Environmental Externalities of Activism*

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Abstract

We study the effect of hedge fund activism on corporate environmental behaviors. Using plant-chemical level data from the EPA, we find that activism campaigns are associated with a 17 percent drop in emissions for chemicals at plants of targeted firms. Campaigns are associated with changes across a wide range of chemicals, including those emitted into the air, water, and ground and those that are harmful to humans. Evidence suggests this change in environmental behavior stems from a drop in production rather than an increase in abatement activities. The net effect on environmental efficiency is positive, with emissions falling by 8 percent per unit of output. Overall, our findings highlight the idea that the benefits of activism are not necessarily confined to shareholders, but may also extend to other stakeholders (e.g., the local community) affected by firms' emissions.

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The traditional goal of corporate governance is to incentivize managers to act in the narrow interest of shareholders. A rich literature argues that activist hedge funds play an important role in achieving this goal, as demonstrated by the significant gains in shareholder value associated with campaigns (e.g., Brav, Jiang, Partnoy, and Thomas, 2008; Klein and Zur, 2009; Bebchuk, Brav, and Jiang, 2015). However, a long-standing question has been to what extent do such gains come at the expense of other stakeholders? In this paper, we study the effect of hedge fund activism on firms' environmental behaviors, which potentially affect the well-being of both employees as well as the surrounding community.[1]

A priori, activism campaigns may lead firms to engage in environmental practices that are socially suboptimal. A corporation is a nexus of both implicit and explicit contracts between the firm and its stakeholders (Coase, 1937; Fama and Jensen, 1983). Similar to hostile takeovers, activism potentially facilitates the breach of implicit contracts (e.g., by replacing managers), resulting in a transfer of wealth from stakeholders to shareholders (Shleifer and Summers, 1988; Pontiff, Shleifer, and Weisbach, 1990). If this is the case, campaigns may be associated with changes in environmental behaviors (e.g., lower investment in pollution abatement) that are privately profitable but socially costly. Consistent with this idea, previous work finds evidence that activism campaigns have adverse effects on employees (e.g., Agrawal and Lim, 2019; Brav, Jiang, and Kim, 2015).

However, there are also reasons why activism campaigns may be associated with improvements in environmental behavior. For one, activists may directly take actions to mitigate risks associated with environmental activities. Krueger, Sautner, and Starks (2019) argue that institutional investors care about climate and environmental risks for both financial reasons (e.g., their effect on expected returns) and non-financial reasons (e.g., peer pressure). While Krueger et al. (2019) do not explicitly consider activist hedge funds, it is possible

[1] For example, Chang et al. (2016) and Graff Zivin and Neidell (2012) study the effects of pollution on worker productivity. Chay and Greenstone (2003), Greenstone and Gallagher (2008), and Currie and Schmieder (2009) study the effects of pollution on local health outcomes.

that activism campaigns address environmental risks. This may be the case, for example, if activists seek to reduce the likelihood of regulatory penalties.[2] Even if activists do not themselves care about environmental risks, the need for support from other shareholders (e.g., in a proxy fight) may limit the scope for environmentally destructive decisions (Hart and Zingales, 2017).

Activists may also indirectly affect environmental practices. For example, Brav, Jiang, and Kim (2015) find that campaigns are associated with gains in both production and labor efficiency. This effect is driven by both gains in efficiency for targets' assets in place as well as divestiture of underperforming assets. To the extent that operational efficiency affects environmental efficiency, changes to firms' business strategies may also lead to improved environmental outcomes (i.e., lower emissions).

We use micro data on toxic emissions from the EPA's Toxic Release Inventory (TRI) to analyze the effect of activism on environmental behaviors. The TRI provides data on emissions into the air, water, and ground, as well as information on abatement and production at the plant-chemical level. The use of this granular data provides insights into changes to specific aspects of firms production processes following activism campaigns. We use an updated sample of activism events from Brav et al. (2008, 2010) to identify plants associated with firms targeted by activists. Of course, activism campaigns are not randomly assigned. To mitigate concerns related to omitted variables, our main analysis controls for time-invariant heterogeneity at the plant-chemical level and time-varying heterogeneity at the chemical-level and industry-level (6-digit NAICS).

Our main analysis studies the effect of activism on the environmental behavior of firms. We find that campaigns are associated with economically large decreases in the emissions

[2]Consistent with this idea, the founder of the activist fund Blue Harbour stated "It [ESG] is hugely important for us, and we put it on the same scale as other things we look at – a companys cash flow, its market share, its management...anything we can do to reduce risk is smart" (*The Financial Times*, 12/26/2017).

of targets. Specifically, emissions at the chemical level fall by approximately 17 percent along the intensive margin. There is also evidence of changes along the extensive margin; the likelihood of stopping the use of a chemical increases by 5 percentage points (66 percent relative to the sample mean) and the likelihood of using a new chemical drops by 1 percentage point (16 percent). The changes along the extensive margin are consistent with evidence that firms divest underperforming assets following an activism campaign (Brav, Jiang, and Kim, 2015).

We find evidence that campaigns are associated with changes across a range of environmental behaviors. The magnitude of the effect is particularly large for air pollution, but campaigns are also associated with a decrease in ground and water emissions. Our findings are driven by campaigns with either general objectives (e.g., "improving the target") or those related to business strategy, as opposed to campaigns that address corporate governance, sale of the target, or capital structure.

We consider two channels that potentially drive the changes in emissions along the extensive margin. First, activists may directly encourage firms to reduce pollution, perhaps to mitigate regulatory risks associated with future emissions. To test this idea, we examine the relation between activism campaigns and investment in pollution abatement. We do not, however, find evidence that campaigns are associated with changes in abatement activities. Specifically, the effects on the likelihood of firms undertaking abatement and the number of abatement actions taken at the plant-chemical level are economically small and statistically indistinguishable from zero.

Second, we analyze whether the effect on emissions stems from changes in the production of targeted firms. Potentially consistent with the idea that activists enhance productive efficiency (Brav et al., 2015), we find that activism is associated with a decrease in production at the chemical-level. Specifically, production growth falls by approximately 2 percentage points per year in the four years following the initiation of a campaign; a normalized measure of the level of production (relative to the first year a chemical is in the sample) falls by approximately 10 percent over the same period. We also find evidence that the drop in production increases the environmental efficiency of firms. Specifically, the level of emissions per unit of normalized production decreases by approximately 8 percent following a campaign, though this effect is statistically noisy for some specifications.

Finally, we also find evidence suggesting that the drop in emissions has positive externalities for other stakeholders (e.g., the surrounding community). Specifically, emissions of chemicals that cause cancer and other chronic diseases fall by 24 percent. Moreover, plants are less likely to be cited for violations of federal pollution laws such as the Clean Air Act, suggesting that there are measurable effects on the environment of the communities that are located near the pollution-emitting facilities.

Overall, our findings have implications for the current debate regarding stakeholder governance. Specifically, recent years have arguably seen a shift away from the shareholder primacy model, with institutional investors, business groups, and legislators emphasizing (to varying degrees) the importance of the relationship between the firm and its stakeholders.[3] Critics often accuse activist hedge funds of myopic behavior ("short termism"), potentially to the detriment of other stakeholders (Lipton, 2013). However, our findings highlight the idea that gains to shareholders are not necessarily at the expense of other stakeholders. Indeed, our results suggest that efficiency gains stemming from activism campaigns may have positive externalities for other stakeholders.

Broadly speaking, our paper contributes to the literature studying corporate social responsibility (CSR). A number of factors influence the adoption of CSR policies, including shareholder engagements (Dimson, Karakaş, and Li, 2015; Flammer, 2015), supply chains (Schiller, 2019), agency conflicts (Cheng, Hong, and Shue, 2016), and political affiliations

[3] For example, Larry Fink ("Purpose and Profit," 1/16/2018), the Business Roundtable ("Statement on the Purpose of the Corporation," 8/19/2019), and Senator Warren ("Companies Shouldnt Be Accountable Only to Shareholders," *Wall Street Journal* 8/14/2018) have stressed the importance of stakeholder interests.

(Di Giuli and Kostovetsky, 2014). A number of papers also study the determinants of firms' environmental behaviors, including public status (Shive and Forster, 2019), government regulation (Bartram, Hou, and Kim, 2018), financial constraints and resources (Kim and Xu, 2018; Cohn and Deryugina, 2018; Goetz, 2019), and legal liability protections (Akey and Appel, 2019).

A related strand of literature studies the effect of hostile takeovers and PE buyouts on various stakeholders (e.g., Cohn, Nestoriak, and Wardlaw, 2019; Eaton, Howell, and Yannelis, 2019; Fracassi, Previtero, and Sheen, 2018; Pontiff, Shleifer, and Weisbach, 1990). There are two important differences between this paper and those that analyze acquistions. First, in an acquisition the acquirer has control of the firm, wheras activism is "influence based" (Brav et al., 2015). Second, while takeovers and buyouts may help to mitigate myopic behavior (e.g., Cohn et al., 2019), activist hedge funds have shorter holding periods, and are often accused of exacerbating such behavior (e.g., Lipton, 2013).

