison with a control group of 1,762 US non–fossil fuel firms. The estimated parameters are derived from pooled-panel models with interaction effects. Here, the investor attention measure is based on the weekly number of times that the Wikipedia page on “fossil fuel divestment” is visited (WIKI). AWIKI is the natural logarithm of the ratio of one plus WIKI during the week to its average during the previous eight weeks. DAWIKI is a dummy variable coded as one if AWIKI exceeds the average of the weekly values of AWIKI plus one standard deviation. FF is a dummy variable coded as one when the given stock is a fossil fuel stock. All the independent variables are defined in Table 2. In Models 1 and 2, investor attention to fossil fuel divestment is measured by AWIKI. In Models 3 and 4, extreme investor attention to fossil fuel divestment is measured by DAWIKI. In each econometric specification, we include year- as well as industry-fixed effects. Standard errors are clustered at the firm level. The sample period is July 2015–June 2020. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$. — means that the parameters are not estimated.

Table 7

Statistics on US fossil fuel–related firms and control firms selected with the nearest-neighbor matching procedure (January 2012–June 2020)

Matching characteristics	Fossil fuel firms		Non–fossil fuel matched firms		Mean Differences
	#firms	Mean	#firms	Mean	
Mahalanobis distance	88	0.087	88	0.087	0.000
SIZE	88	8.120	88	7.963	0.156
ROA	88	0.480	88	0.293	0.187
AC	88	2.646	88	2.662	-0.016
INST	88	4.354	88	4.303	0.051

Notes: The table presents means and means differences for the four firm-level matching characteristics for the 88 US fossil fuel firms (treatment group) and the 88 US non–fossil fuel matched firms (control group). The US non–fossil fuel firms are selected using the nearest-neighbor matching method on the basis of the four averaged firm-level characteristics (i.e., firm size, ROA, analyst coverage, and the percentage of institutional ownership). The Mahalanobis distance denotes the distance between the US fossil fuel firms and the US non–fossil fuel firms across the four matching criteria.

Table 8

Investor attention to fossil fuel divestment and weekly excess returns on US stocks using the nearest-neighbor matching procedure to construct the control sample

	AGSVI		AMC	
	Model 1	Model 2	Model 3	Model 4
C	0.137 (0.22)	-0.279 (0.61)	-1.205*** (0.00)	-0.825 (0.14)
FF	-0.122 (0.10)	-0.076 (0.37)	-0.183*** (0.00)	-0.247*** (0.00)
AGSVI	0.225*** (0.00)	0.119*** (0.00)	—	—
FF*AGSVI	0.136** (0.01)	0.062** (0.01)	—	—
AMC	—	—	0.047** (0.01)	0.045** (0.01)
FF*AMC	—	—	0.067** (0.01)	0.092*** (0.00)
SIZE	—	0.244*** (0.00)	—	0.231*** (0.00)
ROA	—	0.080*** (0.00)	—	0.088*** (0.00)
RET	—	0.399*** (0.00)	—	0.306*** (0.00)
VOL	—	22.13*** (0.00)	—	24.54*** (0.00)
ILLIQ	—	0.055*** (0.00)	—	0.052*** (0.00)
AC	—	-0.221*** (0.00)	—	-0.216*** (0.00)
INST	—	0.389*** (0.00)	—	0.362*** (0.00)
ΔCOAL	—	-0.076*** (0.00)	—	-0.061*** (0.00)
ΔGAS	—	-0.035*** (0.00)	—	-0.024*** (0.00)
ΔOIL	—	0.027*** (0.00)	—	0.034*** (0.00)
RM-RF	—	0.875*** (0.00)	—	0.902*** (0.00)
SMB	—	0.243*** (0.00)	—	0.233*** (0.00)
HML	—	0.074* (0.05)	—	0.173*** (0.00)
MOM	—	-0.312*** (0.00)	—	-0.219*** (0.00)
R ²	0.007	0.528	0.007	0.496
N	70,752	65,069	70,752	65,069

