The Impact of NGO Campaigning on Firms' Stock Performance

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Abstract

Is activism by private political actors effective in imposing costs on socially and environmentally noncompliant firms? In many cases, public regulation is ineffective in curbing harmful behaviour by firms, leaving a large role for activism by private political actors such as non-governmental organizations (NGOs) to pressure firms into adopting responsible practices. The efficacy of such activism depends critically on the ability to financially impact noncompliant firms. This paper empirically tests the impact of NGO campaigning on firm financial outcomes. Using a novel, detailed dataset on NGO campaigns, I investigate the effect of NGOs launching campaign events to target firms on firms' stock performance, measured through their cumulative abnormal returns (CARs). On average, when a firm is faced with a campaign event, CARs decline by 0.1%. When I break down campaign events by issue type, I find that campaign events related to environmental concerns reduce CARs by 0.26%, while there is no significant effect on campaigns related to non-environmental issues. I additionally find that large NGOs with an international outreach are less effective in affecting a firm's CARs than smaller, more localized NGOs. Finally, I test whether NGOs strategically time their campaigning activities and find evidence that NGOs avoid days with newsworthy events that may shift public attention away from their activity. Taken together, the results of this paper provide the most comprehensive evidence of the effectiveness of private politics by NGOs in impacting firms.

Keywords: Corporate Social Responsibility, NGOs, ESG, Event Studies, Sustainability.
JEL Codes: G14, L3, M14, Q5

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1 Introduction

The perils of human-induced climate change are well-documented (Auffhammer, 2018; Hsiang and Kopp, 2018). Increased public regulation in matters such as reducing greenhouse gas or toxic chemical emissions can help countries, municipalities and firms mitigate their impact on the environment, but such regulation is subject to limiting and transitory political realities. Governments could come under the sway of influential lobby groups or powerful donors to sustain negative externalities. In addition, public regulation cannot extend beyond the jurisdictions of a national or subnational government, allowing firms to relocate their production operations from high-regulation to low-regulation jurisdictions (Bazillier et al., 2017; Bénabou and Tirole, 2010; Hanna, 2010). Finally, even if the problems of influential lobby groups and jurisdictional sovereignty could be rectified, there would still remain the possibility that governments have a comparative disadvantage in implementing some types of regulation, such as serving very local needs (Bénabou and Tirole, 2010). For this reason, private political actors such as NGOs who act as watchdogs have a large role in challenging firms that employ socially and environmentally harmful practices.

This paper investigates several empirical questions: first, this paper answers the question as to whether the stock returns of firms respond to targeting by NGOs. Second, this paper investigates the role of issue type in determining the stock market performance of firms in response to NGO campaigning. That is, it examines the question of whether campaigning on certain types of issues, namely, on environmental concerns, affects firms more than non-environmental issues. Finally, the paper also determines whether NGOs strategically time their campaign actions away from days in which they can garner less attention.

The extant literature does not provide a clear picture on the efficacy of NGO activism. Starting with the seminal work of Baron (2001), theoretical advances on the role of private political actors such as NGOs suggest they play a large role in influencing firm behaviour. However, empirical papers offer seemingly contradictory findings on the impact of activism by NGOs on firm financial outcomes. Capelle-Blancard and Petit (2019) find that although negative environmental, social and governance (ESG) news brings about an abnormal stock price decline of around 0.1%, news disseminated by NGOs has no identifiable impact on stock prices. They attribute this phenomenon to the ostensible lack of neutrality of NGOs: investors understand NGOs have a political agenda, and discount information disseminated by them. On the other hand, Couttenier and Hatte (2016) find a large, statistically significant drop of 2% in abnormal returns for sponsoring firms around major sports events such as the Olympics and the FIFA World Cup. The apparent disparity between the findings of the two papers can be explained by the fact that Capelle-Blancard and Petit (2019) follow 100 large firms between 2002 and 2010, while Couttenier and Hatte (2016) primarily examine abnormal stock returns during sports events over the same time period. Thus, in order to answer the question of the efficacy of NGO activism in affecting firms' financial performance, it is necessary to examine a large number of firms across both prominent and ordinary dates.

I first investigate whether campaigning by NGOs affects the stock returns of firms. Using a new dataset of 7,729 NGO campaign events faced by US firms between 2010 and 2015, I employ a financial event study methodology to estimate abnormal returns. I find that on average, a firm's cumulative abnormal returns (CARs) drop by 0.1% around the reporting of a campaign action on an NGO's website. Since the novelty of new information about a firm's disposition would be likely to generate the strongest stock market impact, I find that the impact of campaigning on firms' cumulative abnormal returns is generally stronger for firms targeted less often over the six-year duration of the data. In addition, I find that issue type matters in the reaction in cumulative abnormal returns: Campaign events against firms in which the issue is related to environmental concerns yield a cumulative abnormal return of -0.26%; issues not related to environmental concerns do not yield a statistically significant drop in CARs.

I further test the importance of issue type by adding campaign-specific, year and firm fixed effects, and find that campaign events on environmental issues lead to significantly lower CARs. I find that when using an 11-day window (from 5 days before the event to 5 days after), campaign events on environmental issues are likely to generate CARs between 0.33% and 0.4% lower than non-environmental issues. Next, in order to test the robustness of results of the cross-sectional analysis, I vary the event windows in the baseline specification. I find that the effect of environmental issues on CARs is robust to varying event windows, with no change in significance or direction of the effect as the event window is varied. In addition, I find that the geographic outreach of the NGO, defined as NGO Power, is positively associated with CARs in most specifications. This implies that larger NGOs with an international focus are less effective in influencing firms' abnormal stock returns than smaller, more localized groups.

I then document the heterogeneous effects of being targeted by NGOs by industry downstreamness. Hatte and Koenig (2018) find that NGOs disproportionately target firms in relatively upstream industries involved in the utilization or extraction of natural resources, such as oil and gas extraction or mining. Campa (2018) considers the role of industry downstreamness in affecting firm behaviour upon disclosure of poor environmental performance, and finds evidence that consumer pressure is an important driver of remediation in downstream industries that produce consumer goods. Using a measure of industry downstreamness based on Miller and Temurshoev (2017), I find evidence that firms in more downstream industries are less affected financially by NGO campaigning. While I do not identify a causal mechanism, it is suggestive that the stock returns of firms in downstream industries are less harmed by NGO campaigning because they are more likely to alter their behaviour.

NGOs, like all political actors, seek to maximize pressure on the firms they campaign against. While NGOs do not have direct control over the amount of attention their campaigning behaviour generates, I empirically test whether NGOs time their events to avoid periods of increased intensity of news coverage that may direct public attention away from their activity. To investigate this relationship, I use the median time in minutes devoted to the top 3 news stories across four US broadcasters, defined as news pressure, as a measure for the intensity of news coverage.[1] However, simply examining the relationship between news pressure and the number of campaign actions launched by NGOs in a day will lead to biased parameter estimates, due to both the omission of unobserved variables and reverse causality. The issue of omitted variables could arise because certain days might have increased news pressure and also have more campaign actions launched against firms for reasons other than the news pressure itself. For example, major sports

[1] This measure was first introduced by Eisensee and Strömberg (2007), and further employed by Durante and Zhuravskaya (2018).

events see more actions launched against sponsoring firms (Couttenier and Hatte, 2016). The issue of reverse causality arises since reports of campaign actions can potentially be covered in the news. To obviate this concern, I use days surrounding election dates in member countries of the Organization for Economic Co-operation and Development (OECD) and the Group of Twenty (G20), along with days corresponding to significant political events in the US, as a source of exogenous variation in news pressure. I then employ an instrumental variables strategy using political events that caused a significant rise in news pressure as an instrument, to find that news pressure has a negative impact on the number of events launched by NGOs in a given day. This implies NGOs time their campaigning behaviour away from dates that would generate less attention for their activities.

In order to test whether the effect of news pressure comes from dates that NGOs can plan their activities around, as opposed to idiosyncratic factors increasing news pressure, I conduct a placebo exercise that uses an alternative source of exogenous variation in news pressure. In particular, for a given day, I use the number of deaths in disasters on the day and the past eight days as an instrument for news pressure. Consistent with the hypothesis that NGOs only time their actions around predictable newsworthy events announced many weeks or months in advance, I find no significant relationship between news pressure and the number of campaign actions in a given day.

This paper contributes to several strands of literature. I contribute empirically to the emerging literature on corporate social responsibility (CSR).[2] The literature on CSR traces its origins to Friedman (1970), who famously argued that firms have no social responsibility other than to maximize their profits. Despite this, in recent years, there have been a number of studies examining the role of prosocial activities for a firm, the determinants of CSR adoption, and the consequences of falling short on dimensions of CSR (Hart and Zingales, 2017; Bénabou and Tirole, 2010). Schiller (2018) and Dai et al. (2019) examine the role that customer-supplier relationships in global supply chains play in CSR adoption by firms, finding that customers transmit environmental and social (E&S) policies onto suppliers. Other papers examine the role of investor activism (Barko

[2] For an overview on economic perspectives on corporate social responsiblity see Kitzmueller and Shimshack (2012).

et al., 2018) and institutional investors in E&S adoption (Chen et al., 2019; Dyck et al., 2019).[3] This paper, by focusing on the efficacy of campaigning by NGOs in affecting firm financial outcomes, contributes to the larger literature on socially responsible investing (Capelle-Blancard and Petit, 2019; Couttenier and Hatte, 2016; Enikolopov et al., 2018; Hong and Kacperczyk, 2009) [4] and the causes and consequences of activist actions such as boycotts (Harrison and Scorse, 2010; Heilmann, 2016; Koenig and Poncet, 2019). This paper confirms that new information related to socially irresponsible behaviour results in penalization by shareholders, supplementing previous papers that find that negative information through news dissemination and boycotts lead to improved environmental performance (Campa, 2018; Gupta and Innes, 2014). It also adds understanding to the determinants of the campaigning decisions of NGOs. Though this has been well examined theoretically,[5] recent work has begun empirically examining the role of publicity in determining NGOs' decisions to target firms (Hatte and Koenig, 2018; Couttenier and Hatte, 2016).[6]

Finally, I contribute to the broader understanding of how political actors time their actions to garner more or less attention, and use periods of low or high news pressure in order to do so. By showing that NGOs tend to time their campaign actions to days with lower news pressure, I demonstrate that NGOs try to maximize the reach of their campaigning activities. This is comparable to the findings of Durante and Zhuravskaya (2018), who find that militaries time potentially disreputable actions to when there is more news pressure in order to reduce the reach of their activity. As Eisensee and Strömberg (2007) show with natural disasters, news coverage matters for the likelihood of subsequent remedial action.[7]

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[3] See also Dyck et al. (2008), which examines the impact of lobbying by a single investment fund on corporate governance adoption.

[4] For example, Hong and Kacperczyk (2009) find that large institutional investors tend to shun "sin stocks", generating a large price effect, while Couttenier and Hatte (2016) examine stock returns of firms sponsoring major sports events in response to activist campaigns. See also Lyon and Shimshack (2015), who find that upon the release of Newsweek's ratings program that ranked 500 firms in 2009, firms in the top 100 performed up to 1% better than firms in the bottom 400.

[5] See, for instance, the seminal work of Baron (2001), and Feddersen and Gilligan (2001). Examples of more recent work on strategic behaviour by NGOs include Baron and Diermeier (2007) and Heyes et al. (2018).

[6] Lenox and Eesley (2009) find that larger and more polluting firms with smaller capital reserves tend to be targeted more aggressively by activists.

[7] In the case of Eisensee and Strömberg (2007), remediation came in the form of foreign aid by the US government.

The rest of the paper is structured as follows. Section 2 discusses and summarizes the data. Section 3 outlines the strategy followed for the financial event study and presents the pertinent results. Section 4 discusses the empirical strategy for testing NGOs' timing of campaign actions. Finally, Section 5 concludes.

2 Data

2.1 Data on Campaign Actions

Data on NGO campaigning activity is obtained through Sigwatch, a European consultancy that tracks activist campaigns around the world. Campaign actions provided in the dataset run from 2010 to 2015, and track campaigns by activists against both public and private firms. A campaign is defined by Sigwatch as a series of campaign actions over time. A campaign action, in turn, is an action taken by an NGO or a group of NGOs which contains a new target firm, or a new criticism or allegation against an existing target firm. Campaign actions in the data are original sources of information; previously known messages are not repeated in the dataset, nor does the information arise from social media.[8] A campaign action, therefore, denotes an action undertaken against one firm on a given date by up to five NGOs, for a particular allegation or complaint.

The appendix contains several case examples of campaign actions launched by NGOs. The first example relates to an environmental issue, where the Rainforest Action Network (RAN) staged days of activity against Massey Energy, Alpha Natural Resources, Consol Energy, International Coal Group, and Patriot Group for engaging in mountaintop coal removal mining, and against PNC bank for financing the venture. Each company targeted by RAN corresponds to a separate campaign action. The first example of a non-environmental issue in the appendix is of a call-in launched by Global Exchange and Green America on the issue of cocoa farming and child labour. The targeted company, Hershey's, is being criticized for not participating in certification programs to track its implementation of labour standards for its cocoa suppliers, thus failing to ensure that their cocoa is fair trade.

