Does Greenwashing Pay Off?

An Empirical Analysis of Cheap-Talk in Firm Behaviour.

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Abstract

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1 Introduction

[1]

In recent years, climate change has become an issue of a global importance. Policy-makers, international organizations as well as consumers have been growing more aware of the problems facing the world in the upcoming years. In turn, heightened awareness has led to more and more people becoming educated on the topic of sustainability and climate change prevention. This awareness has lead to a rapid development of sustainable finance and a creation of a large body of ESG investment funds. Companies, trying to answer the needs of consumers have reoriented their supply chains and started transitioning to more sustainable methods of production. At the same time, this structural shift in demand created an avenue for greenwashing.

According to a literature review by Lyon and Montgomery (2015), greenwashing is defined as "any communication that misleads people into adopting overly positive beliefs about an organization's environmental performance, practices, or products". It presents a risk, because some companies can choose to appear as sustainable through making statements or campaigns aimed at sustainable consumers/investors, while not carrying through with investments in sustainability (Barrage et al., 2020; Kim & Lyon, 2015; Marquis et al., 2016). Moreover, theoretical models in Cartellier et al. (2023) and Wu et al. (2020) suggest that there exist equilibria where it is optimal for companies to greenwash, as investments in sustainability are largely unobserved. In sectors with large costs of the transition, this could potentially allow companies to benefit from this shift in demand, while not bearing the costs.[2]

This paper tries to answer the question: Is greenwashing a beneficial strategy for company performance in the presence of a positive sustainability demand shock? My approach consists of two steps. Firstly, I collect and process the sustainability reports for a sample of public companies, for which such reports are available. After processing, the reports are used to create a Cheap-Talk-Index (CTI) that gauges the credibility of

[1]Add more to the literature review, position greenwashing better within the introduction.
[2]Describe more why a risk, look at Lagasio's paper!

climate commitments made by companies (Bingler et al., 2024). This index allows for measuring the likelihood of greenwashing following the contributions of Coen et al., 2022. Secondly, I try to estimate a causal response of cumulative abnormal returns (CAR) of companies stock prices' to greenwashing in presence of a demand shock to sustainability. Using the world-wide September 2019 strikes organized by Fridays For Future (20 & 27 September 2019)[3] and the occurrence of the "Global Week for Future", as the shock and the CTI as the treatment, I test whether the markets have responded differently to firms more likely to greenwash. I find that …This result can be explained by ….

Finally, I use the same procedure to investigate the effects on sales of the above-mentioned companies. I argue that companies trying to be perceived among investors as environmentally friendly, are likely to try to be perceived in the same way by their customers. Using the CTI, I test whether the sales of greenwashing companies have been substantially impacted following the shock. Results indicate that …This result can be explained by …

This study is related to two streams of literature.[4] First, it contributes to the literature concerning the link between financial markets and company's environmental performance. This stream of literature focuses on a set of findings. Some studies focus on the causes of greenwashing (…). Some studies focus on the reaction of the market to stakeholder pressure caused by climate-related events (Birindelli et al., 2023; Bouzzine, 2021; Cartellier et al., 2023; Diaz-Rainey et al., 2021; Schuster et al., 2023). Others focus on the effect of greenwashing on the financial performance of a company *after* company's greenwashing is exposed (Karpoff et al., 2005; Konar & Cohen, 2001; Teti et al., 2024; Torelli et al., 2020) (**add more here**). This study fills the gap, by investigating whether it is profitable for a company to greenwash in presence of rising stakeholder pressures, and *before* the greenwashing of the company is uncovered.

Second, it contributes to literature on the link between consumer behaviour and deception. A number of studies focusing on this topic find that deceptive information, may cause consumers to make less informed choices (Bronnenberg et al., 2015; Rao & Wang,

[3]A series of 4500 strikes across over 150 countries on the last two Fridays of September 2019

[4]Be more explicit about the contributions, describe them more in detail

2017). For example, Barrage et al. (2020), finds that BP's environmental marketing campaign dampened the negative reactions of consumers following an oil spill in which the company was involved. This study complements this literature by testing whether companies can reap the benefits of deception in presence of an increase in consumer activism.

The remainder of the paper is organized as follows. Section 2 describes the events leading up to and after the shock and presents the argument for the choice of the treatment variable. Section 3 outlines the procedures for collecting and processing the data. Section 4 summarizes the used methodology and compares it with the typical difference-in-differences framework. Section 5 describes and interprets the results. Section 6 describes the limitations and concludes.

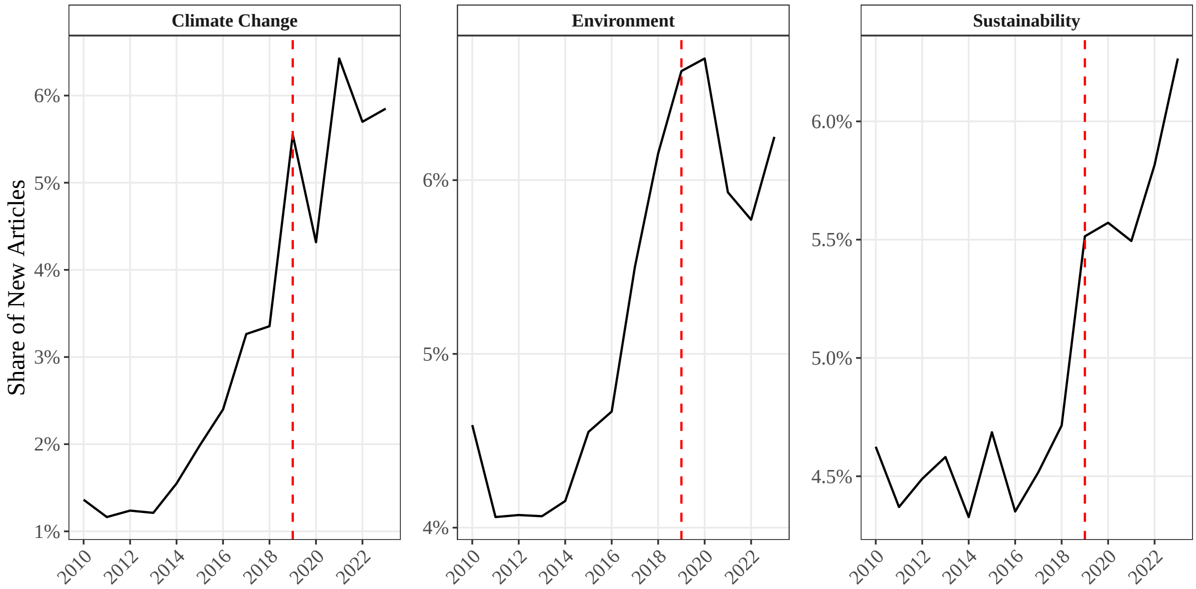
2 Background

2.1 Timeline

The year 2019 was an important year for climate change awareness as well as for climate change policy. The Fridays For Future (FFF) movement started in August 2018 by Greta Thunberg has been picking up in popularity following the release of a previous IPCC report on the commitments needed to stop the rising world temperatures. At the same time, 2019 witnessed many climate-related disasters. It was the second-hottest year since the start of the record keeping in 1880 (National Centers for Environmental Information (NCEI), 2019). According to The Guardian, extreme events such as floods, droughts, storms and wildfires have accounted for more than $100bn worth of damages (Harvey, 2019). This effect is also visible in the news coverage of that year. As evidenced by the Figure 1, 2019 marked a significant increase in new articles related to climate change, environment, and sustainability compared to the previous years. While the overall number of new articles created by the New York Times has been in decline from 2012 until 2019, authors have been writing more articles revolving around these 3 topics.