We also contribute to the literature on hedge fund activism. Previous work documents that campaigns are associated with improvements in the value and performance of targets (e.g., Bebchuk, Brav, and Jiang, 2015; Becht, Franks, Mayer, and Rossi, 2008; Brav, Jiang, Partnoy, and Thomas, 2008; Klein and Zur, 2009).[4] This paper joins the growing literature that studies the effect of activism on stakeholders. For example, evidence suggests that gains from activist interventions may, in part, come at the expense of employees via lower wages (Brav, Jiang, and Kim, 2015) and underfunding of pension plans (Agrawal and Lim, 2019). There is relatively little evidence suggesting that gains from interventions result from expropriation of creditors (e.g., Brav et al., 2008; Klein and Zur, 2011). In contrast to previous work that finds either negative or neutral effects of activism on other stakeholders, our findings suggest that operational efficiency gains associated with campaigns have a positive

[4]See Brav, Jiang, and Kim (2010), Denes et al. (2017), and Gillan and Starks (2007) for comprehensive reviews of the activism literature.

effect on the environmental behavior of targets. These findings therefore have implications for the aggregate welfare effects stemming from hedge fund activism.

1 Data and Methodology

1.1 Data

1.1.1 Toxic Emissions Data

Our sample consists of plants in the EPA's Toxic Release Inventory (TRI) database from 1991–2015. The TRI database provides chemical-level emissions data for plants that have toxic emissions and meet other requirements (e.g., minimum number of employees, operate in certain industries, etc.). All entities, both public and private, are required to report emissions data. For each chemical subject to TRI reporting, plants are required to provide the number of pounds released into the ground, air, and water. Ground emissions consist of waste disposed in underground injection wells, landfills, surface impoundments, or spills and leaks released to land. Air emissions consist of stack or point releases (e.g., through a vent or duct) and fugitive emissions (e.g., evaporative losses). Water emissions consist of releases to streams and other surface bodies of water. We drop observations with zero total emissions (i.e., air + water + ground) emissions in a plant-chemical-year.

We use the EPA's Pollution Prevention (P2) database to analyze firm investment in pollution reduction and facility production. Plants reporting to the TRI database are required to document activities that plants take to reduce hazardous chemical emissions. These efforts are documented at the chemical level. Firms report investment in abatement across many categories. These categories include engaging in better operating practices, making process modifications, taking actions to prevent spills and leaks, and redesigning products so as to use less pollution, among others. The P2 database also includes a field called the production ratio, which is a quantity-based measure of output growth. For example, if a chemical is used to construct manufacture drills, the production ratio would for a given period would be defined as $\frac{\#\, Drills\, Produced_t}{\#\, Drills\, Produced_{t-1}}$. For chemicals that are used as support activities for production rather than for production itself, this measure would similarly indicate the change in usage. When chemicals are used in several activities, plants report a weighted average. Due to errors in the data, we exclude production ratios that are not negative or five or more.

While TRI data are self-reported, evidence suggests firms do not widely misreport emissions. First, while the chemicals that are reported in the TRI are toxic, they are all legal chemicals. There are no penalties associated with high emissions, but there are civil, and potentially criminal penalties associated with misreporting (Greenstone, 2003). The EPA periodically conducts audits to verify data integrity. Their estimates suggest that reported amounts and auditor estimates were within 3% of each other for most industries (EPA, 1998). While there are inaccuracies in the data, existing research suggests that this is due to ignorance, rather than malfeasance(e.g., Brehm and Hamilton, 1996; De Marchi and Hamilton, 2006).

The reporting entity for the TRI is the plant (or facility) that emits pollution. For each plant, we can observe the parent company, defined as highest-level corporation that owns at least 50 percent of voting shares. To account for possible errors or other discrepancies in names, we identify parent using the first 25 alphanumeric characters and remove common suffixes (e.g., "Corp.", "Incorporated", "LLC", etc.). We match these entities to Compustat using a combination of fuzzy matching and manual verification. We use gvkey from Compustat to match TRI observations to the activism data, discussed below.

We obtain information on the toxicity of emissions from the EPA's Integrated Risk Information System (IRIS). IRIS provides information on potential human health effects from exposure to over 400 chemicals. For those chemicals that are known to cause harm to humans, the database includes information on the main biological system impacted by the chemical. We match the IRIS database to TRI using Chemical Abstract Services (CAS) and use the database to identify whether a chemical in TRI poses potential harm to humans, as well as, the main biological system that the chemical may impact. These systems are the developmental, hematologic, hepatic, nervous, and respiratory systems. 58% of the chemicals in our sample are classified as a potential harm to humans.

We obtain data on environmental enforcement actions from the U.S. EPA Enforcement and Compliance History Online (ECHO) website. ECHO data has been used by a variety of researchers in economics and finance, (e.g., Blundell et al., 2018; Heitz et al., 2020). Specifically we download the Federal Enforcement and Compliance (FE&C) data from the Integrated Compliance Information System (ICIS) database and merge this data with our sample of facilities from the TRI database. We identify the whether plants received a violation for one of eight environmental statues including the Clean Air Act, the Clean Water ACt, the Comprehensive Environmental Recovery and Liability Act, and the Resource Conservation and Recovery Act as well as the total amount of monetary fines that were imposed.

1.1.2 Activism Data

We use an updated sample of activism events from Brav et al. (2008) and Brav et al. (2010) for our analysis. The sample of activism campaigns primarily consists of Schedule 13D filings by activist hedge funds from 1994 to 2015.[5] The activism database includes information on the objectives, tactics, and outcomes of activism campaigns. We exclude passive campaigns in which funds do not engage in activism (i.e., engage in communication or otherwise try to influence the target). We match 218 events to firms in the TRI database. The number of matched events is lower than that for manufacturing firms in the Census of Manufacturers (CMF) and Annual Survey of Manufacturers (ASM) databases (Brav et al., 2015), in part

[5] A 13D filing is required when an investor acquires a position of 5 percent or greater and seeks to influence control of the company. If an investment is purely passive (i.e., no intention to exert control), SEC rules may allow an investor to instead file a Schedule 13G.

because not all manufacturing firms have hazardous emissions and are required to report to the EPA. The targeted firms in our sample are, in aggregate, associated with 1,333 plants using 5,174 chemicals.

Figure 1 shows the number of activism events for each year in our sample. Consistent with the time series of activism events reported by (Brav et al., 2010), there are relatively few campaigns in our sample during the 1990s, but the number of campaigns increased significantly beginning in 2005. Figure 2 presents the proportion of plant industries (defined at the three-digit NAICS code) that are subject to hedge fund activism in our sample. The most represented industries in our sample are chemical manufacturing (13.56 percent), nonmetalic mineral product manufacturing (10.7 percent), transportation equipment manufacturing (9.8 percent), waste management and remediation services (8.0 percent), fabricated metal product manufacturing (7.7 percent), and utilities (7.1 percent). Brav et al. (2008) find that there are large, positive abnormal returns when hedge fund activists disclose positions in target firms. We reproduce their finding in our updated sample and verify that abnormal returns are also positive for the subset of activism campaigns that we are able to match with observations in the TRI database in Figure A.1 and Table A.2 in our Internet Appendix

1.2 Summary Statistics

Our main sample consists of approximately 1.18 million plant-chemical level observations. Summary statistics are presented in Table 1. The average total emissions for a chemical in our sample if 59.4 thousand pounds. This variable is highly skewed, however, with a median of 560 pounds. The vast majority (96 percent) of chemicals in the TRI database have some air emissions, which average 22 thousand pounds. Ground emissions are relatively rare (18 percent of observations), but make up the majority of emissions (averaging 33 thousand pounds). While 18 percent of chemicals are released into waterways, total emissions are relatively small, averaging less than 4 thousand pounds. The likelihood that plants in our sample start and stop using chemicals. Specifically, an indicator for sample entry defined at the plant-chemical level average 7 percent, while an indicator from sample exit averages 8 percent. In addition, plants undertake abatement activities for approximately 15 percent of plant-chemical observations annually, with the number of different types of abatement activities averaging 0.21 (i.e., 1.5 activities undertaken conditional on undertaking abatement). Finally, the average and median of the production ratio for our sample is 1.0.

Table A.3 compares characteristics prior to an activism campaign to the rest of the sample. Of course, activism events are not randomly assigned, so there are likely both unobservable and observable differences between the characteristics of observations subject to activism and those that are not. To help identify such (observable) differences, we regress three important aspects of firms' environmental behaviors on the variable *Pre-Activism*, an indicator equal to one in the year prior to an activism campaign. Column (1) shows that emissions for chemicals of plants subject to a campaign in the following year are higher than those that are not, controlling for time-varying heterogeneity at the chemical-level. The magnitude of this difference falls considerably when controlling for time-invariant heterogeneity at the chemical-plant level (column (2)), but the difference remains statistically significant. This difference is consistent with previous work that argues that public firms have a higher propensity to pollute than private ones (Shive and Forster, 2019), because plants subject to activism all have public parents while many other firms in the TRI database do not. Columns (3) – (4) and (5) – (6) conduct a similar analysis for abatement and the production ratio. However, there are not differences between observations subject to activism in the next year and other firms for either specification.

