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Essay in Economics, Political Economy and Climate Transition

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Introduction

This PhD thesis is a compilation of three distinct yet interrelated research papers, each focusing on different aspects of climate change, financial markets, and institutions. In particular, these papers collectively provide insights and contribute to understanding the potential relationships and interlinks between financial markets, socio-environmental impacts and institutional quality. Each paper employs different research methodologies to provide insights for policymakers, investors, firms, and the broader academic community.

The first paper, "What Role do Climate Crises and Social Movements Play in Financial Markets? An Event Study Approach for Financial Markets and Climate-Related Events" examines the impact of climate-related events on listed companies and their stock performance. Focusing on major historical greenhouse gas emitters in four different sectors, we analyze the effect of climate-related events, such as natural disasters caused by human actions, global climate strikes and speeches by Greta Thunberg, on the daily abnormal returns of these companies. The results suggest that, firstly, climate-related events can result, on average, in cumulative abnormal negative returns for those companies in these sectors compared to the renewable energy sector, used as a benchmark for the green sector. Second, for some of these companies, reputation risk may be reduced by high environmental pillar scores that are not perfectly aligned with environmental performances (i.e. GHG emissions). We then assess the impact of climate sentiment on short-term stock market performance, as measured by abnormal returns, finding a positive correlation between the climate-related social media talks and cumulative abnormal returns.

The second paper, "Taxation, Health System Endowment, and Institutional Quality: 'Social Media' Perceptions across Europe" investigates the impact of health system endowment and institutional quality on citizens' attitudes towards taxation. Through sentiment analysis of Twitter users' tweets from France, Germany, Italy, and Spain, the paper examines how the Covid-19 pandemic influenced public taxation sentiment. The study demonstrates that higher health system endowment and institutional quality lead to more positive attitudes towards taxation, suggesting a greater willingness to adopt a progressive tax system.

In particular, two results are worth noting. First, in regions characterised by %higher levels of healthcare expenditure, implying pre-existing a high number of physicians, citizens adopt more positive attitudes towards taxation with respect to the period before the spread of Covid-19. The ability to curb the pandemic with higher health care endowment seems to have been the real game changer with respect to citizens' propensity towards taxation. The COVID-19 health crisis with the consequent economic downturn may have caused the introduction of additional taxation *di per sè*, since several times in history additional taxes have been levied to face an emergent need of (extra) revenues. However, when new taxes are introduced as short-term measures they hardly remain part of long-term government fiscal policy tools. Second, this favourable attitude is more present for area with high quality of institutions, while it vanishes for those where the quality of institutions is low. Where institutions are stronger, more impartial and of higher quality, individuals' attitude towards taxation tend to be more sensitive to how healthcare expenditure is managed. This suggests that widespread support for public policies depends on the quality of the institutions in regions in which they are delivered.

In the third and final paper, "How Environmental Performance and Innovation Affect the Lobbying Expenditures of Firms in the EU" the focus shifts to the relationship between lobbying expenditures, on one side, and the environmental policy stringency regulations, firm-level green innovation, and environmental reputation on the other side. The paper unveils a negative association between lobbying expenditures and environmental performance by analyzing a sample of 590 firms from 43 countries across 98 industries. Our primary objective was to find a correlation and the type of relationship involving three key variables: lobbying expenditure (firm-level), the level of environmental policy performance of each European country, and the environmental reputation level of each company that lobbied between 2012 and 2020. This was done while considering the varying levels of environmental innovation in our analyzed sample.

Our initial hypothesis, confirmed by our results, was to find a robust negative relationship between lobbying activities for firms in countries with high environmental policy performance but with a high level of green innovation. Conversely, we expected to find a strong tendency towards direct lobbying activities for those companies that demonstrate innovative activities in the environmental field but show a competitive disadvantage compared to more innovative companies. Finally, concerning the least environmentally innovative companies, coinciding with the most polluting ones, we expected to find, in line with part of the literature, a weak correlation between their lobbying activities and environmental policy performance.