The pressure exerted on policymakers culminated in September during a series of

Figure 1: Growth in New York Times Coverage by Topic



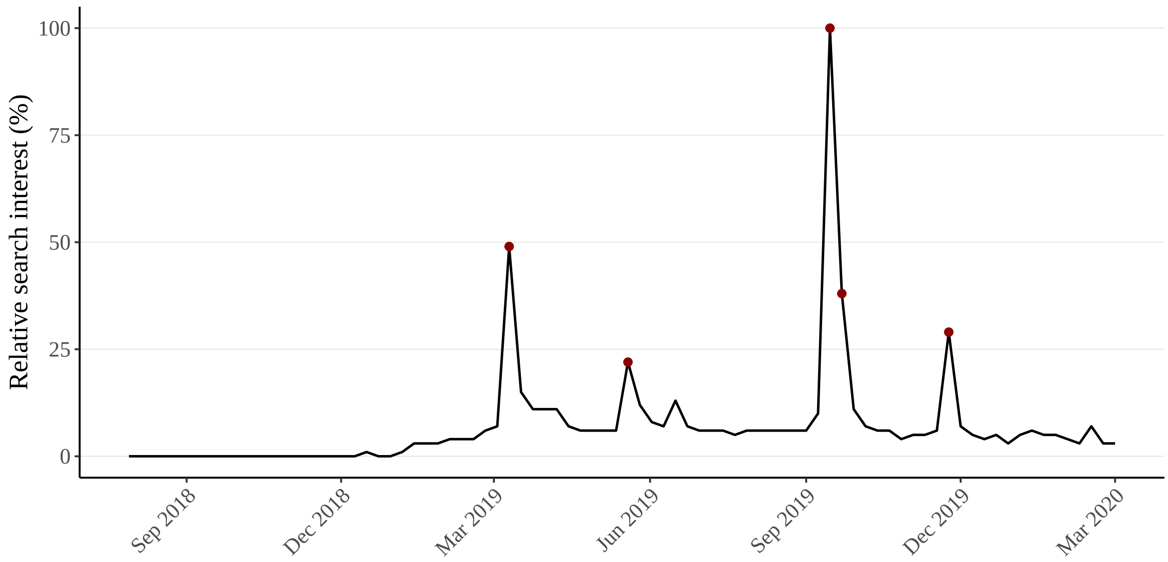
Number of new articles published per year (2010–2023). Red line indicates the year of the shock. Source: New York Times

strikes titled "Global Week for Future" (23–27 September 2019), during which the United Nations Climate Action Summit (UNCAS) took place. In the prior and during that week, FFF organized two global strikes across +270 countries that were attended by 4 million (for both the 20–09–2019 and 27–09–2019 ones) according to the organizers (Fridays for Future, n.d.). The number of participants as well as the interest were an order of magnitude larger than the previously organized events. Moreover, it was the first time when the youth movement was joined by adults with Watts and Laville of The Guardian describing it as:

> *For the first time since the school strikes for climate began last year, young people called on adults to join them – and they were heard. Trade unions representing hundreds of millions of people around the world mobilised in support, employees left their workplaces, doctors and nurses marched and workers at firms like Amazon, Google and Facebook walked out to join the climate strikes.* (Watts & Laville, 2019)

As shown on the Figure 2, strikes related to that week attracted over twice as much attention online as any other strikes organized by FFF. This effect has been amplified by speeches given by Greta Thunberg at the climate strike in New York City and at the

Figure 2: Google Search Trends of "Fridays For Future"



Proportion of searches relative to the most searched, for the whole world. Red dots show major strikes organized my FFF. These strikes happened on the following dates (from left to right): 15–03–2019, 20–09–2019, 27–09–2019, 29–11–2019. Source: Google Trends

UNCAS in which she motivated the strikers as well as attacked the governmental officials for not taking appropriate action on climate change (Thunberg, 2019).

These events had an impact on financial markets. In a 2023 study, Schuster et al. found that the FFF global climate strikes significantly affected the short-term stock performance of firms from the S&P 500 and STOXX Europe 600 indices. They estimated a financial event study and find that the two global climate strikes in September 2019 generally hurt the performance of the companies in these indices.[5]. This is in line with the findings of a theoretical model by Pástor et al. (2021), which argues that sustainable assets outperform other assets, when concerns for sustainability rise.

Overall, the action taken by the FFF grasped the imagination of the public with many people choosing to walk out onto the streets and support their causes. The events gathered news and online attention and can be said to have had an impact on the performance of companies in that period.[6]

[5]Describe more of the study here

[6]Describe here also the events that happened afterwards: the COP of that year (December) and the IPCC report that came out earlier

2.2 ESG Reports

This study uses broadly defined responsibility reports for the construction of the main measure of greenwashing. These reports contain information meant for investors and stakeholders. They inform the reader on initiatives undertaken by the company in various areas related to corporate social responsibility (CSR). This study focuses on the sustainability section of these reports, that contains information on the impact that the company has on the environment, its production standards, as well as the climate risk a company is exposed to. To illustrate, Walmart Inc.'s 2018 Global Responsibility Report contains a dedicated sustainability section that describes the impact of Walmart's activities on the environment. This report also contains a dedicated "ESG commitments" section, that outlines the company's ESG goals and their progress on attaining them.[7]

These reports are desirable for a number of reasons. Firstly, literature points to the fact that investors care about sustainability and climate risks, and that they reward companies when these report on actions related to them (Ilhan et al., 2023; Krueger et al., 2020; Pástor et al., 2021; Testa et al., 2018). From the firm perspective, corporate communication allows it to raise its market value, when they inform their investors sufficiently (Servaes & Tamayo, 2013). Furthermore, by communicating on their ESG activity, they can increase their legitimacy to its stakeholders (Torelli et al., 2020). From this one can conclude that it is in the interest of these companies, to communicate as much information as possible through this channel, to reap the rewards.

However, as these reports do not fall under the oversight of any institutions (unlike e.g. annual earnings reports), they allow companies to introduce deception in their communications. For example, the companies issuing these reports, may overstate their environmental achievements, or understate the damages that they caused, and as such use them to appeal to their stakeholders. There can be many reasons why this behaviour can be incentivized. For example, if investment in sustainability is unobservable, companies may benefit from overstating their actual investments (Wu et al., 2020). Alternatively, if their activity negatively affects the environment, they may desire to diminish the neg-

[7]This Walmart Inc. report, as well as others can be easily accessed here.

ative reputational impacts of their actions (Bingler et al., 2022; Marquis et al., 2016).[8] In addition to over-/under-reporting, companies can also utilize other strategies to impact the perception of the stakeholders. For example, Parguel et al. (2015) and Schmuck et al. (2018) find that referring to nature and including nature-related graphics in their communications can positively influence their perception of the company. Given all of these reasons, they seem to provide a rich source of (possible) greenwashing behaviour.