1.3 Empirical Strategy

Lacking a natural experiment, we employ a similar empirical strategy as Brav et al. (2015). Specifically, we compare the change in outcomes for plants of firms targeted by activists to outcomes for plants that are not targeted. We define our event window begin four years prior to an activism campaign beginning and to end five years after it has started. Our control group are toxic-pollution-emitting facilities that are run by firms that are not the subject of activism campaigns. We drop observations of firms that are the target of activism campaigns outside of the event window, to avoid contamination of our control group with "distantly targeted" plant observations.

Our main empirical specification is

$$log(Lbs\,Pollution_{c,p,i,t}) = \beta\,Activism_{i,t} + \alpha_{p,c} + \alpha_{c,t} + \varepsilon_{c,p,i,t},$$

where c indexes a chemical emitted by a plant p and belonging to parent firm i at time t. *Activism* takes the value of 1 for plants of parent companies that are the target of an activism campaign in the year it is initiated, as well as for the four following years and is zero otherwise. We include plant-chemical fixed effects ($\alpha_{p,c}$) to control for time-invariant heterogeneity at the facility-chemical level (e.g., to control for the fact that different facilities have different technologies and likely use different chemicals). We also include chemical-year fixed effects ($\alpha_{c,t}$) to control for time-varying heterogeneity at the chemical-year. As Chatterji et al. (2009) and DiGiuli (2013) note, there is not a clear way of aggregating pollutants or easily comparing their environmental impact; chemical-year fixed effects allow us to exploit within-chemical-time variation. Given these fixed effects, *Activism* can be interpreted as the change in pollution outcomes for a given plant in the years following a hedge fund activism campaign. In most specifications. We also include industry-year fixed effects, defined using the primary 6-digit NAICs code for each plant to control for time-varying heterogeneity at the industry level. In untabulated analysis, we find similar results using less granular industry classifications (e.g., 4-digit NAICS). In some specifications we also include state-year fixed effects to account for possible regional shocks that impact emissions. We cluster robust standard errors at the parent company level across all specifications.

2 Activism and Firm Emissions

2.1 Intensive and Extensive Margins

Our main analysis examines changes in toxic emissions following activism campaigns. Table 2 reports the effect of emissions along the intensive margin. In columns (1) – (3) we examine how (log) total emissions change following hedge fund activism campaigns. The specification in column (1) includes plant-chemical and chemical-year fixed effects. Column (2) adds industry-year fixed effects to the specification in column (1). Column (3) adds state-year fixed effects. Across all specifications we find that chemical emissions decline after hedge fund activism campaigns. This effect is economically significant. For example, in column (2), our preferred specification, we find that pollution amounts fall by 17.4 percent in the years following an activism campaign. The estimated coefficients are statistically significant at the 1 percent level across all of the specifications.

Hedge fund activism campaigns are not randomly assigned. As such, our findings are correlations and do not have a causal interpretation. Brav et al. (2015), for example, show that firms are often on "downward trend" prior to the initiation of an activism campaign. It is plausible that targeted firms were subject to adverse economic conditions and that plant-level economic activity was trending downwards prior to the activism campaign that *caused* the hedge fund to select these firms as a target. To the extent that plant-level pollution output is generated as a byproduct of decreasing economic activity, such trends would also suggest that pollution may have been decreasing. We examine the possibility of downward trends in pollution output in Figure 3, where we plot the dynamics of *Activism* in the years before and after the activism campaign begins. All coefficients are measured relative to the year before an activism campaign begins. We observe no evidence of a downward trend in pollution output prior to the initiation of an activism event. Moreover, the reduction in pollution begins quickly following the campaign and persists for several years. This figure therefore provides supportive evidence that general trends in the output of pollution are unlikely to explain the reduction in total emissions following an activism campaign.

We next turn to the extensive margin of chemical use. In Table 3 we examine how hedge fund activism is associated with the likelihood that plants discontinue the use of an chemical previously used in their production and that they begin to use a new toxic chemical. We define two new variables for this analysis and perform the same analysis as in Table 2. $\mathbb{1}$*(Stops Using Chemical Pollutant)* takes the value of one in the first year where a plant that had previously reported emissions of a given chemical no longer does (and will not do so at a future point in our sample) and is zero otherwise. $\mathbb{1}$*(Starts Using Chemical Pollutant)* takes the value of one if a plant reports emissions from a chemical that it had not previously reported and is zero otherwise.

The results in Panel A suggest that firms are more likely to stop using chemicals after they become the target of an activism campaign. For example, the point estimate in column (2) is 0.0516, statistically significant at all conventional levels. The coefficients are very stable across empirical specifications, both in terms of magnitude and statistical significance. The results are economically significant as well. The unconditional probability of a firm stopping the use of a chemical is 7.8 percent, suggesting that this increase is roughly two-thirds higher than the baseline probability.

The results in Panel B suggest that firms are also less likely to begin using new chemicals after they are targeted by hedge fund activists. For example, the point estimate in column

(2) is -0.0116, which is statistically significant at the five-percent level. The coefficients across all models are negative and of similar magnitudes although in the case of column (1) statistically insignificant at conventional levels. The economic magnitudes are large, although not as large as our estimates for the probability of a firm discontinuing the use of a toxic chemical. The unconditional probability of a firm starting to use a new chemical is 7.1 percent, suggesting that the decrease is roughly 16 percent of the baseline probability.

2.2 Type of Emissions

Firms emit can emit pollution through three types of media: air, water, and ground. Moreover, a given chemical can be emitted through multiple media. Most industrial pollution involve air emissions, although ground and water emissions non-negligible. 96 percent of chemical-year observations involve positive air pollution, 18 percent involve water pollution and 12 percent involve ground pollution. However, the average amount of ground emissions (conditional on there being a positive emission) is substantially higher. The average amount of non-zero ground emissions is 275,285 pounds, compared to air and water averages of 23,301 and 20,416, respectively.

We examine which types of pollution usage changes most following the beginning of an activism campaign. TRI emissions are reported in each category for each plant-chemical as the total pounds of pollution by media, which means that for many chemical-media observations zero emissions are reported. Therefore, we modify our dependent variable intensive margin analysis to be the $log(1 + Lbs\, Pollution)_{c,p,i,t,m}$, where m additionally indexes the medium of pollution (air, water or ground). We estimate separate regression models for each dependent variable and each medium of emission.

Table 4 presents this analysis. We find that the initiation of an activism campaign is associated with a decrease in the amount of pollution that is used across all media. Our results suggest that, following the initiation of an activism campaign, air emissions decrease by roughly 14.4 percent, statistically significant at the one-percent level, that water emissions decrease by 6 percent, statistically significant at the five-percent level, and that ground emissions decrease by 7.7 percent, which is statistically significant at the five-percent level.

2.3 Activists' Objectives

We next examine whether the objectives of activists affect firms' environmental behaviors. We hypothesize that activists likely have the strongest effect on such behaviors in campaigns that seek to influence aspects of firms' operations. To test this idea, we use the objective classifications proposed by Brav et al. (2008, 2010), to examine how responses differ for different categories of activism campaigns. Campaigns can have multiple objectives. In our sample, 31 percent of campaigns have a general objective, 25 percent address capital structure, 20 percent seek a sale of the target, 33 percent address business strategies, and 50 percent address some aspect of corporate governance.

We rerun our main results but define *Activism* to only include those activism campaigns that are classified in a given category. These results are reported in Table 5. We find that hedge fund activism campaigns are only associated with reduced chemical emissions for events that focus on improving shareholder value (column (1)) or changing a firms strategy (column (2)). These coefficients are -0.250 and -0.131, respectively. Both are statistically significant at the five-percent level or less and are of similar magnitudes to the results that we have previously estimated. In contrast, we find small coefficients that are statistically insignificant for other categories of activism campaigns. Our findings suggest that the types of activism events where activists seek to make changes to a firms operations are most correlated with the declines in pollution output that we document.

3 The Channel

The above results indicate that activism campaigns are associated with changes in firms' environmental behaviors. In this section, we aim to shed light on the channels that drive this effect along the intensive margin. We consider two (non-mutually exclusive) channels. First, activists may directly affect emissions if they encourage firms to invest in abatement technologies. Second, activists may have an indirect effect on emissions via changes in the production process. Specifically, if production falls, this (all else equal) will result in lower emissions.