Some firms face multiple campaign actions on the same day. In this case, it is not

[8]"Social media" includes blogs and tweets. See Koenig (2017).

possible to distinguish to which degree each individual action brought about a change in abnormal stock returns. I define a *campaign event* as a given firm being targeted, on a given day, by one or more campaign actions.[9] About 11% of campaign events against firms involve multiple actions.[10]

2.2 Stock Returns

Data on historical stock returns are acquired from the Center for Research in Security Prices (CRSP), which provides historical stock data for US-listed stocks. In all, the final dataset consists of 405 US publicly listed firms, accounting for a combined total of 7,729 campaign events.

Figure 1 summarizes the number of campaign events faced by firms. The histogram is right-skewed- out of 405 firms, 340 are targeted 30 times or less over the six-year duration of the dataset. 354 firms are targeted 40 times or less, and 369 firms- more than 90% of the firms in the sample- are targeted 50 times or less. Basic summary statistics reflecting the distribution of events faced by the publicly listed firms are provided in Table 1.

The targeted firms are in a wide range of industry groups. Table 2 tabulates the economic sectors of the targeted firms at the level of two-digit North American Industry Classification System (NAICS) sector codes. The three largest sectors in terms of campaign events, 31, 32 and 33, are in manufacturing, with 1242, 1699, and 794 events, respectively. Sectors 21 (Mining, Quarrying, Oil & Gas Extraction) and 22 (Utilities) also have a substantial share of campaign events, with 780 and 591 events against them, respectively.

2.3 Daily News Pressure

In order to test the effect of the intensity of news coverage on the number of campaign actions launched by NGOs, I use data taken from the Vanderbilt Television News Archive (VTNA). These data are accessed through David Stromberg's website. The data combine

[9]As an example, on August 1, 2013, two separate campaign actions were launched against Apple. The first campaign action, by the NGO US PIRG, related to financial transparency. The second campaign action was launched by Friends of the Earth, and pertained to supply chain standards. In my data, these two campaign actions correspond to one campaign event.

[10]The relevant summary statistic is displayed in Table 8, alongside variables that will be introduced in Section 3.

information on coverage from four large US broadcast networks (ABC, CBS, NBC, and CNN) since 1968. The variable of interest, *daily news pressure*, represents the median time in minutes, across the four broadcasts, spent on the three largest news segments of a given day. Table 3 provides summary statistics on daily news pressure and the number of campaign events launched in a day against US firms. The average value of daily news pressure is 8.6 minutes, with an average of 6.6 campaign actions in a day.

2.4 Disasters

In order to run my placebo tests for the role of news pressure, I obtain data on both natural and anthropogenic disasters occurring between 2010 and 2015 from the EM-DAT database, made available by the Center for Research on the Epidemiology of Disasters (CRED).[11] Along with the dates of the incidence of each disaster, the dataset provides estimates of the economic damage caused by the disaster, the number of people affected and the number of deaths caused.

3 Event Study

Several mechanisms exist whereby NGO actions could affect financial outcomes. These mechanisms can be grouped into four distinct categories (Lyon and Shimshack, 2015). First, investors could have preferences for corporate social and environmental responsibility. Such "green" preferences would lead to the penalization of firms revealed to be bad performers, and bring about a reduction in stock prices. Second, investors themselves may not have green preferences, but could believe that a significant number of other investors do have such preferences. A drop in financial performance is not necessarily evidence of investors' preferences themselves. Conversely, a small number of motivated investors with "green" preferences may not be able to significantly move stock prices upon the publication of an NGO report. However, shared belief amongst investors that *other* investors value social and environmental performance would have a similar impact. Third, investors might believe that NGO reports could result in severe consequences through

[11] There are 13 types of disasters reported in the dataset: Animal accidents, droughts, earthquakes, epidemics, extreme temperatures, floods, meteor impacts, insect infestations, landslides, dry mass movements (such as rockfall), storms, volcanic activity and wildfire.

future public regulation, civil suits, or consumer boycotts. Fourth, investors could make inferences about managerial competency, in the sense that poor social or environmental performance could signal less long-run profitability. These four mechanisms suggest that negative NGO campaign actions should adversely impact stock returns. The setup for testing this hypothesis, along with the analysis of the results, are provided in this section.

3.1 Cumulative Abnormal Returns

Estimating the effect of a campaign event on a firm's stock return requires the calculation of returns absent the portion attributed to market factors. These returns, known as abnormal returns are calculated using the following formula:

$$AR^{i}_{jt} = \hat{\epsilon}_{jt} = R_{jt} - E(R_{jt}), \tag{1}$$

where event i affects firm j at time t, R_{jt} is the actual observed return, and $E(R_{jt})$ is the normal return as predicted by a benchmark asset pricing model. In order to calculate abnormal returns, I use the Carhart four-factor model as the benchmark model. The Carhart four-factor model extends the Fama-French three-factor model by adding momentum, which captures the propensity of high-performing stocks to continue performing well, and of low-performing stocks to continue performing poorly, as an additional factor (Carhart, 1997).[12] Normal returns for firm j at time t are given by

$$R_{jt} = R_f + \hat{\alpha}_j + \hat{\beta}_{mj}(R_{mt} - R_f) + \hat{\beta}_{bj}SMB_t + \hat{\beta}_{vj}HML_t + \hat{\beta}_{zj}UMD_t + \hat{\epsilon}_{jt}, \tag{2}$$

where $R_{mt} - R_f$ represents the excess return of the market, SMB_t represents the excess return on small capitalization stocks compared to large capitalization stocks, and HML_t represents the excess return on high book-to-market ratio stocks compared to low book-to-market stocks, and UMD_t represents momentum (Carhart, 1997). The procedure for conducting an event study entails estimating the parameters for the normal returns during a period prior to the event; the estimation window. The parameters for the Carhart four-factor model are estimated over a 250-day window beginning 260 days prior to the event,

[12] Also see MacKinlay (1997); Campbell et al. (1997); Corrado (2011).

and ending 11 days prior to the event: [-260,-11]. The parameters acquired during the estimation window are then used to calculate $E(R_{jt})$, the expected return of the security during a period deemed affected by the event; the event window. Substituting the above equation into the equation for AR^i_{jt}, we arrive at

$$AR^i_{jt} = R_{jt} - R_f - \hat{\alpha}_j - \hat{\beta}_{mj}(R_{mt} - R_f) - \hat{\beta}_{bj}SMB_t - \hat{\beta}_{vj}HML_t - \hat{\beta}_{zj}UMD_t \qquad (3)$$

That is, the abnormal return for firm j faced with event i at time t is the difference between the realized return R_{jt}, and the expected return, calculated by using the estimation window parameter values $\hat{\alpha}_j$, $\hat{\beta}_{mj}$, $\hat{\beta}_{bj}$, $\hat{\beta}_{vj}$, and $\hat{\beta}_{zj}$, and the event window realizations of R_f, R_{mt}, SMB_t, HML_t, and UMD_t.

To allow for the effects of the event to manifest, abnormal returns are aggregated over a time period surrounding the event. This aggregation, known as the cumulative abnormal return, is calculated:

$$CAR^i_{jt}[-n, n] = \sum_{\tau=t-n}^{t+n} AR^i_{jt} \qquad (4)$$

where $CAR^i_{jt}[-n, n]$ is the cumulative abnormal return for firm j with respect to event i, at time t, over an event window of length $(2n + 1)$; that is, from n days before the event to n days after. The formulation of the estimation window and the event window is depicted in Figure 2 .

The aforementioned methodology will yield a cross-section of cumulative abnormal returns for firms targeted by NGOs. In order to test the significance of the events, I construct the standard test statistic:

$$t = \frac{CAAR[-n, n]}{\widehat{\sigma}_{CAR[-n,n]}} \sim N(0, 1) \qquad (5)$$

where CAAR[-n,n] is the average CAR across all events in the sample, and $\widehat{\sigma}_{CAR[-n,n]}$ is the sample standard deviation of CARs over all events in the event window [-n,n].

3.2 Event Window Determination

In order to adequately gauge the effect of campaign events on abnormal stock returns, it is necessary to select an appropriate event window for the purpose of analysis. An event window that is too short might not accurately capture the entirety of the effect of a campaign event, while an event window that is too long might dilute it. Figure 3 maps the full sample average abnormal returns around event dates, starting from 5 days before an event and ending 10 days after the the event. Inspection of the abnormal returns suggests that any effect on daily abnormal returns loses significance after the 5th day following the event. For this reason, for the bulk of my analysis, I set my event window to begin 5 days before the event, and end 5 days after.[13]

3.3 Descriptive Results

Figure 4 shows the evolution of average cumulative abnormal returns (CAAR) in the days around campaign events. The evolution of the CAAR is calculated by first taking the abnormal return for each firm 5 days before the event, and then sequentially adding the abnormal return for the following day to the event window, and continuing this for proceeding days, one day at a time. The CAARs are decreasing in the days following campaign events. The CAAR is significantly lower than 0 at the 10% level by day 5 following the event. Similarly, Figure 3 illustrates the evolution of average abnormal returns. Abnormal returns decrease in the days following campaign events, from the first to the third day after the event. Daily abnormal returns are also significantly lower than zero at the 10% level on day 5 following the event. A clearer visual illustration of the evolution of the full-sample average abnormal returns (AAR) and CAAR is provided in Figure 5 and Figure 6, which display the evolution of the AAR and CAAR without confidence intervals. In Figure 5, AARs begin to decline after the event date, before recovering slightly after the third day. In Figure 6, CAARs, while close to 0 on the event date, fall rapidly afterwards.

In order to understand whether issue type is important in determining CARs, I break campaign events into environmental and non-environmental issue types. Specifically, let ENV^i_{jst} be an indicator for when firm j in industry s faced with campaign event i is

[13] This strategy for determining the event window is most appropriate for my setting of several thousand events and several hundred firms being targeted. Thus, I create a standardized method for ascertaining the average effect of a campaign event across firms and events. For the determination of the event window for relatively few events, see Krivin et al. (2003). Nevertheless, I present results from varying event windows throughout my analysis as a test of robustness.

targeted by only environmental campaign actions at time t. That is, for a given campaign event, let ENV^i_{jst} equal one if all campaign actions are on environmental issues. When I break the sample into environmental and non-environmental campaign events, it becomes apparent that the campaign issue type is important as a determinant of abnormal return response following an event. For environmental campaign events, the evolution of average abnormal returns is depicted in Figure 7. The average abnormal returns are below 0 for each day after the event, and they are significantly negative on the fourth day after the event. The evolution of the CAARs for environmental campaign events is illustrated in Figure 8. It shows a steady decline in CAARs as the event window increases in size.

Corresponding diagrams to Figure 7 and Figure 8 for non-environmental campaign issues are illustrated in Figure 9 and Figure 10, respectively. For non-environmental campaign events, average abnormal returns begin to decrease on the second day after the campaign event, with the AAR being significantly negative on day 3 after the campaign event. However, the AAR rebounds on the fourth day, indicating the absence of a sustained abnormal return response to campaign events on non-environmental issues. This is best illustrated when inspecting the evolution of CAARs as the length of the event window increases. At no point are the CAARs significantly below 0 at the 10% level of significance. This evidence suggests that issue type matters in the determination of the stock price response of firms targeted by activists.

Define a campaign event as positive in sentiment if all the campaign actions on a day targeting a firm praise the firm, and negative in sentiment otherwise. I depict differences in CAARs by the sentiment of the campaign event in Figure 11 and Figure 12. For environmental campaign issues, the CAAR for positive events is roughly constant over time. However, for the subsample that faces negative events, the CAAR becomes steeply negative. The negative CAAR is statistically significant. For non-environmental campaign issues, Figure 12 shows weakly positive abnormal returns after a negative campaign event, and weakly negative returns for positive events. However, neither of these are statistically significant, highlighting the lack of an abnormal return response for non-environmental campaign issues.

3.4 Analysis of Cumulative Abnormal Returns

The analysis of cumulative abnormal returns is tabulated in Table 4, 5, and 6, respectively. In Table 4, CAARs are insignificant for the full sample for event windows [-1,1], [-2,2], and [-3,3], but attain significance thereafter. CAAR[-5,5] is -0.091% and significant at the 10% level. The magnitude of the effect appears to be stronger for firms that are targeted less often. For firms targeted 30 times or less, the effect on CAAR[-5,5] over the 2217 campaign event observations is about -0.2 %, though not statistically significant. For firms targeted 40 times or less (2709 observations), the effect is -0.187% and significant at the 10% level. For firms targeted 60 or less times (3833 observations), the CAAR[-5,5] is -0.199% and significant at the 5% level. Thereafter, the effect on CAARs diminishes as we increase the number of events per firm.

Table 5 displays CAARs by number of events per firm, for non-environmental campaign issues. For firms with less than or equal to 30 events, CAAR[-5,5] is -0.0906% and not statistically significant. The CAAR does not change significantly as the threshold for the number of campaign events per firm is increased. In the full sample, CAAR[-5,5] is 0.0866% and not statistically significant. The full sample results for varying event windows are provided in Column (8). The CAARs over the windows [-1,1] and [-2,2] are approximately 0.1%, but then decrease subsequently to 0.0766%, 0.114% and 0.0866% as the event window is increased with no statistical significance. This provides evidence that for non-environmental campaign issues, there is no statistically significant effect of NGO-initiated campaign events against firms on cumulative abnormal returns.