To demonstrate this, we created a unique database based on lobbying information (company-level expenditure) obtained from the European Transparency Register, the level of green innovation (represented by the number of green patents obtained from the European patent register), and environmental and financial performance for each of the companies involved in lobbying activities in Europe during the selected analysis period. The empirical procedure involved applying a fixed-effects Poisson model, justified by the nature of our available data.

To conclude this introduction, these papers together aim to contribute to a growing body of research on the complex interplay between environmental performance, innovation, lobbying, public sentiment, and institutional quality in the context of climate change, taxation, and health systems. By examining these three papers, this work comprehensively analyses the complex interplay between various actors and elements like institutions and health systems, environmental policies and direct lobbying activity, and climate-related events and financial markets. By shedding light on these critical issues, we aim to contribute to the academic discourse and provide valuable insights for policymakers and stakeholders in their pursuit of a sustainable and resilient future.

What role do climate crises and social movements play in financial markets? An event study approach for financial markets and climate-related events

Giulio Mazzone*

Abstract

In this study, we investigate the impact of climate-related events on listed companies and their stock performance. Our focus is on the major historical greenhouse gas emitters of four different sectors (fossil fuel, transportation, automobile, and financial). We analyze the effect of climate-related events, such as natural disasters caused by human actions, climate global strikes and speeches by Greta Thunberg, on the daily abnormal returns of these companies. The results suggest that, firstly, climate-related events can result, on average, in cumulative abnormal negative returns for those companies in these sectors compared to the renewable energy sector, used as the benchmark for the green sector. Second, for some of these companies, reputation risk may be reduced by high environmental pillar scores that are not perfectly aligned with environmental performances (i.e. GHG emissions). We then assess the impact of climate sentiment on short-term stock market performance, as measured by abnormal returns, finding a positive correlation between the climate-related social media talks and cumulative abnormal returns. To conclude, external events, including climate-related rallies and speeches, are correlated with negative abnormal stock returns in line with investor expectations.

Keywords: Event Study, Abnormal Returns, Reputation Risk, Transition Risk, Climate-related Events.

JEL: C53, C58, G12, G14, G32, L94, Q54.

1 Introduction and context of study

The global economy is facing significant challenges as concerns over environmental degradation and climate change continue escalating. The financial market performance of firms within various industries has been under increased scrutiny in recent years as the physical, transition and reputational risks associated with climate-related events become increasingly evident (Hjort, 2016). In particular polluting sectors may face a significant impact from climate transition risks due to their crucial role in generating or using carbon emissions (Van Benthem et al., 2022).

In addition to the direct environmental risks posed by financial markets, there has been a growing movement of young activists, led by figures such as Greta Thunberg, calling for action on climate change[1]. Her speeches and the global climate strikes have played a significant role in raising awareness of the impacts of human activities on the environment and the need for increased attention and efforts towards reducing the likelihood and severity of future natural disasters. Furthermore, the demonstrations and campaigns led by young activists have pressured corporations and governments to address climate change and reduce the risks associated with their operations.

Moreover, the financial market performance of firms has become increasingly linked to the company's reputation, and its perceived commitment to environmental sustainability and social responsibility also represents other transitional risks (Semieniuk et al., 2021). In general, the risks associated with climate change can be divided into physical and transition risks. Physical risks are directly linked to the impacts of climate change, such as extreme weather events. In contrast, transition risks are associated with the gradual

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[1] Among others: Greta Thunberg. (2019, September 23): How dare you? [Speech]. United Nations Climate Action Summit. New York, NY; Greta Thunberg (2019, January): Full Speech at the World Economic Forum in Davos, Switzerland, https://www.youtube.com/watch?v=H7Dzg-l-F7E.