Notes: This table reports estimated parameters for Eqs. (1) and (2) derived from pooled-panel models with interaction effects using a control sample of 88 US non-fossil fuel matched firms, instead of 1,762. This table presents the effects of the weekly US investor attention to fossil fuel divestment on weekly excess returns on 88 US fossil fuel-related stocks in comparison with a control group of 88 US non-fossil fuel firms. The control sample of 88 US non-fossil fuel firms is constructed following the nearest-neighbor matching procedure on the basis of the four averaged firm-level characteristics (i.e., firm size, ROA, analyst coverage, and the percentage of institutional ownership). FF is a dummy variable coded as one when the given stock is a fossil fuel stock. All the independent variables are defined in Table 2. In each econometric specification, we include year- as well as industry-fixed effects. Standard errors are clustered at the firm level. The sample period is January 2012-June 2020. *** p < 0.01, ** p < 0.05, and * p < 0.1. — mean that the parameters are not estimated.

Table 9

Investor attention to fossil fuel divestment and weekly excess returns on US stocks using a DiD approach

	Event 1	Event 2	Event 3	Event 4	Event 5
C	-0.937 (0.23)	0.987 (0.12)	0.360 (0.66)	0.463 (0.54)	0.347 (0.68)
FF	-0.366 (0.27)	0.015 (0.95)	-1.742*** (0.00)	-0.513 (0.15)	-2.984*** (0.00)
POST	0.283 (0.18)	0.020 (0.90)	-0.073 (0.74)	0.218 (0.13)	-0.093 (0.46)
POST*FF	1.288*** (0.00)	1.454*** (0.00)	1.722*** (0.00)	2.452*** (0.00)	2.159*** (0.00)
SIZE	0.335*** (0.00)	0.063 (0.12)	0.277*** (0.00)	0.247*** (0.00)	0.347*** (0.00)
ROA	0.021 (0.61)	0.190*** (0.00)	-0.010 (0.81)	0.105** (0.01)	-0.015 (0.72)
VOL	8.748* (0.08)	-13.431*** (0.00)	4.200 (0.33)	12.220*** (0.00)	7.684* (0.05)
ILLIQ	0.134*** (0.00)	0.035** (0.01)	0.050*** (0.00)	0.104*** (0.00)	-0.007 (0.71)
AC	-0.113 (0.20)	-0.176** (0.01)	-0.210** (0.02)	-0.337*** (0.00)	-0.273*** (0.00)
INST	0.050 (0.69)	-0.122 (0.26)	-0.209 (0.12)	-0.043 (0.77)	-0.599*** (0.00)
ΔCOAL	-0.126 (0.41)	-0.091* (0.07)	-0.105 (0.57)	-0.102*** (0.00)	0.086** (0.03)
ΔGAS	0.030 (0.23)	0.012 (0.14)	-0.023 (0.11)	0.150*** (0.00)	-0.148*** (0.00)
ΔOIL	-0.023 (0.52)	-0.124 (0.23)	0.015 (0.49)	-0.005 (0.89)	0.085*** (0.00)
RM-RF	0.992*** (0.00)	0.970*** (0.00)	1.094*** (0.00)	0.640*** (0.00)	0.891*** (0.00)
R ²	0.172	0.213	0.133	0.116	0.153
N	13,800	13,800	13,800	13,800	13,800

Notes: This table reports estimated parameters for Eq. (3) derived from DiD regressions. It presents the effects of five different events related to the FFD movement on excess returns on 88 US fossil fuel stocks compared to excess returns on 1,762 non-fossil fuel US stocks. FF is a dummy variable coded as one when the given stock is a fossil fuel stock. A company is considered involved in the fossil fuel industry when it is assigned at least one of the following SIC codes: 12 (coal mining), 3532 (mining machinery), 13 (oil and gas extraction), 291 (petroleum refining), 3533 (oil and gas field machinery and equipment), 46 (pipelines, except natural gas), and 492 (gas production and distribution). The variable POST takes a value of one for the four weeks after a specific event related to the FFD movement and zero otherwise. Events 1-5 are described in Section 2.1 and reported in Figure 1. The other independent variables are defined in Table 2. In each econometric specification, we include year- as well as industry-fixed effects. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$. — means that the parameters are not estimated.