For the shorter event windows [-1,1] and [-2,2], CAARs become positive and statistically significant for the subsample of firms with 150 events or fewer, and remain significant when we expand to the full sample. Expansion of the event window leads to the positive CAARs losing statistical significance. For firms that face 30 events or less, CAAR[-3,3], CAAR[-4,4] and CAAR[-5,5] are -0.0756%, -0.0656% and -0.0906%, respectively, but not statistically significant in any of the cases. The insignificantly negative CAARs diminish further as we incorporate firms with more events in the sample, and the full sample CAARs are weakly positive and statistically insignificant.

Table 6 provides the analogue to the previous table, but for environmental campaign issues. Full sample CAAR[-5,5] is -0.26% and significant at the 1% level, indicating significantly negative cumulative abnormal returns over the 11-day event window. When the event window is shortened to [-4,4], the CAAR is -0.307% and significant at the 1% level. The CAAR is much less pronounced over shorter event windows; -0.176% for the window [-3,3], -0.126% for the window [-2,2] and is insignificant over the window [-1,1]. The relatively large drop in CAAR when we increase the window from [-3,3] to [-4,4] can be understood by inspecting Figure 7, which displays the steep drop in daily AAR on the fourth day following an event.

While CAAR[-1,1] is never significant, CAAR[-2,2] and CAAR[-3,3] are significant when analyzing subsamples that allow firms with more events. The overall effect of environmental campaign events on CAAR[-4,4] and CAAR[-5,5] is stronger for firms that face 30 events or fewer than in the full sample. CAAR[-5,5] for firms that face 30 or fewer events is -0.399% and significant at the 5% level, while CAAR[-4,4] is -0.383% and is also significant at the 5% level. CAARs for shorter event windows are negative, but not statistically significant. CAAR[-4,4] is strongest in magnitude for the subsample that restricts to firms with 100 events or less, with a value of -0.425%, which is significant at the 1% level; relaxing the restrictions further leads to a diminishing CAAR. CAAR[-5,5] is strongest for the subsample for firms with 30 or fewer events. While remaining negative and maintaining statistical significance, CAAR[-5,5] is generally diminishing as we allow for increases in the number of events per firm.

3.4.1 Returns Prior to Event

In order to test the robustness of the attribution of any abnormal return response to the actual campaign event against the firm itself, rather than unobservable factors, I examine whether cumulative abnormal returns in the days prior to the event were significant. That is, I look at CAARs in the days before the actual occurrence of the event. This is important for two reasons. First, it provides a test for, potentially, information leakage of an impending event in advance of the event. Second, it is possible that NGOs launch actions during particularly vulnerable times for firms, perhaps in the days after a major controversy. Significantly negative CAARs prior to the event would obfuscate the credibility of the attribution of any negative abnormal returns during the event window to the event. The absence of significance in pre-event date CAARs would provide evidence in favour of the event itself causing any CAR response.

The evolution of the CAAR prior to the event date with 90% confidence intervals is depicted in Figure 13. Reassuringly, the CAAR at day -1 (i.e. CAAR[-10,-1]) is not significantly different from 0, providing evidence in favour of attributing any significant abnormal returns around the event to the event itself.

3.5 Cross-Sectional Analysis of Campaign Events

3.5.1 Role of Issue Type

In this subsection, I examine the role of issue type in determining cumulative abnormal returns. In addition to issue type, I include controls for variables that could affect CARs and hence confound inference. These include campaign event-specific variables, along with year and firm fixed effects. The regression specification for cumulative abnormal returns by issue type is given as follows:

$$CAR^i_{jst} = \beta_0 + \beta_1 ENV^i_{jst} + \Gamma' X_i + Year_t + \delta_s + \phi_j + u^i_{jst} \tag{6}$$

where ENV^i_{jst} represents, for event i against firm j industry s at time t an indicator variable for environmental issue type, X_i denotes a vector of campaign event-specific variables, and $Year_t$, δ_s, and ϕ_j are year, industry, and firm fixed effects, respectively.

Table 7 displays the results for the cross-sectional regression for issue type and other covariates for CAR[-5,5]. The first column is a simple regression of CAR[-5,5] on the dummy variable for environmental campaign events, ENV.[14] The resultant coefficient on ENV is the difference in CAAR[-5,5] between environmental and non-environmental campaign issues. It is statistically significant at the 1% level and has a value of -0.347%.

The other specifications include covariates that are also likely to affect abnormal returns. These covariates include a variable for NGO Power, which is based on a measure coded by Sigwatch called "ngo_power" that runs, in increments of 0.5, from 0.5 to 2.75 and reflects the geographical outreach of an NGO. An NGO with a value of 0.5 has only a local reach, while an NGO with a value of 2.75 is global in its outreach. To reflect the

[14]For an overview of what constitues an environmental campaign event, see the appendix.

outreach of the most powerful NGO targeting a firm, I have defined NGO Power to be the maximum of "ngo_power" out of all NGOs launching a campaign action against a firm on a given day. In addition, I include indicators for whether there is a partnership between an NGO and a targeted firm during a given campaign event (denoted Partnership), whether the tone of a campaign event is positive, i.e. if all campaign actions launched against a firm on a given day are positive (Positive), and whether a firm is being targeted by an NGO that is headquartered in the US (US NGO). I also include variables for the number of NGOs participating in a given campaign event (Number of NGOs), and the prominence of a campaign event (Prominence). The variable Prominence is based on a campaign action-specific variable coded by Sigwatch, "prom" , that captures the prominence of the mention of a targeted firm in the campaigning NGOs' communications.[15] For a given campaign event, I then code the variable Prominence to be the maximum value of "prom" out all campaign actions. Finally, in order to control for year and firm-level variation in CAR response, I include year and firm fixed effects. The summary statistics for the covariates are provided in Table 8 and Table 9. The covariates are introduced in Columns (2), (3) and (4) of Table 7.

Throughout Columns (2), (3) and (4), the coefficient on ENV remains statistically significant with values of -0.402%, -0.398% and -0.335%, respectively. The sustained significance of ENV despite adding a variety of controls suggests that campaign issues are an important determinant of CARs surrounding an activist-induced event. Additionally, the coefficients on NGO Power are significantly positive in all specifications, at roughly 0.24%, implying that larger NGOs with international outreach are less effective than local groups at affecting firms' abnormal stock returns.

3.5.2 Alternative Event Windows

In order to test the robustness of the relationship between CARs and ENV, I estimate the same equations as in Table 7 with a different event window; CAR[-1,1] is used instead of CAR[-5,5]. The results are tabulated in Table 10. The coefficients on ENV remain

[15]The variable "prom" runs from 1 to 4: +4 implies the mention of the targeted corporation was in the headline of the communication, +3 implies it was mentioned in the first paragraph, +2 implies it was mentioned later in the communication, and +1 implies it was mentioned in a supplementary document (Koenig, 2017).

statistically significant despite the change in event window. The difference in CAAR[-1,1] between environmental and non-environmental campaign event types is displayed in Column (1). The CAAR[-1,1] for environmental campaign issues is 0.14% lower than for non-environmental issues. Columns (2), (3) and (4) add control variables, as in Table 7. The campaign issue is robust to the addition of all campaign-level, year and firm fixed effects, with coefficients of -0.152%, -0.150%, and -0.178%, respectively. The coefficients on NGO Power are also provided in Columns (2), (3), and (4). They are statistically significant and range from 0.106% to 0.109%, consistent with the cross-sectional analysis on CAR[-5,5], suggesting that campaigning by international NGOs is less effective than by geographically limited groups. Interestingly, the number of NGOs participating in a campaign event has a statistically significant effect on CAR[-1,1], with coefficients of approximately 0.1%. This control was not significant for the regressions with CAR[-5,5]. This suggests that the number of NGOs participating has an impact in the initial stock reaction to NGO campaigning, but the impact dissipates when considering longer event windows. In sum, while the magnitude of the coefficients on ENV and NGO Power change, the direction and the significance of the regression coefficients when analyzing CAR[-1,1] are consistent with those in the specification with CAR[-5,5].

Further tests of the robustness of campaign issues in determining CARs are provided in Tables 11 and 12. Table 11 presents regression results with varying event windows. Table 11 presents the results of the regression without year and firm fixed effects. The coefficients on ENV are -0.152%, -0.269%, -0.268%, -0.458%, and -.402% for CAR[-1,1], CAR[-2,2], CAR[-3,3], CAR[-4,4], and CAR[-5,5], respectively. The coefficients on ENV are significant at the 5% level for each of the specifications, and at the 1% level for CAR[-2,2], CAR[-4,4] and CAR[-5,5]. This indicates that the effect of campaign issue type on abnormal returns persists in larger event windows. NGO Power is significant throughout all specifications for at least the 10% level, but is not for CAR[-3,3] (the associated t-statistic is 1.6), consistent with the general hypothesis of NGOs with greater outreach being less successful at influencing CARs.

Table 12 estimates the same equations as in Table 11 but adds year and firm fixed effects. The coefficients on ENV retain their statistical significance, and do not change substantially from the specification without the year and firm fixed effects. The coefficients on NGO Power also remain significant, with the exception of CAR[-3,3].

3.5.3 Role of Industry Downstreamness

In this section I investigate the heterogeneity in response by industry characteristics. The evidence on the role of consumer channels in determining firm outcomes following CSR disclosure does not paint a clear picture. Campa (2018) investigates the role of how close an industry is to final consumers in response to targeting by newspapers. She finds only those firms in industries close to consumers undertake remedial action in response to negative reports in the press about their toxic emissions. Meanwhile, Lyon and Shimshack (2015) do not find any evidence that the consumer channel affects stock returns following disclosure on environmental performance. The authors conclude that final consumer preferences are not a major determinant of firms' market outcomes.

I formalize the notion of downstreamness by using the share of the value of the goods in an industry going to final use.[16] Let S_s denote the share of the value of the goods in six-digit NAICS industry s going directly to final demand, rather than into intermediate production.[17] S_s is a measure of the downstreamness of an industry, as the higher the share of total value in an industry that goes to final consumers, the closer the industry can be considered to consumers. S_s is summarized in Table 9. On average, over all campaign events, about 51% of the value of the goods in targeted firms' industries go to final consumers, with values ranging from 0% to 100%.

If investors believe that consumers are likely to eschew a good upon the launch of an NGO campaign action, then we would expect to see a significant decline in cumulative abnormal returns as the share of the value of the goods going to final consumers increases. On the other hand, consistent with evidence from Campa (2018), investors could expect firms to correct their behaviour following disclosure by NGOs in industries with increased consumer pressure. Then, one would expect to see a stronger stock reaction against targeted firms for whom S_s is lower, as one would expect investors to account for the potential of relatively downstream firms to respond to the threat of lower consumer demand.

[16] A detailed description of the methodology, based on Miller and Temurshoev (2017) is given in the appendix.

[17] There are 188 six-digit NAICS industries in my campaign events data.

Let $SDShare_s$ represent the standardized analogue of S_s. The regression specification for examining the relationship between the share of the value of the goods going to final consumers is given by:

$$CAR^i_{jst} = \beta_0 + \beta_1 SDShare_s + \beta_2 ENV^i_{jst} + \Gamma' X_i + Year_t + \delta_s + u^i_{jst} \tag{7}$$

Table 13 displays the result of the regression with final-use shares. In each specification, the final-use share is significantly positively associated with CAR[-5,5]. The effect ranges from 0.107% in Column (2) to 0.148% in Column (1). In Column (6), with a full set of controls, along with year and industry group (4-digit NAICS) fixed effects, the coefficient is 0.134. The interpretation is that a one standard deviation increase in the share of the value of goods in an industry going to final consumers causes an abnormal return response that is 0.1% to 0.15% higher. This provides suggestive evidence that campaign events against firms in relatively upstream industries lead to a stronger abnormal return response than firms in relatively downstream industries.

4 NGO Targeting Behaviour

4.1 Setup

It is instructive to understand whether NGOs time their campaign actions to when they can garner more attention in the news. To determine whether this is indeed the case, consider the equation:

$$N_t = \beta_0 + \beta_1 D_t + X_t + \epsilon_t \tag{8}$$

where N_t represents the number of campaign actions launched in a day by all NGOs against US firms, D_t represents daily news pressure, the median time in minutes spent on the top three news items across four major US broadcast networks, namely ABC, CBS, NBC and CNN, and X_t represents day-of-week, month and year fixed effects. The relationship between daily news pressure and the number of campaign actions in a day is likely to be biased for two reasons; first, unobservable factors could determine both news pressure and the number of actions launched in a day. For example, a major sporting tournament could significantly affect news pressure, and lead to targeted campaigning by

NGOs against the firms that sponsor the tournament.[18] Second, the number of actions in a day could alter daily news pressure itself. Therefore, it is important to find a source of exogenous variation in daily news pressure.

4.2 IV Strategy & Results

I instrument for daily news pressure by using the dates on or surrounding major political events that are likely to move news pressure, and that occur in a pre-planned manner that allow NGOs ample time in advance to plan actions around. In particular, I use dates on or surrounding national elections in OECD and G20 member countries, along with days corresponding to significant political events in the US. Since I am interested in NGOs' behaviour for pre-planned dates that significantly affect daily news pressure, I exclude parts of elections that do not occur with significant notice, such as second round run-off elections. If an election occurs on Saturday or Sunday, I use the following weekday, since very few campaign actions take place on the weekend.