As a counterargument to the use of the reports, one could argue that they are actually not read by the shareholders, who use the ESG ratings of companies instead. After all, these scores are prepared by professionals who carry out extensive research into the sustainability efforts of these companies and take into account their environmental communications. However, these can often be inconsistent between rating agencies, as shown by Berg et al. (2022) and Chatterji et al. (2016). This suggests that they may not provide a good estimate of company's environmental performance. Therefore, I refrain from using them as my measure of greenwashing. Instead, I chose to use the underlying reports, following the method of Bingler et al., 2024. The method, together with the data collection procedure, are described in the next section.

3 Data

3.1 Cheap-Talk Index

The ESG reports were scraped from the ResponsibilityReports.com. Additionally, the website allowed me to retrieve information on company headquarters location and the approximate number of employees.[9] As the analysis concerns the events of 2019, the scraped data was subset for companies reporting in 2018, to guarantee that the reports did not originate in response to the upcoming shock.

To identify deception in relation to the environmental claims of companies, I implemented the method outlined in Bingler et al. (2024). In this study, the authors create

[8] For a more comprehensive review, see Kim and Lyon, 2015

[9] Table 4 in Appendix A.1 displays the number of reports available per year. The number of published reports increases with time, as communicating sustainability has become more important.

the Climate Cheap-Talk Index (CTI), based on the content of annual financial reports. They use the extracted text to construct and train machine learning models that are then used to examine the level of cheap-talk in a given report.

Their approach is motivated by the work of Coen et al. (2022) and Ramus and Montiel (2005). While the ESG reports can allow for greenwashing (as outlined in the previous section), it is hard to measure it. However, the authors of these two studies find a way. They argue that companies are less likely to follow-up on their commitments if these are stated in a vague and non-specific manner. The CTI, interpreted as a measure of non-specificity of companies climate commitments, can be used as a proxy for greenwashing, under the assumption that the vagueness reflects the deviation of claims of companies, from their statements. This resembles the argument made in Bingler et al. (2022) and Marquis et al. (2016), which argue that companies may want to under-report their impact on the environment if it is negative. However, it must be noted that this is only an approximation, that can suffer from measurement error. Nonetheless, under these conditions it allows for the estimation of the perceived greenwashing of companies.

Their method consist of two steps. First, they access an instance of the ClimateBert model developed by Webersinke et al. (2022). ClimateBert is a transformer-based language model, that was pre-trained on climate-related texts, in addition to regular training. This process, allows the ClimateBert to be more precise in various tasks (such as text classification), because through this pre-training, it became more exposed to domain-specific vocabulary of climate related information. According to the authors, this resulted in a decrease in error rates of the model of up to 35.71% depending on the task. Bingler et al. fine-tune this instance of the model for classifying paragraphs as *climate-related*. This means, that they applied further training to the model, to make it better at predicting whether the text extracted from annual reports is climate related (e.g. mentions sustainability initiatives) or not.

As a second step, they train another instance of the same model to classify paragraphs as *specific* (containing specific commitments) and *non-specific* (containing only vague commitments). This means that they additionally post-train the model, so that it can better differentiate between paragraphs that refer to specific goals of the company (such as "Achieve an 18 percent emissions' reduction in Walmart's own operations by 2025 (over 2015 baseline)" (Walmart Inc., 2018)) and paragraphs that only contain vague statements about climate-related issues (such as "Walmart believes business can play a role in addressing climate change by reducing GHG emissions, and our investments in renewable energy and efficiency underscore that belief"). The procedures that the authors used for training of both of the models are described in Bingler et al. (2022, 2024). Then, they use the set of climate-related paragraphs and the set of specific paragraphs within a report to create the CTI. Equation 1 presents the formula for the index:

$$CTI = \frac{CLIM_i \cap NONSPEC_i}{CLIM_i} \tag{1}$$

Where for a report of company i, $CLIM_i$ represents the number of climate-related paragraphs, $NONSPEC_i$ represents the number of paragraphs containing non-specific commitments, and $CLIM_i \cap NONSPEC_i$ represents the intersection between the two.

In order to apply this method to my data, I proceeded as follows. First, I extracted the text from the reports. This has been done by using blocks contained in the PDF files to preserve the structure of the paragraphs.[10] To further refine the data, each block has been classified as a paragraph, if it spanned at least 3 lines, contained at least 30 words and had at least one full stop. Then, I applied the models trained by the researchers to establish which paragraphs are climate related, and which contain specific commitments.[11] Finally, I aggregated the CTI into quartiles, to create the final treatment-dose variable D_i. The aggregation was carried out for two reasons. Firstly, one could argue that investors/consumers would not see the difference in behaviour of two companies whose score is very close. Therefore, dividing the continuous variable into separate bins would resemble the reasoning of the agents more closely and reduce the noise in the estimation. Secondly, as the index itself is very sensitive to the number of climate related paragraphs, grouping the treatment variable again reduces noise.

[10]By *blocks*, I mean an object within the structure of a PDF file that usually determines the location of a paragraph on a page.

[11]Both of these models can be downloaded from here

3.2 Outcome Variables

The Refinitiv dataset wad used to retrieve data on firms' characteristics, their price indices and their quarterly earnings. Moreover, it was also used to retrieve the prices for regional market indices (e.g. S&P500, MSCI Europe, etc.) that were needed to estimate the normal returns for each company. The characteristic variables include the stock exchange of the listing, country of incorporation, country of domicile, the company's sector and the company's industry. I log-differenced the price indices (defined as the stock price expressed as a fraction of the initial listing price) to transform them into percentage changes. The same has been done for the quarterly earnings and for the values of regional stock indices. I chose the daily frequency for the stock price data and a quarterly frequency for the earnings data. This was motivated by the likely short-term effect on stock prices (as found by Schuster et al. (2023)), and data availability for earnings.[12]

In order to plausibly estimate the effect of the treatment on stock returns, I needed to separate the effects of the market movement from the movement of the stock of the company itself. These abnormal returns were estimated following the market model approach outlined in Mackinlay (1997). This approach relies on estimating the expected stock return by predicting it using the return of the whole market. As the sample contains companies from multiple continents which markets may differ, each company was allocated to a geographical market index by their country of domicile. The allocation can be viewed in Table 6 in the Appendix A. The model has been separately estimated for each company using observations that predate the estimation window of interest. Intervals that were used are reported in Table 7. Below I report the regression specification used for the estimation:

$$RN_{it} = \alpha_i + \beta_i RI_{mt} + \varepsilon_{it} \tag{2}$$

Where, RN_{it} is the return of the security i at time t predicted by the return of its geographical market m, α_i is the regression constant of for the company i, RI_{mt} is the

[12] Table 7 in Appendix A.1 shows the total number of periods that were retrieved.

return of the said market, and $\varepsilon_{i,t}$ is the noise. Finally, as this regression estimates the return of the security predicted by the return of the market, the abnormal return for i in a given time period t is given by the residual ε_{it}.

This type of modelling is sufficient for my use case, as per the work of Mackinlay, employing more sophisticated models (e.g. factor models) yields limited improvement in studies that do not rely on within-group variation, such as within-sector variation.