3.1 Abatement

We begin by examining whether firms' likelihood of reporting pollution abatement changes following an activism campaign. As we describe in more detail in Section 1.1.1, firms document their efforts to reduce pollution emissions in their annual TRI fillings. While they do not report dollar amounts spent on these activities, they do disclose what types of actions they take according to seven categories of reduction. We combine these disclosures into one variable, $\mathbb{1}$(Abatement), which takes the value of one if the firm reports an abatement activity across any category and is zero otherwise. We also consider the (log of one plus) the number of abatement actions that a firm discloses in a given year since most firms do not disclose abatement actions for a given chemical-year.

We report these results in Table 6. We present results for the likelihood of engaging in abatement in columns (1) – (3). We find no evidence that firms' abatement activity changes following the an activism campaign. While the point estimates are all negative, they are not statistically significant at conventional levels. We similarly do not find any evidence that the (log) number of abatement activities changes. The point estimates are negative but statistically insignificant. In untabulated analysis, we also do not find evidence of an effect for the most common abatement activities (e.g., abatement related to process modifications or operating practices). Overall, our findings suggest that activists do not have a direct effect on emissions by encouraging changes to abatement activities.

3.2 Production

We next examine changes in production following the initiation of an activism campaign. We use the production ratio from the TRI database for this analysis. This measure is defined as the quantity of output in a given year, scaled by the output of the previous year for each chemical that is reported. For example, if a chemical is used to produce refrigerators, in time period t this number would be computed as $\frac{\#\, Drills\, Produced_t}{\#\, Drills\, Produced_{t-1}}$. This variable has the advantage of being a quantity-based output measure, which is typically not available in publicly available datasets. However it is has the disadvantage of measuring (one plus) the growth in production rather than its level.[6]

We also use the production ratio to quantify (normalized) production levels for our analysis. We construct proxy for total production, $Cumulative\, Production_{p,c,t}$, by normalizing production to one in the first year that a chemical is reported in the TRI database and "multiply forward" each year by the reported production ratio for each plant-chemical set of observations. Specifically, our measure of normalized production is given by the following expression:

$$Cumulative\, Production_{p,c,t} = \prod_{t \neq 1}^{t} \left(1 \times \frac{Quantity\, Produced_{p,c,t}}{Quantity\, Produced_{p,c,t-1}} \right) = \prod_{t \neq 1}^{t} 1 \times Production\, Ratio_{p,c,t}.$$

We replace missing observations with one when calculating this measure.

Table 7 reports changes in the production ratio and normalized production level following

[6] It is also important to note that if a chemicals not used for production (e.g., those used for cleaning) also have production ratios in the TRI database. However, the ratio for such chemicals measures changes in the activity a chemical is used for rather than production.

an activism campaign. Columns (1) – (3) indicate that production growth falls by roughly 2.5 percentage points following the initiation of an activist campaign. These estimates are statistically significant at the five-percent level in columns (2) and (3), which include a more stringent set of fixed effects, although the coefficients are very stable across models. This decline in production growth is economically significant. The average and median growth rate is 0 (i.e., the mean and median production ratios are 1), making percent comparisons to the mean difficult. However, the standard deviation of the production ratio is 0.42, suggesting that the effect is about 6 percent of a standard deviation. In columns (4) – (6) we examine the log of the normalized production level. We find stronger evidence that the level of production falls following the initiation of an activism campaign. Specifically, our estimates indicate that production decreases between 8.8 percent (column (4)) and 10.3 percent (column (6)). All of the coefficients for production levels are statistically significant at the 1 percent level.

We plot coefficient dynamics for total production in Figure 4. There is little evidence of a pre-trend in production. While this does not imply the effect is causal, it suggests activism campaigns do not, on average, coincide with a general decline in production. Relative to total emissions the decline in production seems to occur more slowly. This is potentially due to pollution being a production input and our measuring capturing an output variable, or due to the fact that we estimate production levels using production ratios, thus introducing noise in this measure.

4 Efficiency of Emissions

To this point, our results indicate that firms' use of toxic chemicals and their output growth decline following the initiation of an activism campaign. A natural question is whether the drop in emissions is purely a consequence of lower emissions, or if emissions are also more efficient (in the sense of output per unit of input). In this section, we examine changes in the efficiency of emissions following an activism campaign to shed light on this question.

For this analysis, it is important to note that we only observe production growth or pollution for chemicals that are reported in the TRI database. We show in Section 2 that the likelihood of firms using particular chemicals changes following an activism campaign, and thus any results on productivity apply only for those chemicals that have not been eliminated from use.[7] We measure the efficiency in year t as the (log) ratio of pollution to the normalized production level measure that we describe above (i.e., $log\left(\frac{lbs\,Pollution_{p,c,t}}{Cumulative\,Production_{p,c,t}}\right)$). All else equal, lower values of this ratio indicate higher efficiency.

Table 8 presents the results of this analysis. We find that activism campaigns are positively associated with production efficiency. For example, the coefficient in column (1) is -0.101 and statistically significant at the 5 percent level. The interpretation of this coefficient is that total emissions per unit of output decreases by 10 percent. Across different specifications in columns (2) and (3), the estimated coefficient remains negative although the magnitude and statistical precision of our estimates is lower as we increase the dimensionality of our fixed effects. In particular, the coefficient in column (3) is -0.059 but not statistically different from zero at conventional levels. Overall, these findings provide suggestive evidence that production efficiency with respect to the use of toxic chemicals increases following an activism campaign.

5 Potential Effects on Local Stakeholders

We finally examine whether the decline in pollution that we have documented so far could have effects on stakeholders of the firm. We do so by first examining whether there are

[7] It is also worth noting that our data does not allow us to estimate total factor productivity, as is often done using plant-level data, such as that data provided by the U.S. Census Bureau, (e.g., Brav et al., 2015; Giroud and Mueller, 2015).

substantial declines in emissions known to cause harm to humans and then by examining whether firms are less likely to be the subject of an environmental enforcement by the EPA.

5.1 Hazards to Human Health

While all of the chemicals that firms are required to report are hazardous, they are not all known to have specific adverse effects on humans. We next examine whether the usage of those chemicals that are known to cause harm to changes following the initiation of an activism campaign. We analyze these chemicals in order to better understand the potential for hedge fund activism to contribute to positive or negative externalities. In the case of manufacturing processes that use toxic chemicals there are potentially two groups of stakeholders that could be impacted by the usage of chemicals that are known to cause harm, employees and local communities. As we describe in Section 1.1.1, we classify chemicals into those chemicals that are known to cause harm to humans and other chemicals. 58 percent of chemical-year observations involve chemicals that are known to cause harm to humans. Average (total) emissions are slightly lower for these chemicals. The average emission for chemicals known to cause human harm is 55,740 pounds, versus 64,127 for other chemicals. We rerun our analysis on these chemicals and further classify them based on the specific human biological system that they may affect.

Columns (1) – (3) of Table 9 document how (log) total emissions of all chemicals known to cause human harm change after the initiation of an activist campaign. We find that emissions of these chemicals decline by roughly a quarter. The coefficients range from -0.231 to -0.253 and are statistically significant at the one-percent level. Columns (4) – (8) further break these results down by the biological system that is impacted by these chemicals. We find that activism campaigns are associated with declines in emissions of chemicals that affect all of the biological systems that are classified. The coefficients range from -0.226, for chemicals that affect the respiratory system, to -0.382, for chemicals that affect the hepatic system. All coefficients are statistically significant at the one-percent level. The reductions in emissions following an activism campaign for these chemicals are larger than for the pooled sample, suggesting that those chemicals that are most likely to impose negative externalities on stakeholders decline the most following the initiation of an activism campaign.

5.2 EPA Enforcements

We further examine whether there are potential externalities on local communities by testing whether plants are less likely to violate environmental laws. Numerous studies suggest that federal statues such as the Clean Air Act (CAA) and Clean Water Act (CWA) have led to substantial improvements in local environmental outcomes.[8] We define a variable $\mathbb{1}$(EPA Enforcement) to take the value of one if a plant receives an enforcement action for any environmental statue in a given year and zero otherwise. The most common enforcement actions are for violations of the CAA, the CWA, and the Comprehensive Environmental Response and Compensation and Liability Act. We also consider the (log of one plus) the amount in fines that a plant receives in a given.

We report these results in Table 10. We present results for the likelihood of a plant receiving an enforcement action in columns (1) – (3). We find that the probability of a firm receiving a violation declines by 0.77 – 0.87 percentage points after it is targeted by an activist hedge fund. The unconditional probability of these events is low, roughly 2 percentage points, which would suggest that the relative decline is economically significant. In columns (4) – (6) we also see that the amount that plants pay in fines declines. We decompose the effect by individual legal statute in Table A.5 in the internet appendix and find that the effect is concentrated in violations of the CAA, which is both the most common type of violation and the type of enforcement that has the largest monetary fines. These

[8]See Currie and Walker (2019) and Shapiro (2019) for recent surveys on the effects of the CAA and CWA.

results are consistent with our results in Section 2.2 where we show that the largest decline in emissions comes from air emissions. These results suggest that the decline in pollution that we document had measurable effects on air quality of the local communities surrounding the pollution emitting facilities.