In order to gather which political events significantly impact news pressure, I regress daily news pressure on indicator variables that equal one if the date coincides with the occurrence of a major political event, or the following Monday if the election occured on Saturday or Sunday.[19] I then code the political events with statistically significant positive coefficients into a variable denoted *Up*, indicating whether the political event brought about a statistically significant increase in daily news pressure. Specifically, I start by employing the following specification:

$$D_t = \alpha_0 + \sum_{a \in A} \lambda_a Pol_{at} + X_t + v_t, \tag{9}$$

where A is the set of major US political events, along with elections in G20 and OECD countries, and Pol_{at} is an indicator variable for days in which political event a in set A is taking place.

The results of the instrument construction are provided in Table 15. All political

[18] Indeed, Couttenier and Hatte (2016) find that firms that sponsor major sporting events such as the FIFA world cups or the Olympics face increased reports by NGOs during the events. Although they do not find a significant increase in the overall *number* of reports by NGOs during this time, it is clear that unobserved factors could affect both D_t and NGO behaviour.

[19] For the full list of political events, please refer to Table 14 in the appendix.

events with coefficients significant at the 10% level are coded into Up_t. In all, there are 20 such political events, and they span 26 days. Column (2) in Table 15 displays the coefficient on Up_t. On a day with a major political event coded into Up_t, daily news pressure is 3.81 minutes larger.

The first and second stage to test the relationship between daily news pressure and the number of events then take the form:

$$D_t = \alpha_0 + \alpha_1 Up_t + X_t + v_t \tag{10}$$

$$N_t = \beta_0 + \beta_1^{IV} D_t + X_t + \epsilon_t \tag{11}$$

where daily news pressure D_t is instrumented by major political events.

The results of the 2SLS regression are presented in Table 16. The first column shows the first stage results, revealing a strong positive relationship between Up_t and daily news pressure. This is corroborated by the significant F-statistic on excluded instruments of 41.44. The second column shows the result from the regression of N_t, the number of actions in a day, on D_t, with D_t instrumented by Up_t. The associated coefficient is significant at -0.843. This implies that a three-minute increase in D_t, similar to a move from the 25th percentile to the 75th percentile of news pressure,[20] leads to approximately 2.5 more actions in a day by NGOs.

4.3 Placebo Tests

My proposed mechanism for why NGOs time their campaigning behaviour relates to their taking advantage of pre-planned political events that significantly alter news pressure. To ensure that other factors are not driving their decisions to launch campaign actions, I conduct placebo tests, in the spirit of Durante and Zhuravskaya (2018). I use the total number of deaths in disasters as an instrument for D_t. Since disasters and associated deaths are unexpected, they should not affect NGOs' campaigning decisions either during their occurrence or in the proceeding days. Since daily news pressure is likely affected by the number of deaths in disasters, deaths in disasters are a plausibly valid instrument for D_t.

[20] The 25th and 75th percentiles of D_t are 6.83 and 9.67, respectively.

Table 17 describes the construction of the instrument for the placebo test. Column (1) displays the results of regressing D_t on the total number of people killed in disasters (in 1000s) on a given day and each of the previous 10 days. On average, an extra thousand people killed in disasters on a given day is associated with D_t being approximately 0.2 minutes higher. The associated coefficient for the day after is higher, at 0.256. The effect of an extra 1000 people killed attenuates for further lags, remaining statistically significant until the eighth lag. For the ninth and tenth lags, the effect is no longer significant. I therefore code the total number of deaths in disasters on a given day and the previous eight days into a single variable. The results of regressing D_t on this variable are displayed in Column (2) of Table 17. The coefficient is highly statistically significant- at the 1% level, indicating that it is a strong instrument for D_t.

Table 18 displays the results of the 2SLS regression. The first stage is displayed in Column (1). The instrument is highly significant, and the associated F-statistic on excluded instruments is 48.97. The results in the second stage, shown in Column (2), show that the coefficient on daily news pressure is insignificant at -0.0389. Column (3) shows the reduced-form OLS result, which is also insignificant at -0.00113. The implication of this result is that NGOs only time their campaigning activity away from predictable events announced significantly in advance that push news pressure up, rather than in response to unpredictable events that may also increase it.

5 Conclusion

The threat of activism by NGOs is an important deterrent for firms from falling short on various dimensions of corporate social responsibility. This paper uses a novel dataset on NGO campaign actions to show that activism in the form of campaign actions can significantly affect abnormal stock returns. Campaign issues matter; campaign issues related to environmental concerns garner much more of an abnormal return effect than other issues. This finding is significant as it demonstrates that firms have an incentive to improve environmental performance even in the absence of public regulation. Further, given that 100 firms produce the fossil fuels responsible for 71% of global greenhouse gas emissions, the monitoring and targeting of polluting firms by NGOs has the potential to play a major role in the battle against climate change (Economist, 2019).

The paper further finds that cumulative abnormal returns surrounding campaign events tend to diminish in size as firms are targeted more frequently. This suggests investors update their beliefs about firms' social or environmental performance even for relatively rarely targeted firms, and that more frequently targeted firms have the information related to their social or environmental performance already incorporated into their price, irrespective of the novelty of additional allegations or complaints.

This paper also provides evidence that NGOs time their campaigning activity to avoid days with newsworthy events that compete for the public's attention. Strategic decision-making by NGOs around times where firms are more likely to be in the spotlight has been discussed in the literature, but the general question of whether NGOs strategically time their activity to the news cycle has not been identified empirically.

This paper can motivate further research in several ways. First, while this paper looks at the broader question of how activism can impact firms financially, its findings can motivate more directed investigations into how activism can contribute to firms' decision making. Given the significantly negative impact on environmental issues, further research can examine firm responses to campaigning on environmental issues. The more pronounced effects for upstream industries merits further examination. Researchers have documented the existence of industries that enact substantive change in response to pressure alongside industries that engage in "window-dressing". Determining the relationship between such behaviour and the financial harm caused by NGOs is an important avenue for further research. Second, it can guide more research on the strategic behaviour of NGOs. While much has been discussed in the literature about the selection of target firms, only recently has the timing of actions been investigated empirically.

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6 Appendix

Variable Descriptions

Variable	Description
NGO Power	Geographical outreach of an NGO.
ENV	Dummy variable for environmental campaign event.
US NGO	Dummy variable for whether an NGO is headquartered in the US.
Partnership	Dummy variable for whether an NGO has a partnership with a firm.
Prominence	Prominence of the mention of a firm in an NGO's communication.
Positive	Dummy variable for whether an event is positive in tone.
Number of NGOs	Number of NGOs taking part in a campaign event against a firm.
Daily News Pressure (D_t)	Time spent on the top 3 news stories on ABC, CBS, NBC, and CNN.
Number of actions (N_t)	Number of actions launched by NGOs in a day.
Share (S_s)	Share of the value of goods in industry s going to final consumers.
$SDShare_s$	Standardized share of the value of goods in industry s going to final consumers.
Pol_{at}	Dummy variable for political event a at date t.
Up_t	Dummy variable for political events that caused a statistically significant increase in daily news pressure.
$DisasterDeaths_t$	The number of deaths in disasters at date t.
$Past8DaysDeaths_t$	The number of deaths in disasters on day t and the past 8 days.

Criteria for Classifying Environmental Campaigns

- All campaign issues related to pollution due to the release or spillage of toxic materials into the environment such as greenhouse gases, toxic chemicals or nuclear safety are considered environmental campaigns.
- Campaign issues related to the impact of an activity on indigenous peoples' are social issues and not considered environmental.
- If an issue pertains to access to water, it is not environmental, but if it pertains to the environmental impact of improper water usage, then it is environmental.
- Impact on animals can be either:
  - If an activity affects animal populations' traditional habitats by rendering them inhabitable, or endangers animal populations through toxic spills, release of chemicals, dredging, or human-induced climate change, then it is environmental.

  - If an activity affects animals as a direct result of human cruelty or actions, such as animal testing of chemicals, overfishing, culling of seals for fur, then it is an animal welfare issue, and not environmental.

- If a campaign issue is against the financing of certain practices or industries because they are environmentally-unfriendly, then it is environmental. But if the issue is, for example, related to landfills, but relates to protecting consumers from monopolies in landfill ownership, then it is not environmental.

- Even within industry groups that are arguably environmentally unfriendly, whether the activity campaigned against is environmental is important. For example, if the issue is corruption in oil and gas contracts, then it is not environmental. Similarly, certain campaign issues related to natural resources, such as that of worker safety in coal mines, are not environmental, but issues related to the environmental impact of coal mining are environmental.

- All campaign issues related to the supply chain responsibility of fashion (for example issues related to sweatshops or factory safety) are not considered environmental campaigns- though there might be environmental components to some such campaigns.

Campaign Action Case Examples

The following examples are reports of campaign actions, provided by Sigwatch:

Environmental Campaign Actions

1. In the U.S., Rainforest Action Network is mobilising supporters to stage days of action on Nov 18 at PNC bank offices across the country, in protest at financing of mountaintop removal coal mining. RAN claimed PNC is now the lead supplier of funding for companies involved in this activity, and named Massey Energy, Alpha Natural Resources, Consol Energy, International Coal Group and Patriot Coal.

2. In the U.S., Center for Environmental Health (CEH), Citizens Campaign for the Environment, Food & Water Watch (FWW), and Frack Action, with eight other environ-

mental groups called on the New York Governor to reject the oil and gas fracking Revised Draft Supplemental Generic Environmental Impact Statement (RDSGEIS) because of alleged conflicts of interest. The groups claimed that Ecology and Environment (E&E), Alpha Geoscience, and URS Corporation, who were retained by city departments to work on the RDSGEIS, are all members of the Independent Oil and Gas Association of New York (IOGA NY), which is allegedly the leading voice for fracking in New York and which had received USD2 million last year from Exxon Mobil to run a pro-fracking campaign.

Non-Environmental Campaign Actions

1. *In the U.S., Global Exchange, Green America and allies launched a phone-in to Hershey's to demand it go fair trade to keep out cocoa associated with child labour. Hershey is being singled out for allegedly failing to participate in any certification programs to track its global supply chain and institute labour standards for its cocoa suppliers, and for restructuring its global manufacturing leading to fewer jobs for unionised workers.*

2. *Oxfam claimed that poultry workers are among the most vulnerable and exploited workers in the U.S.. The companies are accused of relying on cheap and easily coerced immigrant and prison labor, skimping on health and safety, and treating their staff like a disposable commodity, and that while the annual income for many poultry workers is between USD20,000 and USD25,000, the CEO of Sanderson Farms made the same amount in one eight-hour day. The NGO also claimed that for every dollar consumers spend on McDonald's Chicken McNuggets, only about two cents goes to workers in the processing plants. Oxfam is hoping to apply the same consumer pressure to promote reduced antibiotic usage in food production and increased number of cage-free hens.*

Construction of the Output Shares Going to Final Consumers

In this section, I document my methodology for constructing the share of output going to final consumers. My methodology is based on the measure of upstreamness discussed in Miller and Temurshoev (2017). Although I use a modified version, I briefly explain the measure here. Consider the total value of gross output in industry s, denoted x_s. The equation for x_s can be given by:

$$x_s = f_s + \sum_c z_{sc} \tag{12}$$

where f_s is the value going to final use, and $\sum_c z_{sc}$ is the sum over all industries c the intermediate output sales going from industry s to industry c.

We can then construct the input coefficient for industry s going to industry c as $a_{sc} = \frac{z_{sc}}{x_c}$. The interpretation for the input coefficient a_{sc} is the dollar amount of industry s's output needed for a dollar's worth of industry c's output. The aforementioned equation for x_s can then be restated as:

$$x_s = f_s + \sum_c a_{sc} x_c \tag{13}$$

The equation for x_c is identical to the previous equation for x_s. By substituting the corresponding equation for x_c over all c, the equation for x_s can be then written as:

$$x_s = f_s + \sum_c a_{sc} f_c + \sum_{c,d} a_{sd} a_{dc} f_c + \sum_{c,d,e} a_{se} a_{ed} a_{dc} f_c + ... \tag{14}$$

The index for upstreamness can then be calculated as:

$$u_s = 1 * \frac{f_s}{x_s} + 2 * \frac{\sum_c a_{sc} f_c}{x_s} + 3 * \frac{\sum_{c,d} a_{sd} a_{dc} f_c}{x_s} + ... \tag{15}$$

Construction of the full measure of upstreamness is not necessary for the purposes of developing a proxy for the level of consumer pressure faced in a particular industry. Instead, I truncate the above formulation and use $S_s = \frac{f_s}{x_s}$, the share of the value of the goods in an industry that comes from final use. I do this by using input-output tables from the Bureau of Economic Analysis (BEA) to calculate the total intermediate output value ($\sum_c z_{sc}$) for each industry s. I then generate the total value of output for each industry, x_s, by adding the total intermediate output value, $\sum_c z_{sc}$, with the value that goes to final use, f_s. Then, finally, to calculate the share in industry s going to final demand, I divide the value of the goods in the industry that go to final demand by the industry's total output.