Moreover, the abnormal returns for each of the securities were later cumulatively summed to arrive at the Cumulative Abnormal Return (CAR). This was done, as aggregation across time is needed in order to draw useful inference from the results of the actual study. This results from the fact that estimating the average abnormal returns directly would not take into account the path of the data following treatment, but only the instantaneous effect of the treatment dose.

3.3 Merging

In the last step of the data preparation, the two datasets were merged. As this process was difficult and required multiple steps, its description is included in the Appendix A.3. Overall, the final dataset contained 795 companies, with 57 being dropped due to inability to be merged.[13]

4 Methodology

This section describes the methodology used in the attempt to estimate the causal effect of greenwashing on company performance. My initial approach was to use a classic Difference-in-Differences (DiD) methodology with binary treatment, however upon consideration I decided to implement a variation of DiD with multivalued treatment following Callaway et al. (2025). This approach is motivated by the fact, that the market may react differently to firms that use more cheap talk in their communication. This method also allows for estimation of experiments in settings without an untreated group, where the

[13] I believe that the 57 is incorrect, I still need to resolve it. Note: I am yet to include descriptive statistics here

group with the lowest treatment-intensity is used as a comparison.

Given the use of newly developed methods in this study, I chose to contrast their methodology with the well-understood traditional DiD framework to better illustrate how this approach can improve upon the default approach. Therefore, the methodology is divided into three parts. Firstly, I will cover the conventional difference-in-differences design. Then I will contrast it with the implemented design using multivalued treatment. Finally, I will describe the differences in the taken approach when estimating the effect on sales of companies instead of stock prices.

4.1 Default Difference-in-Differences

Conventional Difference-in-Differences studies aim to estimate the causal effect of a policy by comparing units over time and then comparing those changes across groups. In order to separate the causal effect, they require two main assumptions explained below.[14]

Parallel trends (PT) assumption, which requires that in the absence of treatment, the outcomes of the units assigned to the treatment group would have evolved in the same way (in terms of the trend) as the outcomes of the units that were not assigned to treatment. In my example, it implies that in the absence of cheap-talk of a company, their stock price/sales would have evolved in the same way as the stock price/sales of those that do not engage in cheap talk.

No-anticipation assumption, imposes that the individuals do not act in anticipation of the treatment. In my example, it implies that before the shock, the investors do not expect the greenwashing firms to perform differently from non-greenwashing firms after the shock, and therefore choose not to adjust their portfolios in advance of it. In other words, belonging to the treatment or the control group should not matter for the outcomes of the companies before the climate strikes shock.

Under these two assumptions and an additional assumption on independent sampling, the treatment effect can be recovered using the following regression specification utilizing two-way-fixed-effects (TWFE):

[14] A formal treatment of these assumptions can be found in Appendix B.1

$$Y_{i,t} = \alpha_i + \Phi_t + \beta^{twfe} D_i \cdot Post_t + \varepsilon_{i,t} \tag{3}$$

Where Y_{it} is the outcome variable, α_i is the entity fixed effect, Φ_t is the time fixed effect, D_i is the binary treatment dummy, $Post_t$ is the post-treatment period dummy. In this setting, β^{twfe} recovers the average treatment effect.[15]

Although the interpretation of this treatment effect has been well described, it is not useful when analysing cases with multiple treatment doses, as it can be shown that the TWFE parameter becomes a weighted average of dose-ATT's, with weights that deprive this parameter of its causal interpretation (Callaway et al., 2025). Therefore, in the following section, I describe the methodology of an adjusted framework.

4.2 Multivalued Difference-in-Differences

In order to incorporate the multivalued treatment into my study, I implemented the framework developed by Callaway et al. (2025). This is not the only approach present in the literature (see De Chaisemartin et al., 2024), however I deemed it the most suitable based on the required setting. This method was developed in the context of estimating the average treatment effect in settings where there is no treatment in pre-event periods. De Chaisemartin et al. differs in this regard, as it relies on treatment being positive in the periods prior to the event, and it requires a change in intensity in the event-period, to retrieve the average treatment effect. As in my case the treatment is fixed for a unit, but varies in intensity between them, this requires the Callaway et al. (2025) approach. It proposes the use of a multivalued treatment, where the single dummy D_i can be replaced with multiple dummies $D_{i,d} \in \mathcal{D}$ that show that the unit i has received the dose d, where d refers to the "bins" that signify different treatment intensity. Then, this approach compares the dose of a group $D_{i,d}$, to the untreated group $D_{i,0}$.

This framework shares the no-anticipation and the independent sampling assumptions with the conventional DiD literature, however the differences arise in the parallel-trends assumption. In this setting, the traditional PT assumption allows for the estimation of

[15] Note: Cite studies that mention problems with TWFE estimators?

each of the individual intensity parameters (i.e. ATT for each treatment is still recovered), however, a stronger assumption is needed to compare the effects across these estimators. Therefore, this assumption is required in order to assess the effect of higher greenwashing intensity of a firm.

The **Strong Parallel Trends (SPD) assumption** requires that the average evolution of outcomes for the entire treated population if all experienced dose d is equal to the path of outcomes that dose group d actually experienced (Callaway et al., 2025). This assumption is called the strong parallel trends, as it implies that the average response to the treatment would be the same for all dose groups, if they were to receive (for example) a lower dose d. It is more restrictive than the regular parallel trends assumption, and the researchers themselves argue that it may be unreasonable in many cases due to treatment effect heterogeneity of different groups. However, under this assumption, one can estimate the average causal response parameter, which the researchers denote as $ACRT$. They show that the $ACRT$ is equal to the difference in average potential outcomes between dose level d and the next lowest dose, scaled by the difference between these two doses.

Furthermore, the authors extend this framework to allow for estimation of treatment effects, where there are no untreated units, implying a setting where all dose-groups are compared to the lowest-dose group. While in the case with an untreated group the ATT estimates the effect of switching from no treatment to a treatment of dose d, they show that in this case, the ATT compares the change from low-intensity treatment to high intensity treatment. This introduces a selection bias which cannot be solved with a standard parallel trends assumption, and therefore calls for the use of the strong parallel trends. Due to the fact that in my setting there are no explicitly untreated companies, but only companies that are in the lowest quartile of the CTI index, this assumption is required for the whole estimation process.

In order to retrieve the causal effect, I estimate the following multivalued specification:

$$Y_{i,t} = \alpha_i + \phi_t + \sum_{d=2}^{4} \beta_d \cdot 1\{D_{i,d} = d\} \cdot Post_t + \varepsilon_{i,t} \tag{4}$$

Where $Y_{i,t}$ is the outcome variable, α_i are the unit fixed effects, ϕ_i are the time fixed effects, $1\{D_i = d\}$ is a dummy variable equal to 1 if the unit i belongs to the treatment group d, $Post_t$ is the dummy variable equal to one in the post-treatment period, and $\varepsilon_{i,t}$ is the standard normal noise. The standard errors are clustered at the company (i) level, following Abadie et al. (2022).[16] Note that $d = 1$ is omitted, as the regression is estimated relative to the lowest dose group. In this specification, each β_d estimates the difference between $ATT(d)$ and the $ATT(d_L)$, which is average difference in outcomes when treated with d instead of d_L. Formally, it can be expressed as:

$$\beta_d = E[Y|D = d] - E[Y|D = d_L] = ATT(d) - ATT(d_L) = E[Y_{t=2}(d) - Y_{t=2}(d_L)] \quad (5)$$