6 Conclusion

While there is considerable evidence that activism campaigns have positive effects on shareholder value, their effects on other stakeholders are unclear. One possibility is that shareholders gains come at the expense of other stakeholders (Shleifer and Summers, 1988). Alternatively, activism may have a positive effect on other stakeholders, perhaps as a result of improvements in risk management or operational efficiency (Brav, Jiang, and Kim, 2015; Krueger, Sautner, and Starks, 2019). In this paper, we examine these competing hypotheses in the context of firms' environmental behaviors.

We find that activism campaigns are associated with reduced toxic emissions for targets. The economic magnitude of this effect is large, corresponding to a drop of 17 percent along the intensive margin. Campaigns are associated with changes across a wide range of chemicals, including those emitted into the air, water, and ground and those that are harmful to humans. We do not find evidence that firms are more likely to engage in abatement activities following an activism campaign. Rather, the change in emissions appears to be driven by lower production. We also find evidence that campaigns are associated with improved environmental efficiency (i.e., emissions per unit of output). Overall, our findings suggests that hedge fund activism is associated with positive externalities for other stakeholders affected by the environmental behavior of targets.

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Figure 1: **Time Series of Activism Campaigns**

This figure shows the distribution of hedge fund activism campaigns matched to the Toxic Release Inventory from 1994–2015. Activism events are from the updated sample constructed by Brav et al. (2008, 2010).

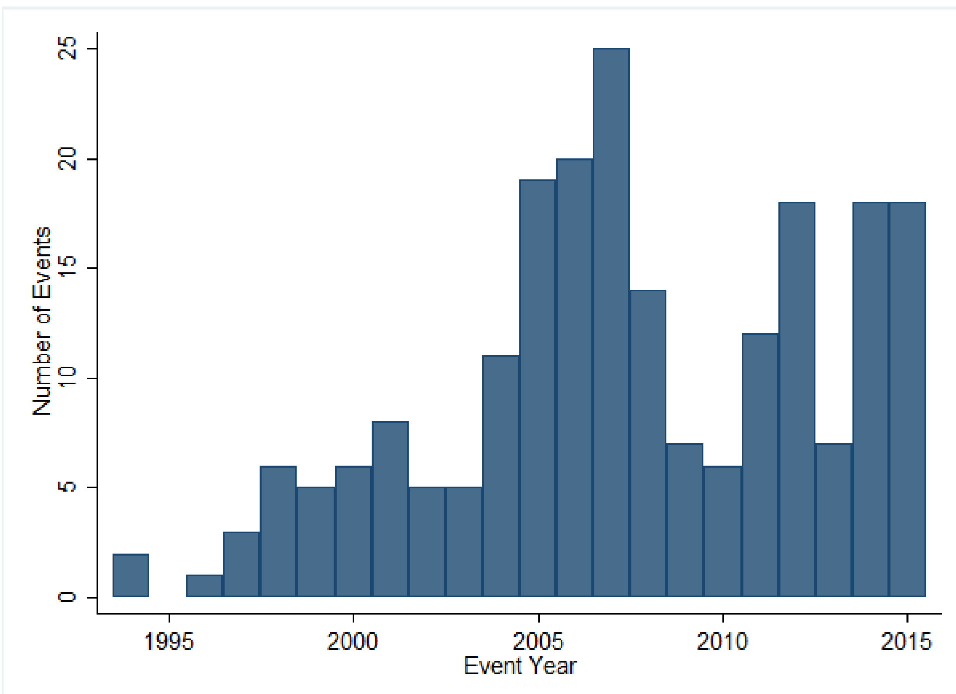


Figure 2: **Distribution of Plant Industries for Activism Targets**

This figure shows the distribution industries (defined at the three-digit NAICS) for plants of firms targeted by activists in our sample. Activism events are from the updated sample constructed by Brav et al. (2008, 2010).

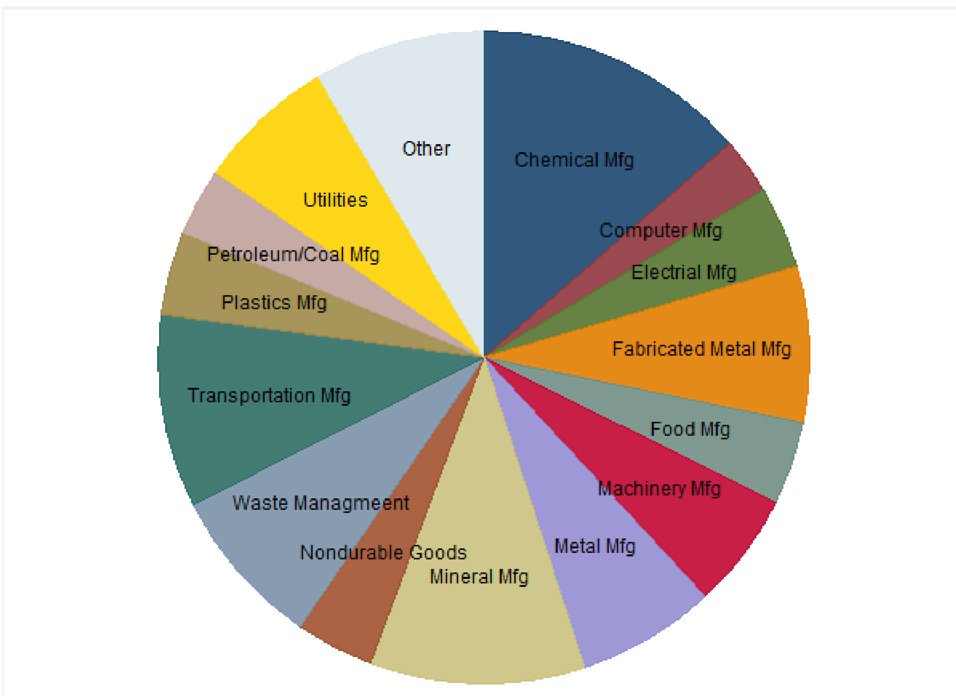


Figure 3: **Hedge Fund Activism and Total Emissions Dynamics**

This figure plots the treatment dynamics in our sample for the natural logarithm of total emissions. Coefficients are estimated using the baseline regression specification, except *Activism* is replaced with indicators for each year before/after a campaign. Regressions include plant-chemical, chemical-year and industry-year fixed effects. All coefficients are estimated relative to the year before a campaign. Standard errors are clustered by parent firm.

Treatment Dynamics — Log(Total Emissions)

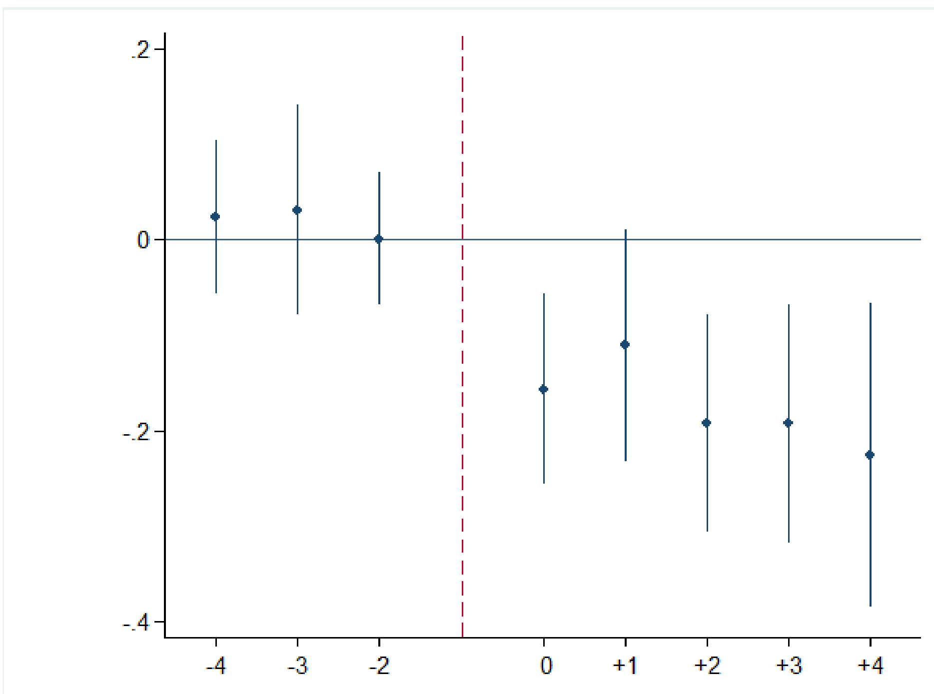


Figure 4: **Hedge Fund Activism and Normalized Production Dynamics**

This figure plots the treatment dynamics for the natural logarithm of the level of normalized production. Coefficients are estimated using the baseline regression specification, except *Activism* is replaced with indicators for each year before/after a campaign. Regressions include plant-chemical, chemical-year and industry-year fixed effects. All coefficients are estimated relative to the year before a campaign. Standard errors are clustered by parent firm.