Figures and Tables

Figure 1: Histogram of Number of Campaign Events per Firm for Public US Firms

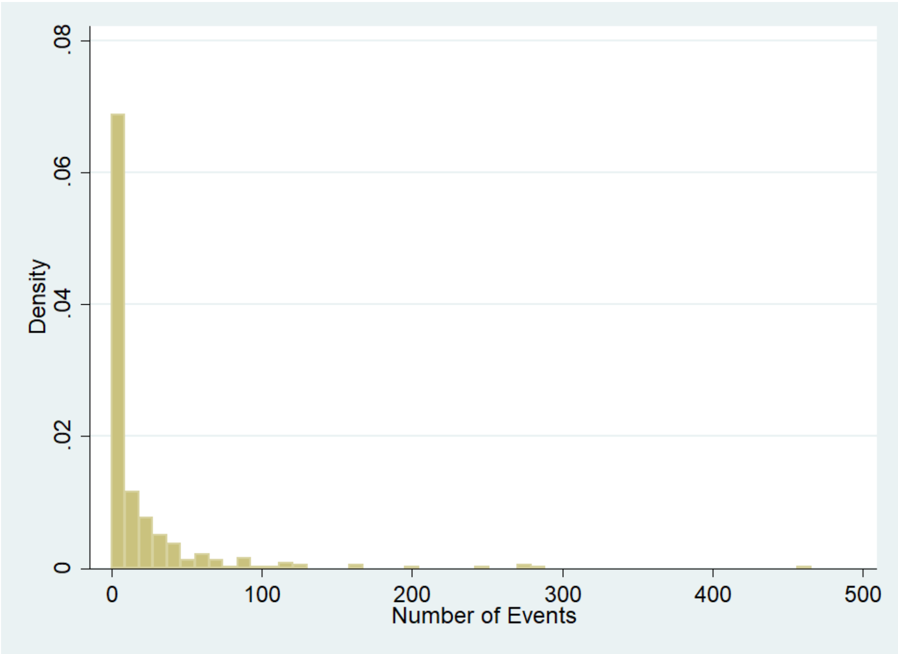

Table 1: Basic Summary Statistics for Public US Firms

	Count
No. of Firms ($\leq$ 50 events)	369
No. of Firms ($\leq$ 40 events)	354
No. of Firms ($\leq$ 30 events)	340
Year 2010	626
Year 2011	1132
Year 2012	1455
Year 2013	1462
Year 2014	1564
Year 2015	1490
No. of Industry Sectors	22
No. of Firms	405
No. of Campaign Events (Total)	7729

Figure 2: Event Study Horizon

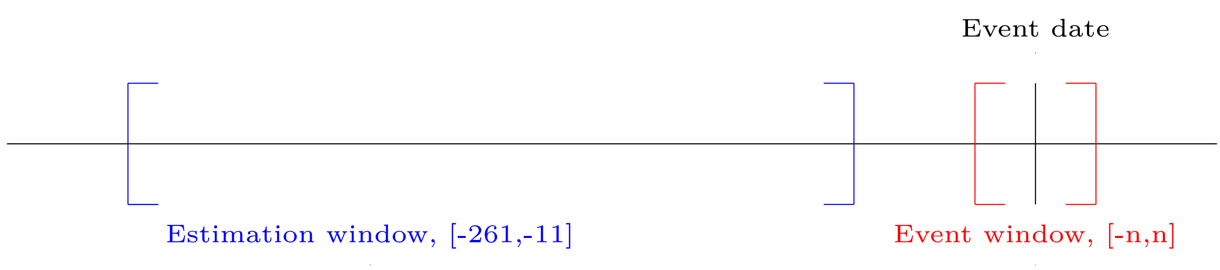

Table 2: Industry Sectors of Targeted Public US Firms

Sector	2-digit NAICS	No. Firms	No. Events
Agriculture, Forestry, Fishing & Hunting	11	2	18
Mining, Quarrying, Oil & Gas Extraction	21	45	780
Utilities	22	54	591
Construction	23	2	3
Manufacturing	31	32	1242
Manufacturing	32	49	1699
Manufacturing	33	68	794
Wholesale Trade	42	8	169
Retail Trade	44	22	403
Retail Trade	45	15	359
Transportation & Warehousing	48	10	62
Transportation & Warehousing	49	1	13
Information	51	27	512
Finance & Insurance	52	30	541
Real Estate & Rental & Leasing	53	9	15
Professional, Scientific, & Technical Services	54	8	25
Management of Companies & Enterprises	55	1	37
Administrative & Support & Waste Management & Remediation Services	56	5	14
Healthcare & Social Assistance	62	1	3
Arts, Entertainment, & Recreation	71	1	5
Accomodation & Food Services	72	14	437
Other Services (except Public Administration)	81	1	7
	Total	405	7729

Table 3: Summary statistics for Daily News Pressure and Daily Number of Actions

	No. of Days	Mean	SD	Min	Max	p25	p50	p75
Daily News Pressure (D_t)	2140	8.578076	2.604553	2.833333	25.83333	6.833333	8	9.666667
Daily No. of Actions (N_t)	2148	6.599628	7.84686	0	57	0	4	10

This table displays summary statistics for Daily News Pressure (D_t) and the number of actions in a day (N_t).

Figure 3: Evolution of Average Abnormal Returns around the Campaign Event with 90% Confidence Intervals

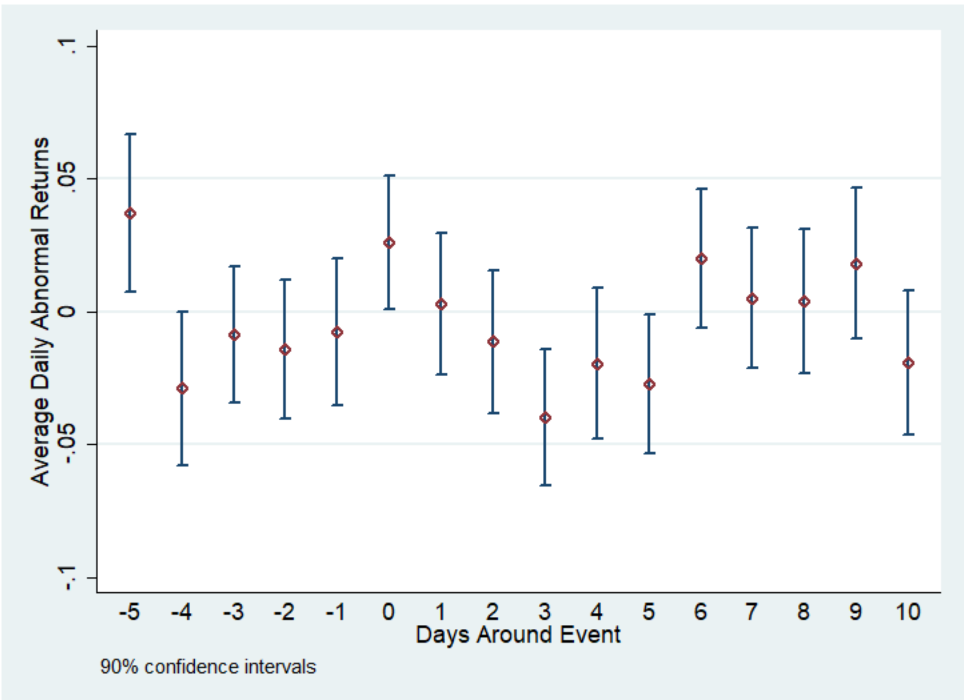

Figure 4: Evolution of Average Cumulative Abnormal Returns around the Campaign Event with 90% Confidence Intervals

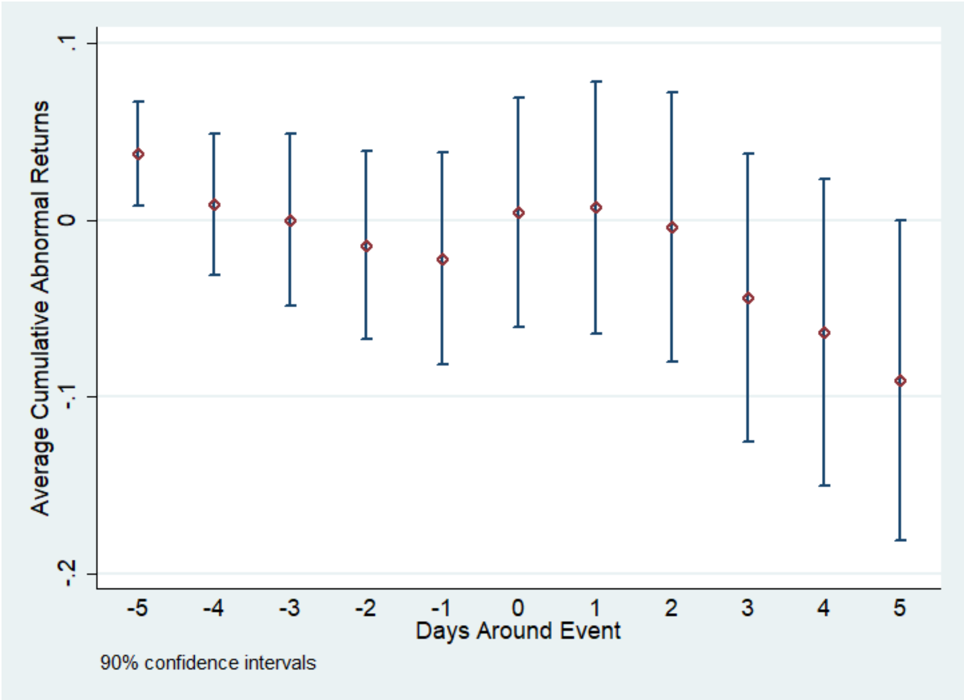

Figure 5: Evolution of Average Abnormal Returns around the Campaign Event

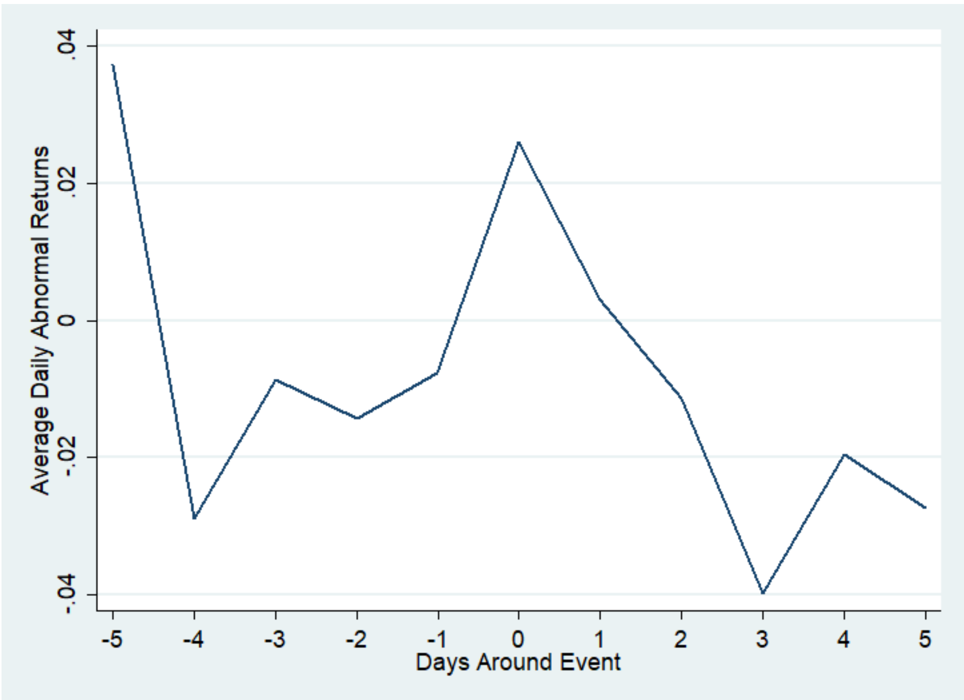

Figure 6: Evolution of Average Cumulative Abnormal Returns around the Campaign Event

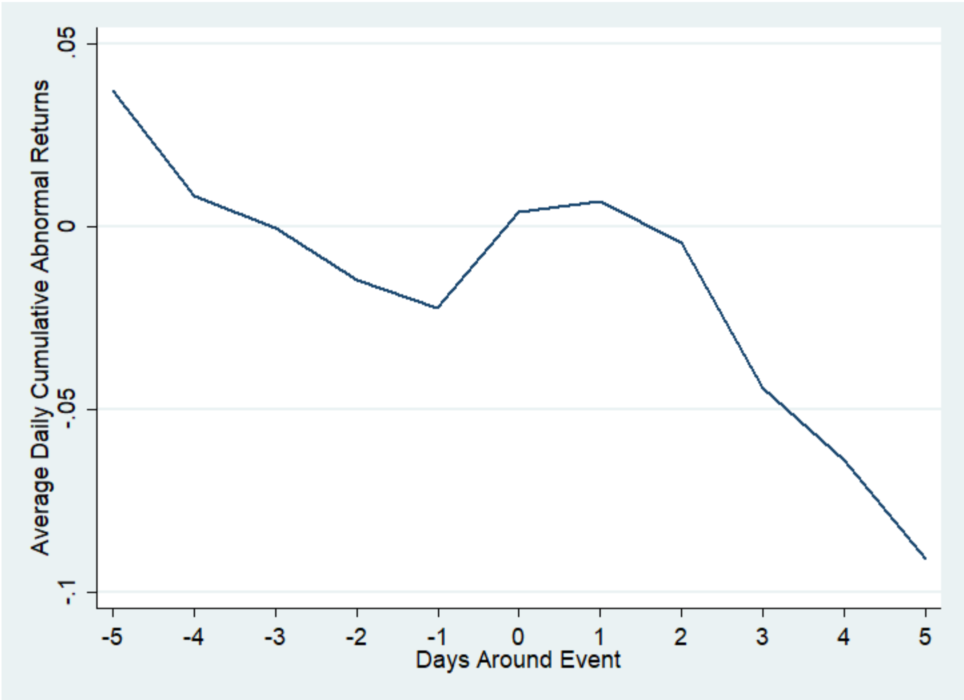

Figure 7: Evolution of Average Abnormal Returns around the Campaign Event with 90% Confidence Intervals, Environmental Campaign Events