This is a common approach adopted by many applied researchers (Acemoglu & Finkelstein, 2008; Deschênes & Greenstone, 2011). While this approach does not summarize the effect of the policy with one parameter, in the same way as the β^{twfe} does, Callaway et al. argue for this as their preferred specification. According to their study, estimating these parameters separately omits the weighting problem faced by specifications such as:

$$Y_{i,t} = \alpha_i + \phi_t + \beta^{twfe} Post_t \cdot (d_j - d_{j-1}) + \varepsilon_{i,t} \quad (6)$$

Where the β^{twfe} tries to aggregate the dose-specific ATT's into a single number. They propose their own aggregation scheme that estimates ...[17]

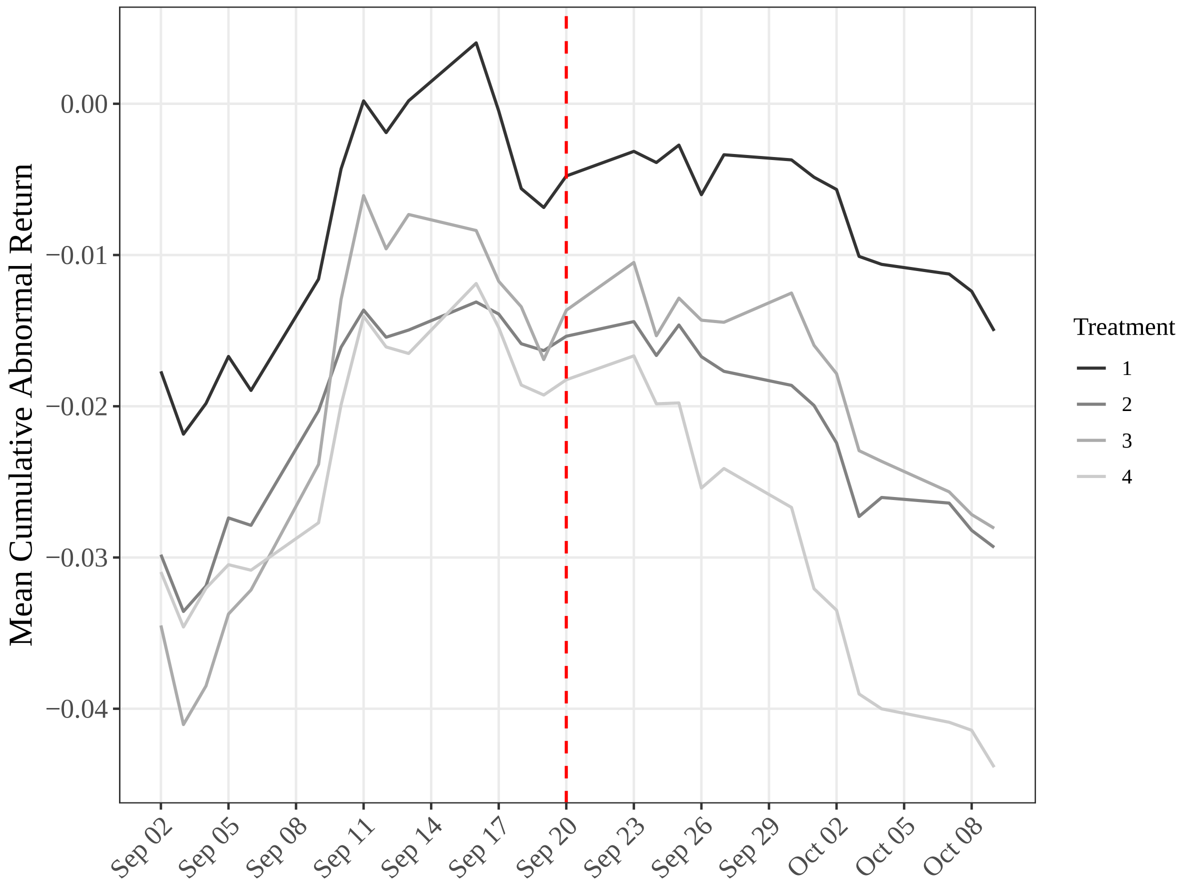
4.3 Validity of Assumptions — Stock Prices

The chosen framework requires no-anticipation and the strong parallel trends assumptions. With respect to the SPT, this assumption may be concerning, as in the same way as in Koenig and Schindler (2023), the companies self-select into being treated. To alleviate this concern, Figure 3 shows that the firms stock prices followed similar paths

[16]Note: forgot to talk about the event window!

[17]Explain that the researchers have their own preferred way, but it does not they do not show whether it can be used with no-untreated unit scenario. State that therefore, you limit yourself to showing the dynamic $ATT(D_i)$ for each treatment group.

Figure 3: Mean Cumulative Abnormal Return (Daily)



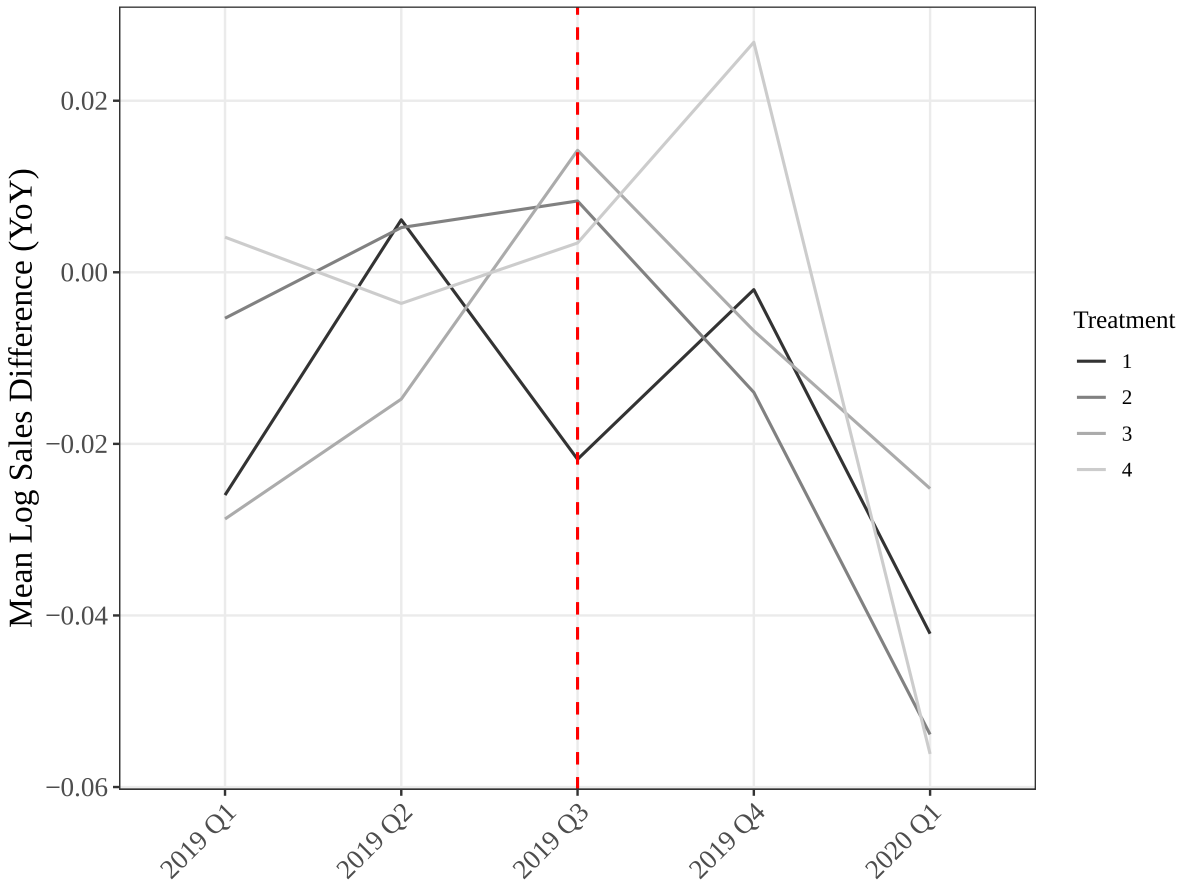
Treatment Groups indicated with numbers from (lowest dose) 1–4 (highest dose). Red line indicates the first Fridays For Future climate strike during the Global Week For Future. Source: Refinitiv