Treatment Dynamics — Log(Normalized Production Level)

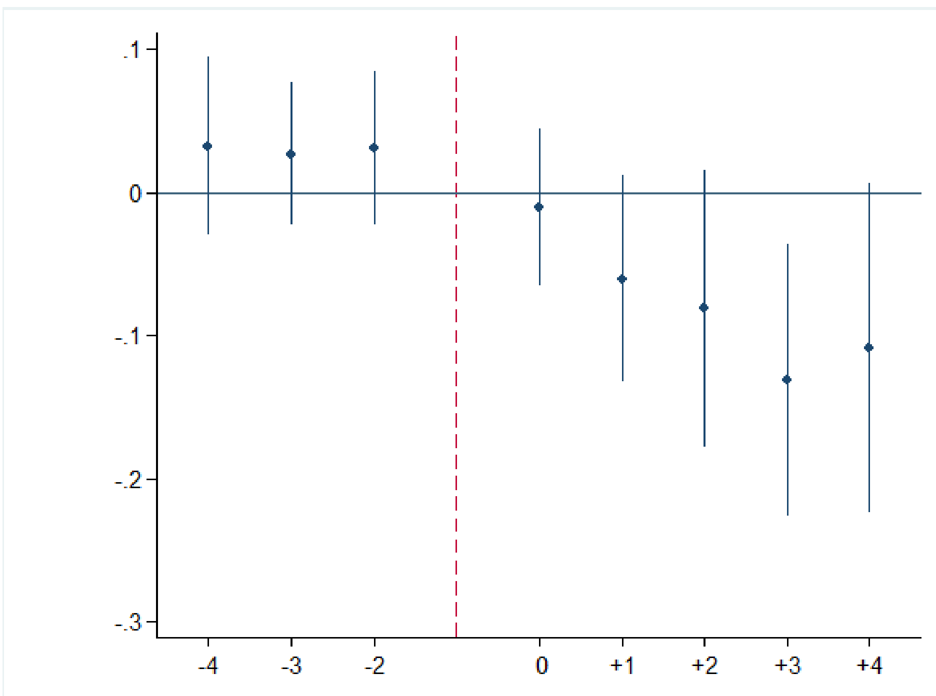


Table 1: **Summary Statistics**

The following table presents summary statistics for environmental characteristics. All variables are defined at the plant-chemical-year level. Variables are defined in Table A.1.

Variable	**Number**	**Mean**	**Median**	**SD**
Total Pollution (lbs)	1,180,093	59,474	560	1,887,544
Air Pollution (lbs)	1,180,093	22,360	362	253,641
Water Pollution (lbs)	1,180,093	3,691	0	150,639
Ground Pollution (lbs)	1,180,093	33,422	0	1,864,287
$\mathbb{1}$(Emits Air Pollution)	1,180,093	0.96	1.00	0.21
$\mathbb{1}$(Emits Water Pollution)	1,180,093	0.18	0	0.38
$\mathbb{1}$(Emits Ground Pollution)	1,180,093	0.12	0	0.33
$\mathbb{1}$(Starts Using Chemical)	1,180,093	0.07	0	0.26
$\mathbb{1}$(Stops Using Chemical)	1,180,093	0.08	0	0.27
$\mathbb{1}$(Abatement)	1,180,092	0.15	0	0.35
# Abatement Actions	1,180,092	0.21	0	0.59
Production Ratio	1,120,186	1.00	1.00	0.42

Table 2: **Hedge Fund Activism and Total Emissions**

This table uses OLS regressions to examine the change in intensive margin of emissions after an activism campaign. The dependent variable is the log of total emissions for a given plant-chemical observation. *Activism* is an indicator that takes the value of 1 in the year that an activism campaign begins and for the four years afterwards and is zero otherwise. Fixed effects are indicated in the table. Robust standard errors clustered by parent firm are reported in parentheses. All variables are defined in Table A.1. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	log(Total Emissions)		
	(1)	(2)	(3)
Activism	-0.187***	-0.174***	-0.162***
	(0.0519)	(0.0404)	(0.0388)
Plant-Chemical FE	x	x	x
Chemical-Year FE	x	x	x
Industry-Year FE		x	x
State-Year FE			x
Observations	1,101,340	1,100,155	1,100,150
R-squared	0.912	0.915	0.916

Table 3: **Hedge Fund Activism and Likelihood of Chemical Use**

This table uses OLS regressions to examine changes in the extensive margin of emissions after an activism campaign. The dependent variable in Panel A is an indicator that takes the value of one if a firm stops using a toxic chemical. The dependent variable in Panel B is an indicator that takes the value of one if a firm begins using a new toxic chemical. *Activism* is an indicator that takes the value of 1 in the year that an activism campaign begins and for the four years afterwards and is zero otherwise. Fixed effects are indicated in the table. Robust standard errors clustered by parent firm are reported in parentheses. All variables are defined in Table A.1. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A — Stopping Use of a Chemical

	𝟙(Stops Using Chemical)		
	(1)	(2)	(3)
Activism	0.0567***	0.0516***	0.0522***
	(0.00748)	(0.00891)	(0.00899)
Plant-Chemical FE	x	x	x
Chemical-Year FE	x	x	x
Industry-Year FE		x	x
State-Year FE			x
Observations	1,101,340	1,100,155	1,100,150
R-squared	0.328	0.349	0.351

Panel B — Starting Use of a Chemical

	𝟙(Starts Using Chemical)		
	(1)	(2)	(3)
Activism	-0.00993	-0.0116**	-0.0122**
	(0.00659)	(0.00483)	(0.00485)
Plant-Chemical FE	x	x	x
Chemical-Year FE	x	x	x
Industry-Year FE		x	x
State-Year FE			x
Observations	1,101,340	1,100,155	1,100,150
R-squared	0.342	0.377	0.379

Table 4: **Hedge Fund Activism and Types of Emissions**

This table uses OLS regressions to examine changes in the intensive margin of air, water, and ground emissions after an activism campaign. The dependent variables are the log of one plus pounds of ground, water or air emissions for a given plant-chemical observation. *Activism* is an indicator that takes the value of 1 in the year that an activism campaign begins and for the four years afterwards and is zero otherwise. Fixed effects are indicated in the table. Robust standard errors clustered by parent firm are reported in parentheses. All variables are defined in Table A.1. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	log(1+Air)	log(1+Water)	log(1+Ground)
	(1)	(2)	(3)
Activism	-0.144***	-0.0602**	-0.0767**
	(0.0388)	(0.0253)	(0.0326)
Plant-Chemical FE	x	x	x
Chemical-Year FE	x	x	x
Industry-Year FE	x	x	x
Observations	1,100,155	1,100,155	1,100,155
R-squared	0.914	0.865	0.897

Table 5: **Emissions by Campaign Objective**

This table uses OLS regressions to examine the change in emissions associated with activism campaigns based on the campaign objective. The dependent variable is the log of total pollution for a given plant-chemical observation. *Activism* is an indicator that takes the value of 1 in the year that an activism campaign of a given engagement category as noted in the table begins and for the four years afterwards and is zero otherwise. Fixed effects are indicated in the table. Robust standard errors clustered by parent firm are reported in parentheses. All variables are defined in Table A.1. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	log(Total Emissions)				
Campaign Obj.	General	Strategy	Governance	Sale	Capital Structure
	(1)	(2)	(3)	(4)	(5)
Activism	-0.250***	-0.131**	0.0173	-0.0766	0.00223
	(0.0847)	(0.0575)	(0.0623)	(0.0749)	(0.0734)
Plant-Chemical FE	x	x	x	x	x
Chemical-Year FE	x	x	x	x	x
Industry-Year FE	x	x	x	x	x
Observations	1,124,669	1,123,784	1,126,936	1,130,002	1,125,150
R-squared	0.915	0.915	0.914	0.910	0.915

Table 6: **Hedge Fund Activism and Pollution Abatement**

This table uses OLS regressions to examine changes in abatement associated with hedge fund activism campaigns. The dependent variable in columns (1)–(3) is an indicator that takes the value of one for if a plant reported engaging in activities designed to reduce pollution for a given plant-chemical observation. The dependent variable in columns (4)–(6) is the log of one plus the number of abatement activities at the plant-chemical level. *Activism* is an indicator that takes the value of 1 in the year that an activism campaign begins and for the four years afterwards and is zero otherwise. Fixed effects are indicated in the table. Robust standard errors clustered by parent firm are reported in parentheses. All variables are defined in Table A.1. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	$\mathbb{1}$(Abatement)			log(1+# Abatement)		
	(1)	(2)	(3)	(4)	(5)	(6)
Activism	-0.00822	-0.00947	-0.0116	-0.00714	-0.00910	-0.0109
	(0.00878)	(0.00833)	(0.00837)	(0.00687)	(0.00665)	(0.00669)
Plant-Chemical FE	x	x	x	x	x	x
Chemical-Year FE	x	x	x	x	x	x
Industry-Year FE		x	x		x	x
State-Year FE			x			x
Observations	1,101,340	1,100,155	1,100,150	1,101,340	1,100,155	1,100,150
R-squared	0.549	0.565	0.569	0.571	0.586	0.589