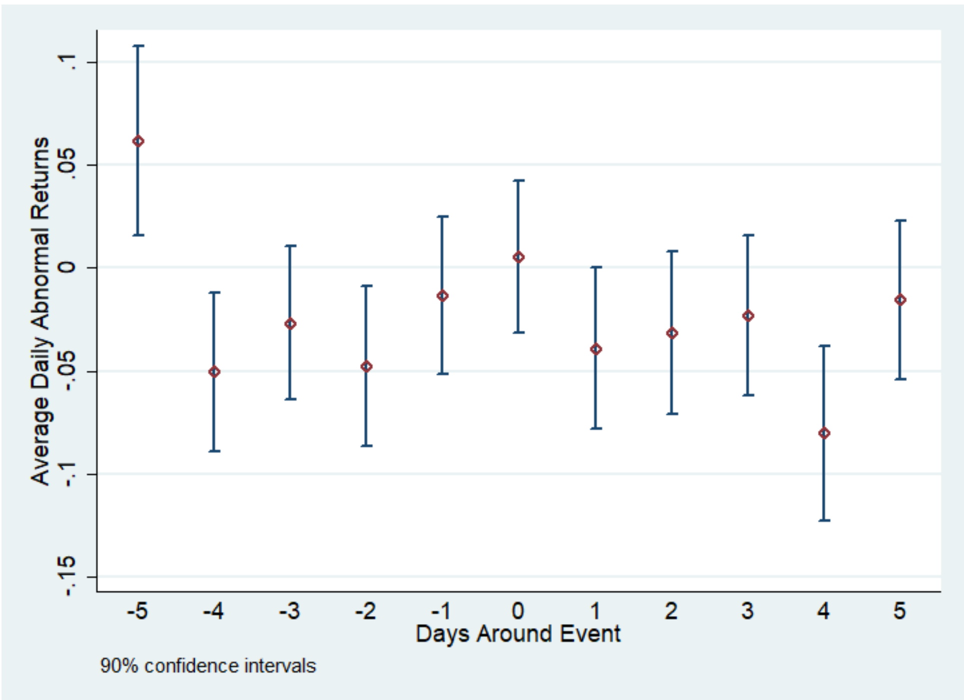

Figure 8: Evolution of Average Cumulative Abnormal Returns around the Campaign Event with 90% Confidence Intervals, Environmental Campaign Events

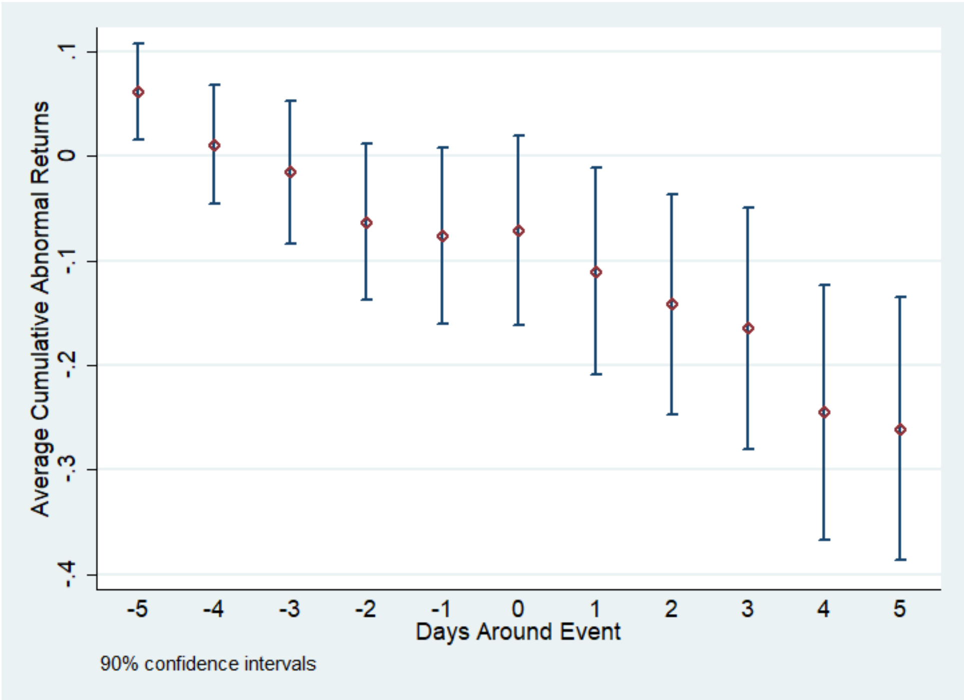

Figure 9: Evolution of Average Abnormal Returns around the Campaign Event with 90% Confidence Intervals, Non-Environmental Campaign Events

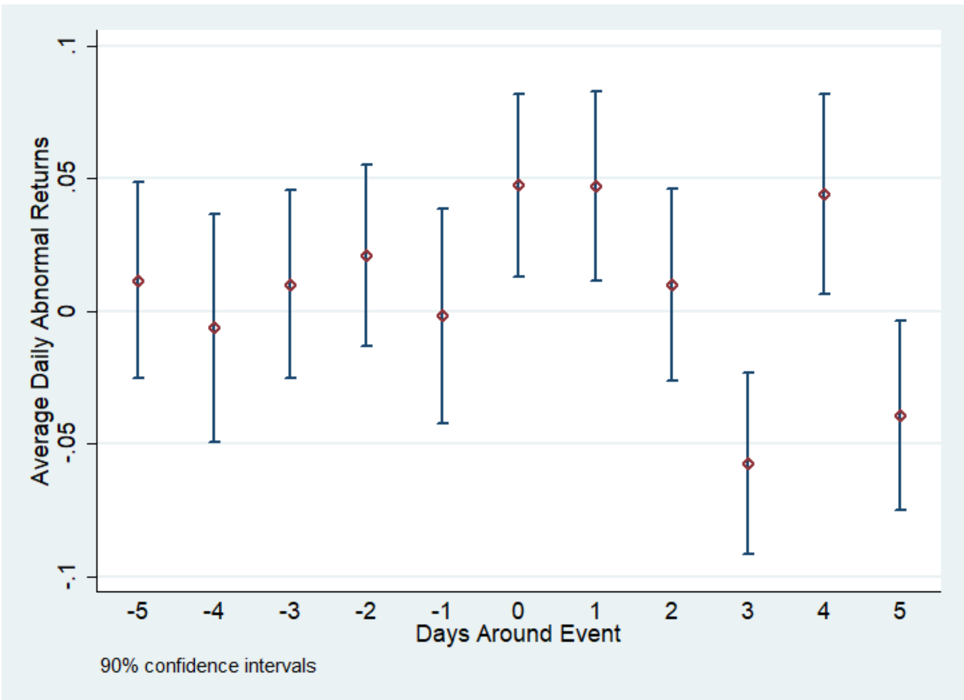

Figure 10: Evolution of Average Cumulative Abnormal Returns around the Campaign Event with 90% Confidence Intervals, Non-Environmental Campaign Events

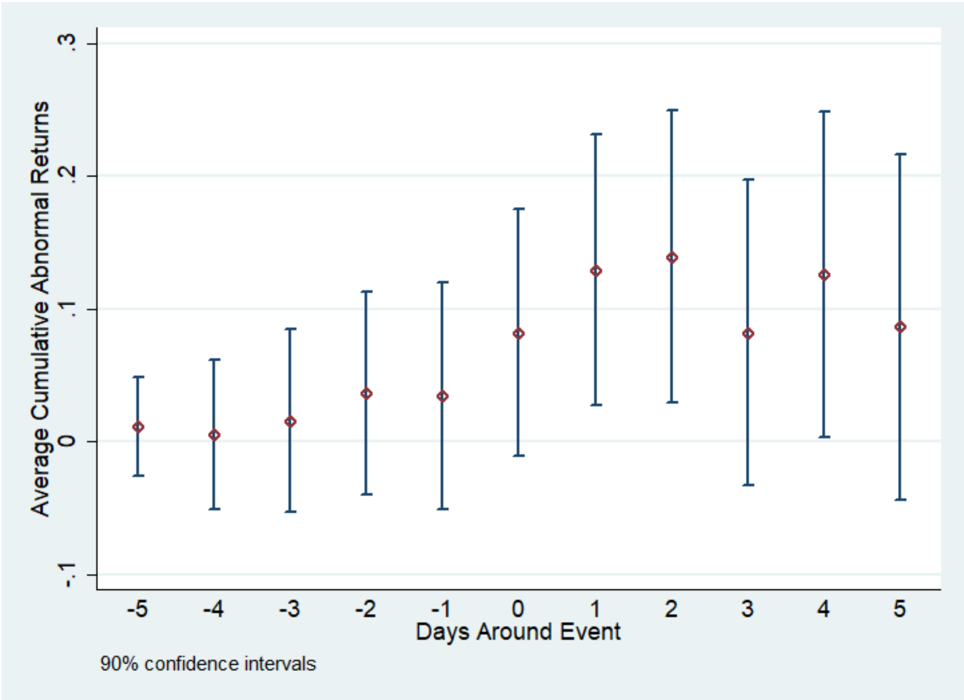

Figure 11: Evolution of Average Cumulative Abnormal Returns around the Campaign Event, Environmental Campaign Events

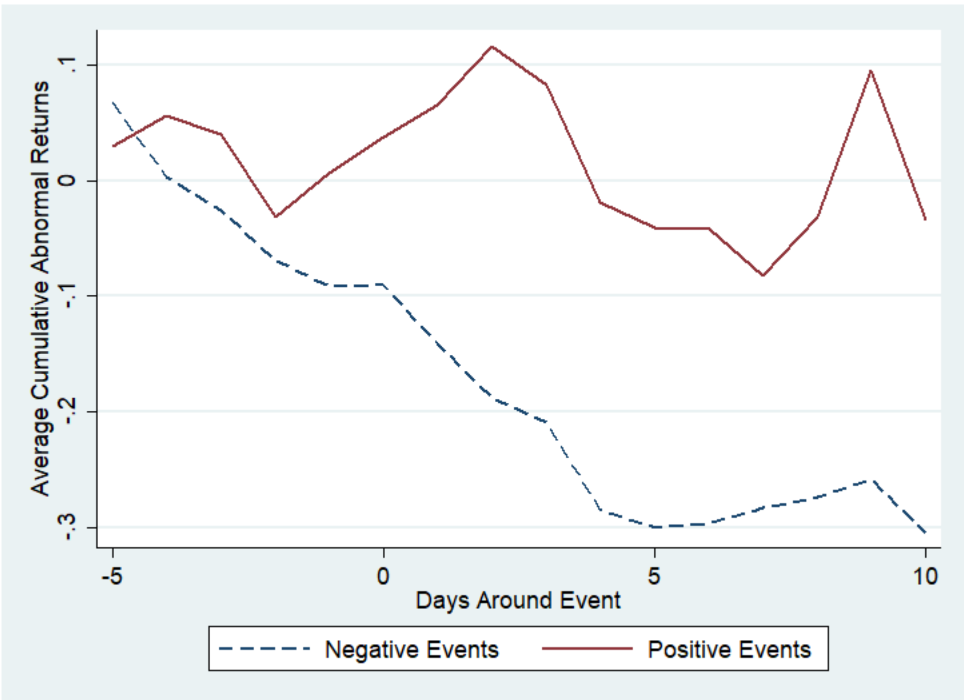

Figure 12: Evolution of Average Cumulative Abnormal Returns around the Campaign Event, Non-Environmental Campaign Events

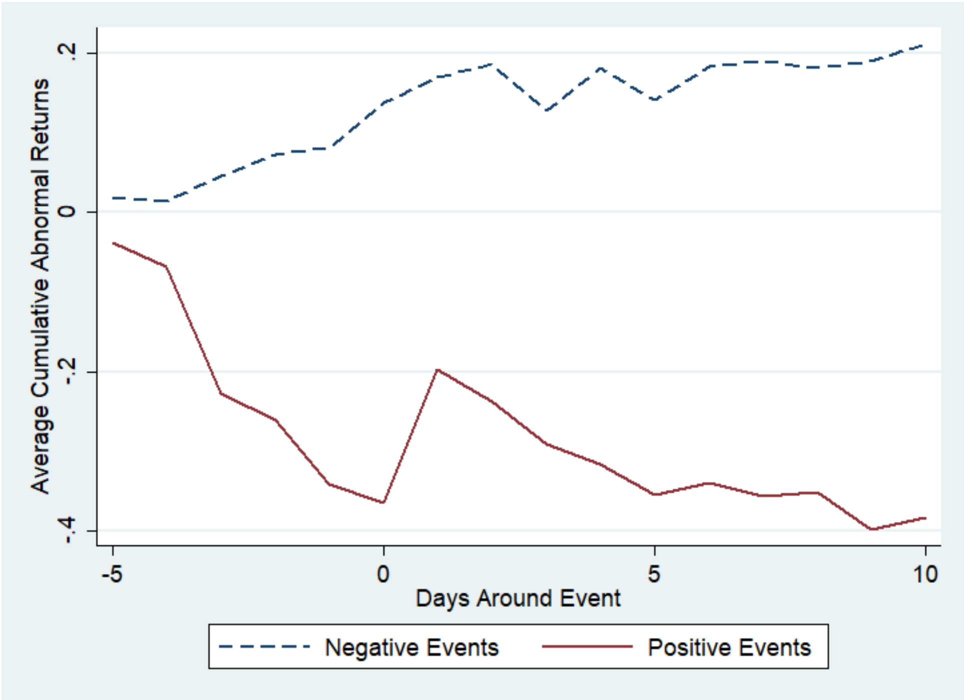

Figure 13: Evolution of Average Cumulative Abnormal Returns in Days Prior to Event, with 90% Confidence Intervals