no matter their treatment assignment. Furthermore, an event study is run in the next section to evaluate the possibility of pre-trends. However, it has to be noted that the authors of Callaway et al. (2025) state that this method of evaluating the existence of pre-trends has low power, and therefore the lack of significance within the pre-trends does not necessarily imply that they actually do not exist. Nonetheless, the event study is estimated as per the standard practice. With respect to the no-anticipation assumption, concerns are more pronounced. In their event study, Schuster et al. (2023) found evidence of anticipation of the stock market within a period of 20 days prior to the FFF strikes. In order to alleviate this concern, an analysis is performed with the shock date being shifted to multiple different dates preceding the shock.

4.4 Validity of Assumptions — Sales

The argument with respect to the sales data follows similar reasoning, however seems to be less plagued by the necessary assumptions. The relative lack of interest in climate change and sustainability seems to validate the fact that there should be no differences prior to the shock in the quarterly sales of treated and untreated companies. Therefore, as long as the treatment is evenly distributed across different firms (Figure 4), the SPT assumption should hold. Nonetheless, it is analysed with an event study. With regard to the no-anticipation assumption, one could argue that consumers may need more time to re-orient their spending to more sustainable sources, following such an increase in interest. In such case they would be less likely to adjust their consumption prior to the FFF climate strikes, assuming that they would have heard about these protest before they happened. Therefore, in this case the assumptions seem more probable. On the other hand, one must acknowledge, that in this scheme, the CTI works only as a proxy to the belief of consumers about the greenwashing-intensity of the companies. This is not an obvious assumption, as firms may try to be more (or less) deceitful to consumers than to investors. However, given the lack of public information on marketing spending in relation to ESG, it is reasonable to assume that firms communicate similarly with both consumers and investors, and therefore that their ESG reports would reflect their sustainability-oriented marketing.

Figure 4: Year-over-Year Change in Quarterly Sales



Treatment Groups indicated with numbers from (lowest dose) 1–4 (highest dose). Red line indicates the quarter which witnessed the Global Week For Future. Source: Refinitiv

5 Results

5.1 Stock Prices Response to Greenwashing

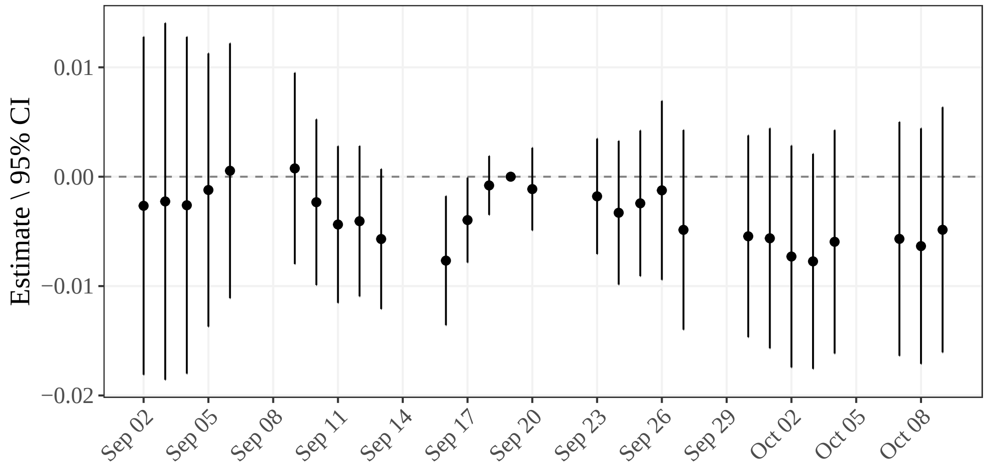
5.2 Sales Response to Greenwashing

Result table:

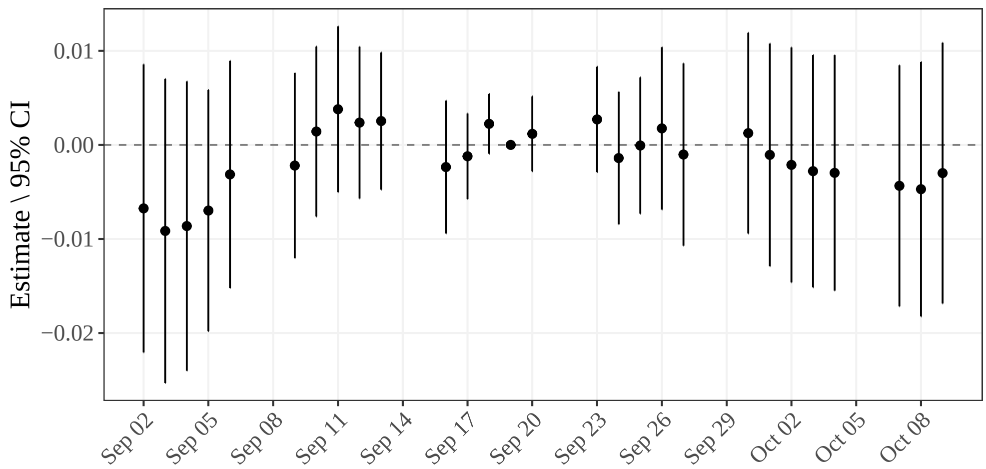
Event study plots:

Figure 5: Event Study Results — Stock Prices

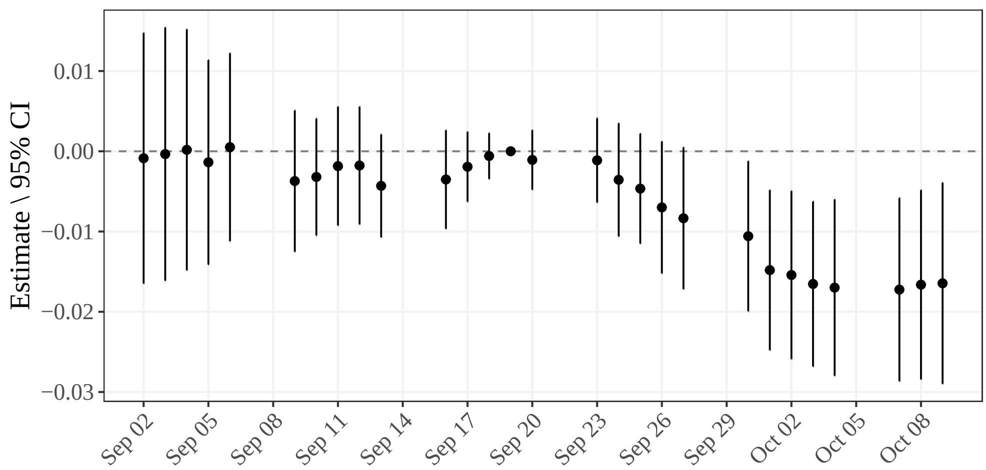
(a) Group 2



(b) Group 3



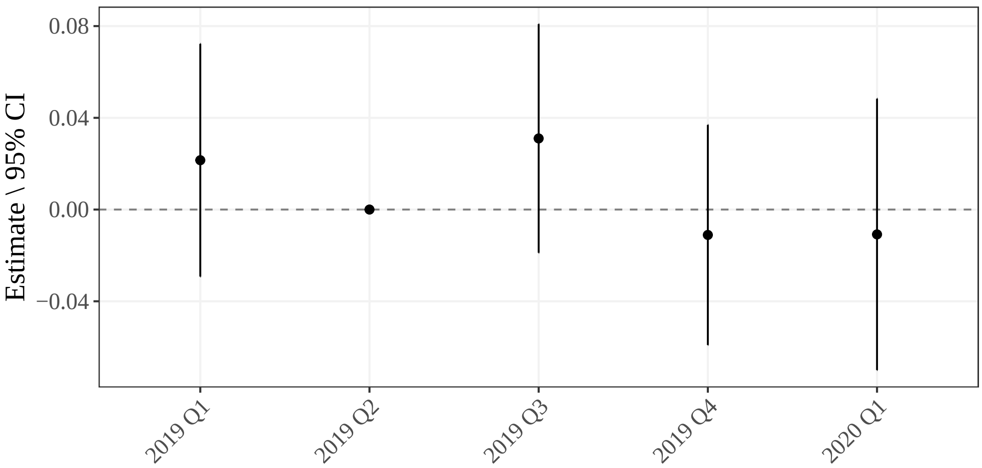
(c) Group 4



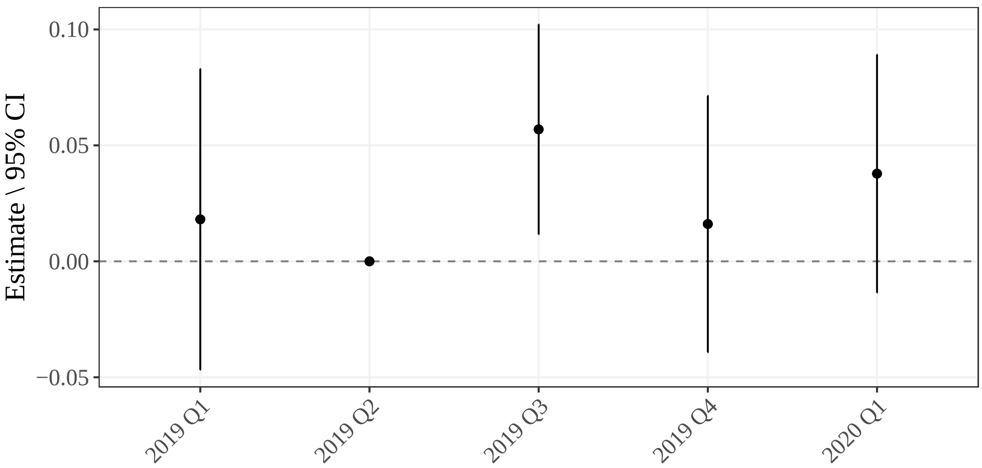
Stock price performance event studies for individual treatment groups. Groups 2,3,4 received their respective dose. **NOTE: Make sure that the final version is prettier**

Figure 6: Event Study Results — Sales

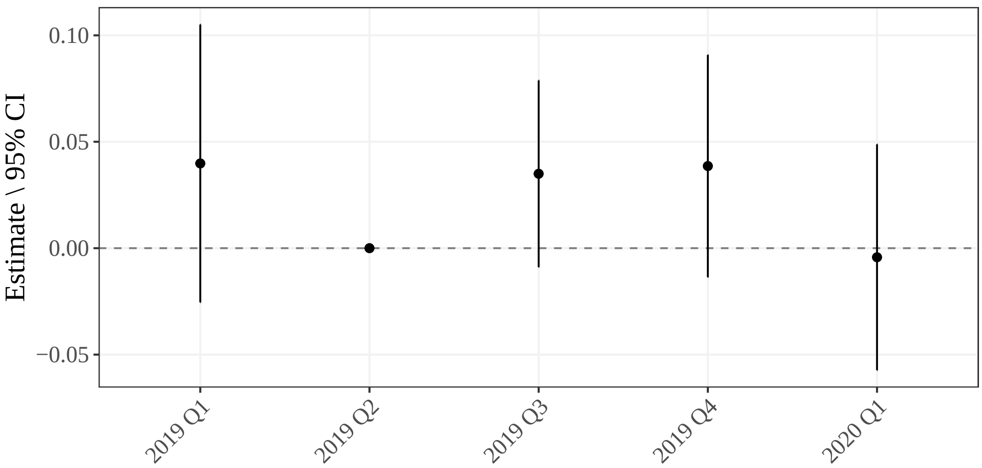
(a) Group 2



(b) Group 3



(c) Group 4



Sales performance event studies for individual treatment groups. Groups 2,3,4 received their respective dose. **NOTE: MAKE SURE THAT THE FINAL VERSION HAS QUARTERS AND NOT NUMS**

Table 1: Results of Estimation

Variables	CAR (1)	Δ_4 Log of Sales (2)
$Post \times D_2$	-0.0020	-0.0077
	(0.0054)	(0.0150)
$Post \times D_3$	0.0008	0.0279*
	(0.0058)	(0.0158)
$Post \times D_4$	-0.0091*	0.0032
	(0.0054)	(0.0160)
Entity FE	✓	✓
Time FE	✓	✓
Observations	17,752	2,515
Within R^2	0.00266	0.00185
R^2	0.90320	0.09844

Estimation Results of regressing the difference in differences on cumulative abnormal returns and the 4-quarter log difference of sales. Time FE is at the day level for (1) and Quarter for (2) **Add p-values and more description**

6 Discussion

List of things to add to the discussion:

- Could've weighted my regression somehow to make it more accurate?
- Better greenwashing measurements are needed
- some of the consumers may not be impacted as they may be businesses etc.