Table 7: **Hedge Fund Activism and Production**

This table uses OLS regressions to examine how production changes after a hedge fund activism campaign begins. The dependent variable in columns (1)–(3) is the production ratio. The dependent variable in columns (4)–(6) is the log of the normalized production level (i.e., production level relative to first year in the sample). *Activism* is an indicator that takes the value of 1 in the year that an activism campaign begins and for the four years afterwards and is zero otherwise. Fixed effects are indicated in the table. Robust standard errors clustered by parent firm are reported in parentheses. All variables are defined in Table A.1. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Production Ratio			log(Normalized Production Level)		
	(1)	(2)	(3)	(4)	(5)	(6)
Activism	-0.0279*	-0.0277**	-0.0272**	-0.0876***	-0.0969***	-0.103***
	(0.0162)	(0.0119)	(0.0114)	(0.0252)	(0.0280)	(0.0313)
Plant-Chemical FE	x	x	x	x	x	x
Chemical-Year FE	x	x	x	x	x	x
Industry-Year FE		x	x		x	x
State-Year FE			x			x
Observations	1,041,796	1,040,652	1,040,646	1,097,171	1,095,985	1,095,980
R-squared	0.263	0.299	0.303	0.722	0.734	0.738

Table 8: **Hedge Fund Activism and the Efficiency of Emissions**

This table uses OLS regressions to examine how the efficiency of emissions changes after a hedge fund activism campaign. The dependent variable is the log of total pollution/the normalized production level for a given plant-chemical observation. *Activism* is an indicator that takes the value of 1 in the year that an activism campaign begins and for the four years afterwards and is zero otherwise. Fixed effects are indicated in the table. Robust standard errors clustered by parent firm are reported in parentheses. All variables are defined in Table A.1. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	log(Pollution / Normalized Prod.)		
	(1)	(2)	(3)
Activism	-0.101**	-0.0781*	-0.0593
	(0.0448)	(0.0420)	(0.0448)
Plant-Chemical FE	x	x	x
Chemical-Year FE	x	x	x
Industry-Year FE		x	x
State-Year FE			x
Observations	1,097,171	1,095,985	1,095,980
R-squared	0.902	0.906	0.907

Table 9: **Hedge Fund Activism and Hazardous Emissions**

This table uses OLS regressions to examine how pollution usage changes after a hedge fund activism campaign begins. The dependent variable is the log of total emissions for a given plant-chemical observation. The sample only contains chemicals that have been classified as hazards to human health in the IRIS database. Columns (1)–(3) include all hazardous chemicals; columns (4)–(8) limit the sample to chemicals that affect particular systems of the human body. *Activism* is an indicator that takes the value of 1 in the year that an activism campaign begins and for the four years afterwards and is zero otherwise. Fixed effects are indicated in the table. Robust standard errors clustered by parent firm are reported in parentheses. All variables are defined in Table A.1. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	log(Total Hazardous Emissions)							
System Affected =	All Systems			Nervous	Respiratory	Developmental	Hematologic	Hepatic
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Activism	-0.253***	-0.241***	-0.231***	-0.271***	-0.226***	-0.274***	-0.234***	-0.382***
	(0.0697)	(0.0546)	(0.0535)	(0.0620)	(0.0745)	(0.0815)	(0.0661)	(0.131)
Plant-Chemical FE	x	x	x	x	x	x	x	x
Chemical-Year FE	x	x	x	x	x	x	x	x
Industry-Year FE		x	x	x	x	x	x	x
State-Year FE			x					
Observations	643,530	642,082	642,073	296,644	182,675	129,711	127,225	99,695
R-squared	0.885	0.891	0.892	0.893	0.895	0.871	0.891	0.897

Table 10: **Hedge Fund Activism and Environmental Enforcements**

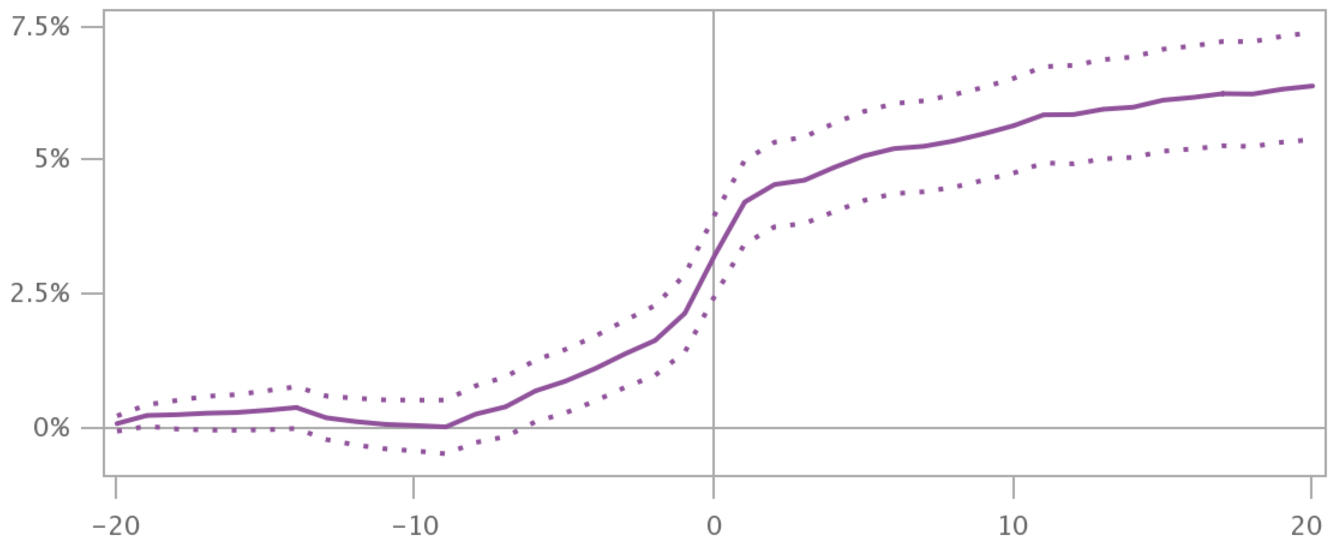
This table uses OLS regressions to examine how the federal environmental enforcements change after a hedge fund activism campaign begins. The dependent variable in columns (1) – (3) is an indicator that takes the value of one if a plant was subject to an EPA violation in a given year and zero otherwise. The dependent variable in columns (4) – (6) is the log of one plus the total amount of fines paid in a given year by a plant. *Activism* is an indicator that takes the value of 1 in the year that an activism campaign begins and for the four years afterwards and is zero otherwise. Fixed effects are indicated in the table. Robust standard errors clustered by parent firm are reported in parentheses. All variables are defined in Table A.1. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	𝟙(EPA Enforcement)			log(1+Total Fines)		
	(1)	(2)	(3)	(4)	(5)	(6)
Activism	-0.00766**	-0.00839**	-0.00863**	-0.101*	-0.115**	-0.116**
	(0.00362)	(0.00357)	(0.00355)	(0.0530)	(0.0538)	(0.0530)
Plant FE	x	x	x	x	x	x
Year FE	x			x		
Industry-Year FE		x	x		x	x
State-Year FE			x			x
Observations	352,805	351,110	351,089	352,805	351,110	351,089
R-squared	0.116	0.149	0.156	0.111	0.148	0.155

Figure A.1: **Cumulative Abnormal Returns**

This figure plots Cumulative Abnormal Returns (CARs) from 20 days to 20 days after before hedge funds disclose positions in target firms. Panel A plots the entire sample of events from the updated sample first used by Brav et al. (2008), while panel B plots the sample of events that are non-passive that we have matched to the Toxic Release Inventory database form the basis of our sample, i.e., those events that form our main sample. CARs are computed using the Fama-French four-factor model.