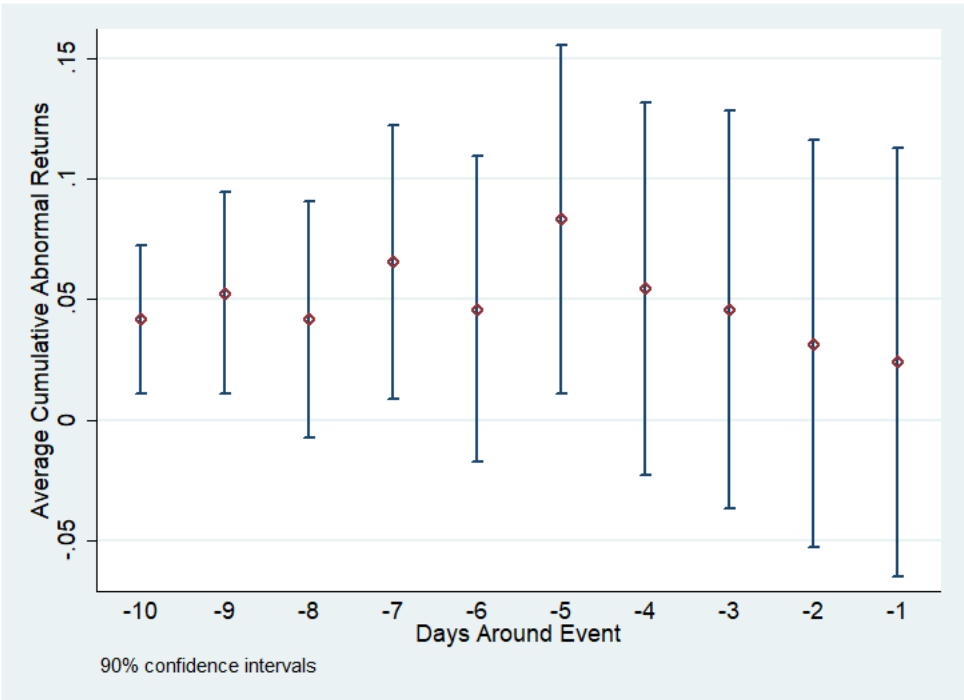

Table 4: Average Cumulative Abnormal Returns for Firms, by Number of Campaign Events

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\leq$ 30 Events	$\leq$ 40 Events	$\leq$ 50 Events	$\leq$ 60 Events	$\leq$ 100 Events	$\leq$ 150 Events	$\leq$ 200 Events	Full Sample
CAAR[-1,1]	0.00869	0.0282	-0.00830	0.0342	0.00514	0.0146	0.0168	0.0215
	(0.0655)	(0.0552)	(0.0513)	(0.0485)	(0.0420)	(0.0362)	(0.0357)	(0.0284)
CAAR[-2,2]	-0.0487	-0.0101	-0.0409	0.00403	-0.0279	-0.0126	-0.00481	-0.00408
	(0.0852)	(0.0720)	(0.0668)	(0.0620)	(0.0543)	(0.0467)	(0.0459)	(0.0364)
CAAR[-3,3]	-0.106	-0.0554	-0.100	-0.0691	-0.110^{*}	-0.0733	-0.0628	-0.0526
	(0.101)	(0.0860)	(0.0798)	(0.0739)	(0.0648)	(0.0558)	(0.0549)	(0.0435)
CAAR[-4,4]	-0.236^{*}	-0.173^{*}	-0.206^{**}	-0.151^{*}	-0.193^{**}	-0.142^{**}	-0.131^{**}	-0.101^{**}
	(0.121)	(0.102)	(0.0936)	(0.0871)	(0.0751)	(0.0648)	(0.0637)	(0.0505)
CAAR[-5,5]	-0.256^{*}	-0.167	-0.188^{*}	-0.128	-0.156^{*}	-0.120^{*}	-0.113	-0.0909^{*}
	(0.133)	(0.112)	(0.102)	(0.0951)	(0.0819)	(0.0707)	(0.0696)	(0.0550)
N	2053	2602	3095	3501	4670	5658	5821	7729

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 5: Average Cumulative Abnormal Returns for Firms, by Number of Campaign Events; Non-Environmental Campaign Events

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\leq$ 30 Events	$\leq$ 40 Events	$\leq$ 50 Events	$\leq$ 60 Events	$\leq$ 100 Events	$\leq$ 150 Events	$\leq$ 200 Events	Full Sample
CAAR[-1,1]	0.0754	0.0429	0.0365	0.101	0.0884	0.102**	0.0997**	0.0929**
	(0.0981)	(0.0793)	(0.0763)	(0.0720)	(0.0599)	(0.0511)	(0.0502)	(0.0409)
CAAR[-2,2]	0.00692	-0.00150	0.0201	0.0905	0.104	0.135**	0.141**	0.124**
	(0.125)	(0.101)	(0.0987)	(0.0903)	(0.0753)	(0.0641)	(0.0628)	(0.0512)
CAAR[-3,3]	-0.0756	-0.0862	-0.0708	-0.0181	0.0183	0.0806	0.0916	0.0766
	(0.146)	(0.119)	(0.116)	(0.106)	(0.0874)	(0.0750)	(0.0735)	(0.0599)
CAAR[-4,4]	-0.0656	-0.0615	-0.0291	0.0487	0.0528	0.116	0.126	0.114
	(0.184)	(0.148)	(0.141)	(0.129)	(0.106)	(0.0901)	(0.0881)	(0.0715)
CAAR[-5,5]	-0.0906	-0.0623	-0.0332	0.0650	0.0399	0.0858	0.0932	0.0866
	(0.208)	(0.167)	(0.157)	(0.142)	(0.117)	(0.0996)	(0.0976)	(0.0791)
N	951	1254	1456	1728	2270	2823	2943	3777

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 6: Average Cumulative Abnormal Returns for Firms, by Number of Campaign Events; Environmental Campaign Events

	(1) $\leq$ 30 Events	(2) $\leq$ 40 Events	(3) $\leq$ 50 Events	(4) $\leq$ 60 Events	(5) $\leq$ 100 Events	(6) $\leq$ 150 Events	(7) $\leq$ 200 Events	(8) Full Sample
CAAR[-1,1]	-0.0489	0.0146	-0.0481	-0.0314	-0.0736	-0.0724	-0.0679	-0.0468
	(0.0878)	(0.0768)	(0.0691)	(0.0651)	(0.0587)	(0.0514)	(0.0508)	(0.0394)
CAAR[-2,2]	-0.0967	-0.0181	-0.0951	-0.0802	-0.153*	-0.160**	-0.154**	-0.126**
	(0.116)	(0.102)	(0.0907)	(0.0851)	(0.0780)	(0.0677)	(0.0669)	(0.0517)
CAAR[-3,3]	-0.132	-0.0267	-0.126	-0.119	-0.232**	-0.226***	-0.221***	-0.176***
	(0.140)	(0.124)	(0.110)	(0.103)	(0.0951)	(0.0826)	(0.0816)	(0.0630)
CAAR[-4,4]	-0.383**	-0.278**	-0.363***	-0.346***	-0.425***	-0.399***	-0.394***	-0.307***
	(0.158)	(0.140)	(0.124)	(0.117)	(0.106)	(0.0931)	(0.0919)	(0.0710)
CAAR[-5,5]	-0.399**	-0.264*	-0.325**	-0.315**	-0.341***	-0.325***	-0.324***	-0.260***
	(0.170)	(0.152)	(0.134)	(0.126)	(0.114)	(0.100)	(0.0990)	(0.0766)
N	1102	1348	1639	1773	2400	2835	2878	3952

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 7: Cross-sectional Analysis of CAR[-5,5]

	(1) CAR[-5,5]	(2) CAR[-5,5]	(3) CAR[-5,5]	(4) CAR[-5,5]
ENV	-0.347***	-0.402***	-0.398***	-0.335**
	(0.126)	(0.129)	(0.127)	(0.138)
NGO Power		0.245***	0.240**	0.244***
		(0.0928)	(0.0923)	(0.0865)
Partnership		0.397	0.357	0.344
		(0.319)	(0.325)	(0.317)
Positive		-0.151	-0.148	-0.156
		(0.185)	(0.187)	(0.215)
US NGO		0.130	0.129	0.142
		(0.114)	(0.115)	(0.155)
Number of NGOs		-0.0482	-0.0451	-0.0821
		(0.0986)	(0.100)	(0.0985)
Prominence		0.0382	0.0649	0.0834
		(0.0691)	(0.0653)	(0.0632)
Year F.E.	No	No	Yes	Yes
Firm F.E.	No	No	No	Yes
Constant	0.0866	-0.425*	-0.0762	-0.0601
	(0.0703)	(0.241)	(0.332)	(0.344)
N	7729	7729	7729	7729
R^2	0.001	0.003	0.004	0.092

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Note: This table displays results examining the role of environmental issue types, denoted by the dummy variable ENV, in determining CAR[-5,5]. Column (2) adds covariates for NGO Power, Partnership, Positive, US NGO, Number of NGOs and Prominence. Column (3) adds year fixed effects,while Column (4) adds firm fixed effects. Standard errors are clustered at the 4-digit NAICS level.

Table 8: Descriptive Statistics of Key Indicator Variables

	N	Mean	Min	Max
Panel A: Non-Environmental Campaign Events				
Positive	3777	.1106698	0	1
Partnership	3777	.0068838	0	1
Multiple Actions	3777	.1209955	0	1
US NGO	3777	.6404554	0	1
Panel B: Environmental Campaign Events				
Positive	3952	.1520749	0	1
Partnership	3952	.0318826	0	1
Multiple Actions	3952	.1024798	0	1
US NGO	3952	.6647267	0	1
Panel C: All Campaign Events				
Positive	7729	.1318411	0	1
Partnership	7729	.0196662	0	1
Multiple Actions	7729	.111528	0	1
US NGO	7729	.6528658	0	1

This table displays summary statistics of key indicator variables.

Table 9: Descriptive Statistics of Key Variables

	N	Mean	SD	Min	Max
Panel A: Non-Environmental Campaign Events					
Prominence	3777	2.647074	.9484251	1	4
Share	3777	61.36466	30.06208	0	100
Number of NGOs	3777	1.402436	.8185964	1	5
NGO Power	3777	1.664085	.5642618	.5	2.75
Panel B: Environmental Campaign Events					
Prominence	3952	2.669028	1.002539	1	4
Share	3952	41.05366	30.69566	0	100
Number of NGOs	3952	1.540739	.9560635	1	5
NGO Power	3952	1.882338	.5989555	.5	2.75
Panel C: All Campaign Events					
Prominence	7729	2.6583	.9764681	1	4
Share	7729	50.97922	32.03727	0	100
Number of NGOs	7729	1.473153	.894158	1	5
NGO Power	7729	1.775682	.5923569	.5	2.75

This table displays summary statistics of key variables.

Table 10: Cross-sectional Analysis of CAR[-1,1]

	(1) CAR[-1,1]	(2) CAR[-1,1]	(3) CAR[-1,1]	(4) CAR[-1,1]
ENV	-0.140**	-0.152**	-0.150**	-0.178***
	(0.0593)	(0.0587)	(0.0587)	(0.0681)
NGO Power		0.106**	0.109**	0.109**
		(0.0501)	(0.0493)	(0.0483)
Partnership		-0.00822	-0.0208	0.0449
		(0.175)	(0.176)	(0.190)
Positive		0.0402	0.0368	0.00758
		(0.0974)	(0.0983)	(0.105)
US NGO		0.0445	0.0423	0.0244
		(0.0508)	(0.0507)	(0.0702)
Number of NGOs		-0.0938**	-0.0952**	-0.101**
		(0.0439)	(0.0450)	(0.0444)
Prominence		-0.0317	-0.0210	-0.0110
		(0.0370)	(0.0338)	(0.0343)
Year F.E.	No	No	Yes	Yes
Firm F.E.	No	No	No	Yes
Constant	0.0929**	0.0986	0.0929	0.174
	(0.0358)	(0.146)	(0.140)	(0.132)
N	7729	7729	7729	7729
R^2	0.001	0.003	0.003	0.097

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Note: This table displays results examining the role of environmental issue types, denoted by the dummy variable ENV, in determining CAR[-1,1]. Column (2) adds covariates for NGO Power, Partnership, Positive, US NGO, Number of NGOs and Prominence. Column (3) adds year fixed effects,while Column (4) adds firm fixed effects. Standard errors are clustered at the 4-digit NAICS level.