Table 2: Robustness Checks Results

	CAR	
Variables:	(1)	(2)
$POST_{-5} \times D_2$	-0.0018	
	(0.0056)	
$POST_{-5} \times D_3$	0.0017	
	(0.0059)	
$POST_{-5} \times D_4$	-0.0070	
	(0.0056)	
$POST_{-10} \times D_2$		-0.0030
		(0.0071)
$POST_{-10} \times D_3$		0.0058
		(0.0073)
$POST_{-10} \times D_4$		-0.0067
		(0.0069)
Entity FE	✓	✓
Day FE	✓	✓
Observations	17,752	17,752
Within R^2	0.00169	0.00242
R^2	0.90311	0.90318

Estimation Results of regressing the difference in differences on cumulative abnormal returns and the 4-quarter log difference of sales. **Add p-values and more description**

Table 3: Average Causal Responses

	CAR	Δ_4 Log of Sales
Variables	(1)	(2)
$ACRT(D_3)$	0.0028	0.0356**
	(0.0053)	(0.0169)
$ACRT(D_4)$	-0.0099*	-0.0247
	(0.0053)	(0.0178)

Estimation of ACRT resulting from the regression. $ACRT(D_2)$ is ommited as it can't be estimated (D_1 is the lowest dose)

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A Data

ADD SOURCES TO ALL OF THE TABLES + ADD GENERAL NOTES SO THAT THEY ARE SELF-EXPLANATORY

A.1 Tables

Table 4: Number of reports per year

Year	Number of Reports
2023	1859
2022	2020
2021	1733
2020	1355
2019	1081
2018	852
2017	686
2016	558
2015	475
2014	415
2013	357
2012	300
2011	252
2010	216

Table 6: Allocation of countries to regional markets

Country	Market Index
United States	S&P 500 Composite
Canada	S&P 500 Composite
Bermuda	S&P 500 Composite
Cayman Islands	S&P 500 Composite
Mexico	MSCI EM Latin America
Puerto Rico	MSCI EM Latin America
Costa Rica	MSCI EM Latin America
Barbados	MSCI EM Latin America
Panama	MSCI EM Latin America
Colombia	MSCI EM Latin America
Brazil	MSCI EM Latin America
Chile	MSCI EM Latin America
Peru	MSCI EM Latin America
Uruguay	MSCI EM Latin America
Argentina	MSCI EM Latin America
United Kingdom	MSCI Europe
Ireland	MSCI Europe
Switzerland	MSCI Europe
Netherlands	MSCI Europe
Greece	MSCI Europe
Germany	MSCI Europe
Belgium	MSCI Europe
Denmark	MSCI Europe
Monaco	MSCI Europe
Luxembourg	MSCI Europe
France	MSCI Europe
Sweden	MSCI Europe
Isle of Man	MSCI Europe
Spain	MSCI Europe
Finland	MSCI Europe
Romania	MSCI Europe

Note: All indices denominated in dollars (but actually as % of their listing price I think)

Country	Market Index
Italy	MSCI Europe
Austria	MSCI Europe
Jersey	MSCI Europe
Guernsey	MSCI Europe
Turkey	MSCI Europe
Hong Kong	MSCI Pacific
Singapore	MSCI Pacific
Japan	MSCI Pacific
Australia	MSCI Pacific
New Zealand	MSCI Pacific
Papua New Guinea	MSCI Pacific
China	MSCI AC Asia
India	MSCI AC Asia
South Korea	MSCI AC Asia
Taiwan	MSCI AC Asia
Mongolia	MSCI AC Asia
Indonesia	MSCI AC Asia
Philippines	MSCI AC Asia
Israel	MSCI World
Kazakhstan	MSCI World
United Arab Emirates	MSCI World
South Africa	MSCI World

Note: All indices denominated in dollars (but actually as % of their listing price I think)

Table 5: Sample Composition

ICB Industry				Number of Employees				Country of Domicile			
Industry	Total	Treated	Control	Employees	Total	Treated	Control	Country	Total	Treated	Control
Industrials	120 (19%)	59 (18%)	61 (19%)	10,000+	487 (62%)	250 (63%)	237 (61%)	United States	376 (59%)	164 (51%)	212 (66%)
Consumer Discretionary	99 (15%)	30 (9.4%)	69 (21%)	1001–5000	134 (17%)	70 (18%)	64 (16%)	United Kingdom	64 (10%)	38 (12%)	26 (8.1%)
Financials	87 (14%)	65 (20%)	22 (6.9%)	5001–10,000	120 (15%)	54 (14%)	66 (17%)	Canada	55 (8.6%)	30 (9.4%)	25 (7.8%)
Basic Materials	83 (13%)	347 (15%)	36 (11%)	201–500	20 (2.5%)	10 (2.5%)	10 (2.6%)	Australia	48 (7.5%)	31 (9.7%)	17 (5.3%)
Consumer Staples	57 (8.9%)	20 (6.3%)	37 (12%)	501–1000	13 (1.6%)	5 (1.3%)	8 (2.1%)	Other	97 (15%)	56 (17%)	41 (12%)
Technology	52 (8.1%)	36 (11%)	16 (5.0%)	11–50	8 (1.0%)	5 (1.3%)	3 (0.8%)	Unknown	155	84	71
Utilities	47 (7.3%)	10 (3.1%)	37 (12%)	51–200	6 (0.8%)	4 (1.0%)	2 (0.5%)				
Health Care	46 (7.2%)	28 (8.8%)	18 (5.6%)	1–10	1 (0.1%)	1 (0.3%)	0 (0%)				
Telecommunications	20 (3.1%)	14 (4.4%)	6 (1.9%)	Unknown	6	4	2				
Energy	17 (2.7%)	7 (2.2%)	10 (3.1%)								
Real Estate	12 (1.9%)	3 (0.9%)	9 (2.8%)								
Unknown	155	84	71								
Total	N = 795	N = 403	N = 392	Total	N = 795	N = 403	N = 392	Total	N = 795	N = 403	N = 392

Table 7: Estimation periods for each frequency

Frequency	Normal Returns Estimation	Event Window
Weekly	2016–01–01 — 2019–06–30	2019–07–01 — yyyy—mm—dd
Quarterly (Sales)		

NOTE: THINK WHETHER TO INCLUDE NUMBER OF PERIODS OF ESTIMATION, THINK WHETHER THAT SHOULD BE SYMMETRICAL FOR EACH OF THE FREQUENCIES

A.2 Cheap-Talk Index

The models for estimation were retrieved from ...

The table below presents multiple examples of data classified by the researchers in training the model: ...

Reports that contained less than 3 climate related paragraphs were dropped due to having to little data, which was prone to producing outliers.

A.3 Merging

The merging of the data was a difficult process, as company names are often reported differently between different services. Multiple strategies were used to merge the data. Firstly, the data was merged on the names retrieved from the ResponsibilityReports.com and the longest version of names available in the Refinitiv database. **This resulted in ... observations**. After that, the datasets were merged on the stock tickers conditional on being listed on the same exchange. **This resulted in ... observations**. Finally, the remaining companies were merged using fuzzy matching. **Unfortunately this has left ... observations missing**.

B Models

B.1 Formal assumptions

In order to formally describe the assumptions, I adopt the potential outcomes framework of Rubin, 1974

B.1.1 Parallel Trends (PT)

Formally it is given by:

$$\mathbb{E}[Y_{i,2}(0) - Y_{i,1}(0)|D_i = 1] = \mathbb{E}[Y_{i,2}(0) - Y_{i,1}(0)|D_i = 0] \tag{7}$$

B.1.2 No anticipation

Formally, the assumption is defined as:

$$Y_{i,1}(0) = Y_{i,1}(1) \text{ for all } i \text{ with } D_i = 1 \tag{8}$$