(a) **All Events**



(b) **Non-passive Events with TRI Data**

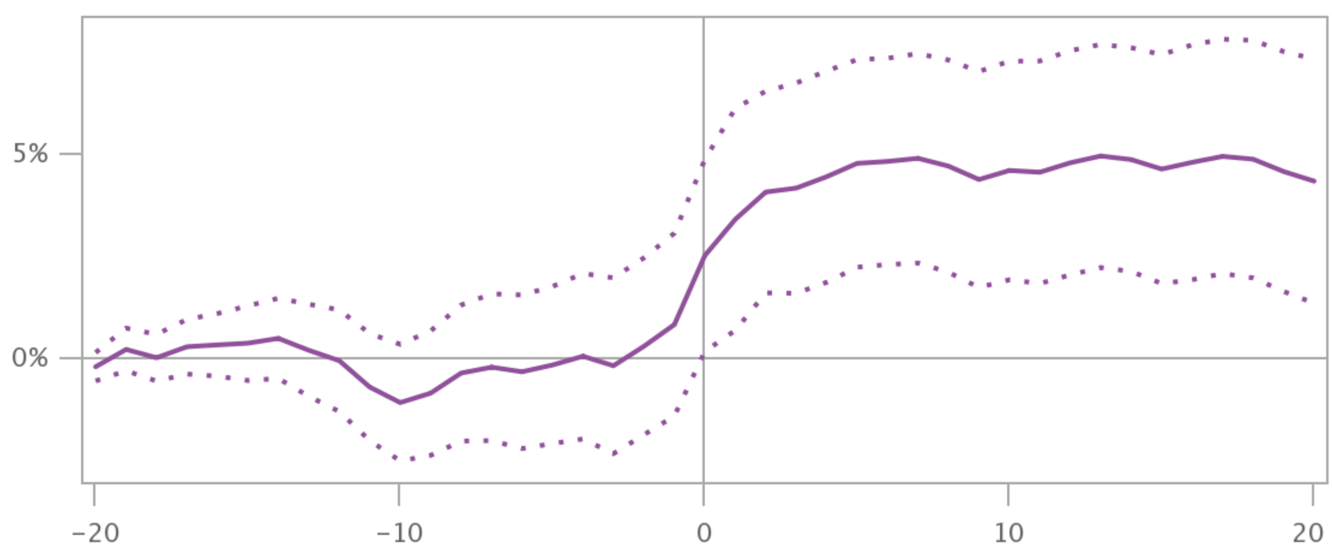


Table A.1: **Variable Definitions**

This table provides the source and definition for the variables used in the analysis.

Activism Variables		
Activism	Brav et al. (2008, 2010)	Indicator equal to 1 for years 0-4 after firm targeted by activist
Objective - General	Brav et al. (2008, 2010)	Indicator equal to 1 for years 0-4 for campaigns with general objective (e.g., improve the firm)
Objective - Strategy	Brav et al. (2008, 2010)	Indicator equal to 1 for years 0-4 for campaigns related to business strategy
Objective - Governance	Brav et al. (2008, 2010)	Indicator equal to 1 for years 0-4 for campaigns related to governance issues
Objective - Sale	Brav et al. (2008, 2010)	Indicator equal to 1 for years 0-4 for campaigns that seek to sell the target
Objective - Capital Structure	Brav et al. (2008, 2010)	Indicator equal to 1 for years 0-4 for campaigns related to capital structure
Environmental Variables		
Total Pollution	TRI Database	Lbs of total emissions (Air+Water+Ground)
Air	TRI Database	Lbs of air emissions (stack + fugitive emissions)
Water	TRI Database	Lbs of surface water emissions
Ground	TRI Database	Lbs of ground emissions (onsite + underground injection)
Abatement	TRI P2 Database	Indicator for abatement activity
# Abatement	TRI P2 Database	Number of abatement actives
Productivity Ratio	TRI Database	Final output year t/ Final output year t-1
Normalized Production	TRI Database	Cumulative productivity ratio (first year in sample = 1)

Table A.2: **CAR Summary Statistics**

This table presents Cumulative Abnormal Returns and Buy-and-Hold Abnormal Returns for various windows around the first event associated with hedge funds taking positions in target firms. Panel A presents summary statistics for the updated sample of Brav et al. (2008), Panel B presents summary statistics for the sample that we are able to match to firms in the TRI database, while Panel C presents summary statistics for the sample of that we are able to match to firms in the TRI database that engage in activism. The events in Panel C form the sample that we use for the main analysis in the paper. The mean abnormal return in each sample is statistically significant at conventional levels.

Panel A — All Events				
	Number	**Mean**	**Median**	**SD**
CAR (-5,+5)	3,456	0.044	0.034	0.18
CAR (-10,+10)	3,461	0.054	0.042	0.23
CAR (-20,+20)	3,460	0.061	0.055	0.30
BHAR (-5,+5)	3,456	0.044	0.032	0.24
BHAR (-10,+10)	3,461	0.052	0.037	0.28
BHAR (-20,+20)	3,460	0.048	0.040	0.36
Panel B — Events Matched to TRI				
	Number	**Mean**	**Median**	**SD**
CAR (-5,+5)	308	0.042	0.031	0.11
CAR (-10,+10)	307	0.043	0.038	0.17
CAR (-20,+20)	306	0.031	0.033	0.23
BHAR (-5,+5)	308	0.041	0.032	0.12
BHAR (-10,+10)	307	0.041	0.038	0.18
BHAR (-20,+20)	306	0.024	0.028	0.24
Panel C — Active Events Matched to TRI				
	Number	**Mean**	**Median**	**SD**
CAR (-5,+5)	212	0.052	0.040	0.12
CAR (-10,+10)	211	0.054	0.046	0.16
CAR (-20,+20)	211	0.043	0.049	0.22
BHAR (-5,+5)	212	0.052	0.040	0.13
BHAR (-10,+10)	211	0.055	0.044	0.18
BHAR (-20,+20)	211	0.039	0.043	0.23

Table A.3: **Pre-Activism Characteristics**

The following table uses OLS to examine differences in outcome variables prior to the beginning of an activism campaign. Dependent variables are either the log of total pollution, an indicator that takes the value of one if a firm engages in abatement activities in a given year, or the production ratio, as indicated in the table below. *Pre-Activism* is an indicator variable that takes the value of one if the firm will be subject to an activism campaign in the following year and is zero otherwise. Fixed effects are indicated in the table. Robust standard errors clustered by parent firm are reported in parentheses. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	log(Total Emissions)		$\mathbb{1}$(Abatement)		Production Ratio	
	(1)	(2)	(3)	(4)	(5)	(6)
Pre-Activism	0.730***	0.108***	-0.0107	-0.000195	-0.0186	-0.00591
	(0.131)	(0.0315)	(0.00948)	(0.00635)	(0.0136)	(0.0137)
Chemical-Year FE	x	x	x	x	x	x
Plant-Chemical FE		x		x		x
Observations	1,139,633	1,097,171	1,139,633	1,097,171	1,081,651	1,041,796
R-squared	0.424	0.913	0.076	0.548	0.042	0.262

Table A.4: **Hedge Fund Activism and EPA Fines**

This table uses OLS regressions to examine how the federal environmental enforcements change after a hedge fund activism campaign begins. The dependent variable is the log of one plus the total amount of fines paid in a given year by a plant. *Activism* is an indicator that takes the value of 1 in the year that an activism campaign begins and for the four years afterwards and is zero otherwise. The sample is restricted to plants that received at least one EPA violation over the sample period. Fixed effects are indicated in the table. Robust standard errors clustered by parent firm are reported in parentheses. All variables are defined in Table A.1. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	log(1+Total Fines)		
	(1)	(2)	(3)
Activism	-0.376*	-0.538**	-0.576**
	(0.211)	(0.228)	(0.225)
Plant FE	x	x	x
Year FE	x		
Industry-Year FE		x	x
State-Year FE			x
Observations	79,708	77,553	77,518
R-squared	0.060	0.161	0.185

Table A.5: **Hedge Fund Activism and Environmental Enforcements by Statute**

This table uses OLS regressions to examine how the federal environmental enforcements change after a hedge fund activism campaign begins. The dependent variable is an indicator that takes the value of one if a plant was subject to an EPA violation in a given year and zero otherwise. The dependent variable in each column is measured for a different legal statue which is indicated above the column number. CAA stands for the Clean Air Act, CWA stands for the Clean Water Act, FIFRA stands for the Federal Insecticide, Fungicide, and Rodenticide Act, CERCLA stands for the Comprehensive Environmental Recovery and Liability Act, RCRA stands for the Resource Conservation and Recovery Act, SDWA stands for the Safe Drinking Water Act and TSCA stands for the Toxic Substance Control Act. *Activism* is an indicator that takes the value of 1 in the year that an activism campaign begins and for the four years afterwards and is zero otherwise. Fixed effects are indicated in the table. Robust standard errors clustered by parent firm are reported in parentheses. All variables are defined in Table A.1. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Legal Statute	CAA	CWA	FIFRA	CERCLA	RCRA	SDWA	TSCA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Activism	-0.00583**	-0.00277	9.13e-05	-0.00123	0.00179	-0.000346	-0.000264
	(0.00295)	(0.00170)	(0.000729)	(0.00100)	(0.00204)	(0.000246)	(0.000612)
Plant FE	x	x	x	x	x	x	x
Industry-Year FE	x	x	x	x	x	x	x
Observations	351,110	351,110	351,110	351,110	351,110	351,110	351,110
R-squared	0.130	0.131	0.159	0.121	0.118	0.114	0.116