Table 11: Cross-sectional Analysis of CARs with varying event windows

	(1) CAR[-1,1]	(2) CAR[-2,2]	(3) CAR[-3,3]	(4) CAR[-4,4]	(5) CAR[-5,5]
ENV	-0.152**	-0.269***	-0.268**	-0.458***	-0.402***
	(0.0587)	(0.0943)	(0.112)	(0.152)	(0.129)
NGO Power	0.106**	0.132*	0.161	0.181*	0.245***
	(0.0501)	(0.0734)	(0.101)	(0.0978)	(0.0928)
Partnership	-0.00822	0.0856	0.102	0.370	0.397
	(0.175)	(0.202)	(0.270)	(0.287)	(0.319)
Positive	0.0402	0.0185	-0.0705	-0.0830	-0.151
	(0.0974)	(0.133)	(0.161)	(0.163)	(0.185)
US NGO	0.0445	0.0673	0.0870	0.0866	0.130
	(0.0508)	(0.0682)	(0.0885)	(0.0910)	(0.114)
Number of NGOs	-0.0938**	-0.103	-0.154	-0.0833	-0.0482
	(0.0439)	(0.0633)	(0.0967)	(0.0883)	(0.0986)
Prominence	-0.0317	-0.0122	0.00162	0.0601	0.0382
	(0.0370)	(0.0445)	(0.0480)	(0.0698)	(0.0691)
Year F.E.	No	No	No	No	No
Firm F.E.	No	No	No	No	No
Constant	0.0986	0.0354	-0.0283	-0.277	-0.425*
	(0.146)	(0.167)	(0.189)	(0.227)	(0.241)
N	7729	7729	7729	7729	7729
R^2	0.003	0.003	0.003	0.003	0.003

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Note: This table displays results examining the role of environmental issue types, denoted by the dummy variable ENV over varying event windows, beginning with CAR[-1,1] in Column (1) and expanding to CAR[-5,5] by Column (5). All columns add covariates for NGO Power, Partnership, Positive, US NGO, Number of NGOs and Prominence. Standard errors are clustered at the 4-digit NAICS level.

Table 12: Cross-sectional Analysis of CARs with varying event windows and Controls

	(1) CAR[-1,1]	(2) CAR[-2,2]	(3) CAR[-3,3]	(4) CAR[-4,4]	(5) CAR[-5,5]
ENV	-0.178***	-0.261***	-0.221**	-0.372***	-0.335**
	(0.0681)	(0.0916)	(0.109)	(0.135)	(0.138)
NGO Power	0.109**	0.127*	0.147	0.163*	0.244***
	(0.0483)	(0.0732)	(0.0978)	(0.0933)	(0.0865)
Partnership	0.0449	0.0535	0.0280	0.300	0.344
	(0.190)	(0.224)	(0.276)	(0.285)	(0.317)
Positive	0.00758	-0.0214	-0.0641	-0.0929	-0.156
	(0.105)	(0.149)	(0.189)	(0.189)	(0.215)
US NGO	0.0244	0.0334	0.0906	0.135	0.142
	(0.0702)	(0.0866)	(0.123)	(0.131)	(0.155)
Number of NGOs	-0.101**	-0.122*	-0.175*	-0.103	-0.0821
	(0.0444)	(0.0635)	(0.0973)	(0.0834)	(0.0985)
Prominence	-0.0110	0.0373	0.0517	0.0975*	0.0834
	(0.0343)	(0.0398)	(0.0424)	(0.0568)	(0.0632)
Year F.E.	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes
Constant	0.174	0.0713	0.0405	-0.0158	-0.0601
	(0.132)	(0.182)	(0.234)	(0.278)	(0.344)
N	7729	7729	7729	7729	7729
R^2	0.097	0.091	0.099	0.098	0.092

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Note: This table displays results examining the role of environmental issue types, denoted by the dummy variable ENV over varying event windows, beginning with CAR[-1,1] in Column (1) and expanding to CAR[-5,5] by Column (5). All columns add covariates for NGO Power, Partnership, Positive, US NGO, Number of NGOs and Prominence, and contain year and firm fixed effects. Standard errors are clustered at the 4-digit NAICS level.

Table 13: Analysis of Share of the Value of Goods in an Industry Going to Consumers

	(1) CAR[-5,5]	(2) CAR[-5,5]	(3) CAR[-5,5]	(4) CAR[-5,5]	(5) CAR[-5,5]	(6) CAR[-5,5]
$SDShare_s$	0.148**	0.107*	0.113*	0.127*	0.130**	0.134*
	(0.0692)	(0.0640)	(0.0644)	(0.0711)	(0.0634)	(0.0711)
ENV		-0.331***	-0.323***	-0.245**	-0.318**	-0.302**
		(0.119)	(0.116)	(0.122)	(0.128)	(0.133)
NGO Power		0.240**	0.235**	0.225**	0.242***	0.257***
		(0.0921)	(0.0915)	(0.0904)	(0.0917)	(0.0926)
Partnership		0.376	0.336	0.264	0.231	0.231
		(0.317)	(0.322)	(0.323)	(0.322)	(0.322)
Positive		-0.214	-0.214	-0.202	-0.133	-0.165
		(0.189)	(0.194)	(0.203)	(0.213)	(0.216)
US NGO		0.131	0.130	0.116	0.123	0.129
		(0.115)	(0.116)	(0.129)	(0.132)	(0.146)
Number of NGOs		-0.0401	-0.0363	-0.0355	-0.0470	-0.0641
		(0.0968)	(0.0980)	(0.0969)	(0.0958)	(0.0985)
Prominence		0.0360	0.0621	0.0476	0.0548	0.0700
		(0.0674)	(0.0636)	(0.0590)	(0.0619)	(0.0617)
Year F.E.	No	No	Yes	Yes	Yes	Yes
Sector F.E.	No	No	No	Yes	No	No
Subsector F.E.	No	No	No	No	Yes	No
Industry Group F.E.	No	No	No	No	No	Yes
Constant	-0.0909	-0.450*	-0.0874	-0.0720	-0.0702	-0.0819
	(0.0647)	(0.239)	(0.334)	(0.337)	(0.326)	(0.330)
N	7729	7729	7729	7729	7729	7729
R^2	0.001	0.003	0.004	0.008	0.016	0.033

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Note: This table displays results examining the role of the share of the value of goods in an industry going to final consumers in determining CAR[-5,5]. $SDShare_s$ represents a standard deviation shift in the share the value of goods in industry s going to final consumers. Column (2) adds covariates for ENV, NGO Power, Partnership, Positive, US NGO, Number of NGOs and Prominence. Column (3) adds year fixed effects,while Column (4) adds sector fixed effects. Columns (5) and (6) are identical to Column (4) except that instead of sector fixed effects (2-digit NAICS) they employ subsector (3-digit NAICS) and industry group fixed effects (4-digit NAICS), respectively. Standard errors are clustered at the 4-digit NAICS level.

Table 14: List of Political Events

India election 2014	UK election 2015	Canada election 2015
UK election 2010	EU election 2014	Obama Inauguration 2013
US election 2012	Israeli election 2013	Israeli election 2015
New Hampshire Primaries 2012	Republican Convention 2012	Democratic Convention 2012
Super Tuesday 2012	Iowa Caucus 2012	State of the Union (2010-2015)
Russia election 2012	German election 2013	Italian election 2013
Australia elections 2013	Japanese election 2014	Japanese election 2012
South Africa election 2014	Turkish general election 2011	Turkish general election 2015
Turkish Presidential election 2014	Iceland parliamentary election 2013	Argentina election 2011
Argentina general election 2015	Brazil election 2010	Brazil election 2014
Mexico election 2012	South Korea election 2012	France election 2012
Indonesian elections 2014	Swiss election 2015	Swiss election 2011
Sweden election 2014	Sweden election 2010	Spain election 2015
Spain election 2011	Slovenia election 2014	Slovenia election 2011
Slovakia election 2014	Portugese election 2011	Polish election 2015
Polish election 2010	Norwegian election 2013	New Zealand election 2014
New Zealand election 2011	Dutch election 2012	Luxembourg election 2013
Lithuania election 2011	Latvia election 2014	Ireland election 2011
Iceland presidential election 2012	Belgian election 2014	Austrian presidential election 2010
Austrian legislative election 2013	Chilean election 2013	Czech legislative election 2010
Czech legislative election 2013	Czech election 2013	Danish election 2011
Danish election 2015	Estonia election 2011	Estonia election 2015
Finland presidential election 2012	Finland election 2011	Finland election 2015
Greek legislative election 2015	Greek election 2012	Hungary elections 2014

Table 15: Construction of Up_t Variable

	(1)		(2)
	D_t		D_t
UK Election 2010	1.812***	Up_t	3.810***
	(0.470)		(0.592)
Obama Inauguration	4.599***		
	(0.398)		
US Election 2012	7.753***		
	(0.484)		
New Hampshire Primaries	0.962**		
	(0.382)		
Republican Convention	6.443***		
	(0.404)		
Democratic Convention	3.934***		
	(0.382)		
Super Tuesday	3.136***		
	(0.542)		
Iowa Caucus	3.548***		
	(0.383)		
German Election	2.535***		
	(0.398)		
Japanese Election 2012	6.160***		
	(0.506)		
Turkish Presidential Election 2014	2.074***		
	(0.441)		
Brazil Election 2010	0.860*		
	(0.503)		
South Korea Election 2012	1.459**		
	(0.551)		
Slovakia Election 2014	1.138**		
	(0.559)		
Polish Election 2010	1.147*		
	(0.668)		
Dutch Election 2012	7.571***		
	(0.386)		
Ireland Election 2011	1.379**		
	(0.602)		
Austrian Legislative Election 2013	1.035**		
	(0.398)		
Danish Election 2015	8.037***		
	(0.572)		
Greek Legislative Election 2015	1.979***		
	(0.431)		
Other Elections & US Political Events	Yes		
DOW, Month, Year F.E.	Yes		Yes
N	2140		2140
R^2	0.133		0.116

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Note: This table displays the construction of the variable Up_t which is used as an instrument for daily news pressure, D_t. The days with statistically significant increases in news pressure are displayed in Column (1). Other major elections in OECD and G20 countries and major US political events are included in the specification. The statistically significant positive coefficients are coded into the variable Up_t, displayed in Column (2). All specifications include day of week, month, and year fixed effects. Standard errors are clustered at the month-year level.

Table 16: 2SLS Estimates for Number of Campaign Actions per Day and *Daily News Pressure*

	(1st Stage) D_t	(2nd Stage) N_t	(OLS) N_t
Up_t	3.810***		-3.206***
	(0.592)		(0.634)
Daily News Pressure (D_t)		-0.843***	
		(0.200)	
DOW, Month, Year F.E.	Yes	Yes	Yes
N	2140	2140	2148
F-stat (excl. instruments)	41.44	41.44	

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

This table displays first and second stage results of the two stage least squares regression of the number of campaign actions launched in a day on daily news pressure. Column (1) displays the results of the first stage. The instrument Up_t is statistically significant, with an associated F-statistic of 41.44. Column (2) displays the results of the second stage. Column (3) displays the baseline OLS regression of Up_t on the number of campaign actions launched in a day. All specifications include day of week, month, and year fixed effects. Standard errors are clustered at the month-year level.

Table 17: Instrument Construction for Placebo IV regressions

	(1) D_t		(2) D_t
$DisasterDeaths_t$	0.207*	$Past8DaysDeaths_t$	0.0266***
	(0.111)		(0.00381)
$DisasterDeaths_{t-1}$	0.256***		
	(0.0701)		
$DisasterDeaths_{t-2}$	0.0365***		
	(0.00405)		
$DisasterDeaths_{t-3}$	0.0304***		
	(0.00462)		
$DisasterDeaths_{t-4}$	0.0333***		
	(0.00348)		
$DisasterDeaths_{t-5}$	0.0295***		
	(0.00383)		
$DisasterDeaths_{t-6}$	0.0272***		
	(0.00415)		
$DisasterDeaths_{t-7}$	0.0199***		
	(0.00300)		
$DisasterDeaths_{t-8}$	0.0150***		
	(0.00432)		
$DisasterDeaths_{t-9}$	-0.00201		
	(0.00452)		
$DisasterDeaths_{t-10}$	0.00370		
	(0.00346)		
DOW, Month, Year F.E.	Y		Y
N	2130		2132
R^2	0.113		0.111

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Note: This table displays the construction of the variable $Past8DaysDeaths_t$ which is used as an instrument for daily news pressure, D_t, in placebo IV regressions. The coefficients on the first 10 lags are displayed in Column (1). The lags with statistically significant positive coefficients are coded into the variable $Past8DaysDeaths_t$, displayed in Column (2). $Past8DaysDeaths_t$ includes the deaths on a given day and the 8 days prior. All specifications include day of week, month, and year fixed effects. Deaths are reported in 1000s. Standard errors are clustered at the month-year level.

Table 18: Placebo IV regressions

	(1st Stage) D_t	(2nd Stage) N_t	(OLS) N_t
$Past8DaysDeaths_t$	0.0266***		-0.00113
	(0.00381)		(0.00330)
Daily News Pressure (D_t)		-0.0389	
		(0.125)	
DOW, Month, Year F.E.	Yes	Yes	Yes
N	2132	2132	2140
F-stat (excl. instruments)	48.97	48.97	

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

This table displays first and second stage results of the placebo two stage least squares regression of the number of campaign actions launched in a day on daily news pressure. Column (1) displays the results of the first stage. The instrument $Past8DaysDeaths_t$ is statistically significant, with an associated F-statistic of 48.97. Column (2) displays the results of the second stage. Column (3) displays the baseline OLS regression of $Past8DaysDeaths_t$ on the number of campaign actions launched in a day. All specifications include day of week, month, and year fixed effects. Standard errors are clustered at the month-year level.