shift towards a low-carbon economy and its attendant structural changes. Each risk type has distinct transmission channels to the economy and the financial system. Transition risks emerge from the potential aftermath of transitioning towards a low-carbon economy, which may cause economic shocks with financial implications, mainly if the transition needs to be adequately anticipated and coordinated. The nature of these shocks can vary greatly (Bolton et al., 2021). According to the Bank of England (2015), *climate transition risk* is defined as the risks that could emerge from the "*transition towards a more carbon-efficient economy, which changes in technology, policy, or investor sentiment could bring about*". The adjustments could lead to a reevaluation of multiple asset values. If such changes occur more quickly than businesses can handle, it may jeopardize the economy's financial stability. So, the climate transition risk is becoming increasingly important in the current economic and financial landscape (Dunz et al., 2021). This risk depends on various factors, including changes in policy and legislation relating to energy generation, renewable energy targets, and sustainable land use. Moreover, technological advancements in areas such as renewable energy, battery storage, and electrification of transport, aviation, and agriculture have the potential to impact the global economy significantly. In addition, changes in demand for products and commodities, such as fossil fuels or lithium, may pose market risks for various sectors. Finally, *reputational risks* associated with the transition to a Net Zero economy may arise from concerns among shareholders, consumers, and investors regarding the environmental impact of economic and financial activities (Bolton et al., 2021; Bank of England, 2015).

The impact of such reputation risks on the financial market performance of firms within the oil industry and the most polluting sectors has been a subject of growing interest for academics and investors. The growing body of research on this topic highlights the importance of understanding the impact of environmental and social risks on the financial market performance of firms.

Given all of the above, in this study, we aim to examine climate-related events' impact on firms' financial market performance within four significant industries: fossil fuels, transportation, financials and automobiles sector. The relevance of our work is based on understanding the relationship between climate-related events and financial market performance, which is now crucial for investors, regulators, and policymakers as they seek to mitigate the risks and capitalize on opportunities arising from the transition to a low-carbon economy.

Based on that, the first objective of this study is to analyze the financial market performance of firms within the four selected sectors in response to natural disasters and climate-related events. So, our analysis aims to investigate the possible magnitude of the impact of these events on stock returns of the above-mentioned sectors with respect to the renewable energy sector used as a benchmark for the green sector. Through an event-study analysis, we will explore the effects of specific climate-related events on stock returns between 2019 and 2021.

At the core of our investigation lies the first research question of our work: how does the financial market performance of firms within the five selected sectors respond to natural disasters and climate-related events? To address this question, we put forth two competing hypotheses. A first possible hypothesis suggests that investors demonstrate environmental awareness by incorporating the adverse effects of climate-related events into their stock market evaluations and choosing stocks from less polluting sectors. In contrast, the alternative hypothesis contends that investors exhibit no environmental awareness, overlooking the implications of climate-related events on the stock market and not selecting stocks from less polluting sectors. In other words, we expect firms within the polluting sectors under-perform in reaction to climate-related events. To test our first hypothesis, after calculating the cumulative abnormal returns of the stocks in our sample, we will empirically test whether being in the most polluting sectors is statistically significant w.r.t being in a green sector in calculating the magnitude of events on returns.

Second, this paper contributes to the growing body of literature on the financial implications of climate-related risks by examining the role of reputation and transition risks in different industries and providing a novel perspective on the alignment between investor reactions and public sentiment. In particular, our analysis focuses on firms within these four sectors, which have significant exposure to climate-related risks. Through the event-study analysis, we will also explore the effects of specific climate-related events on stock returns and examine the role of reputation and transition risks in shaping investor perceptions and financial market outcomes.

Building upon our investigation, we introduce a second research question to examine further investor behaviour: to what extent do investors incorporate potential reputational and transition risks associated with natural disasters and climate-related events when making investment decisions in the four selected sectors? In addressing this question, we propose two additional competing hypotheses. The first hypothesis posits that investors, in their financial decisions, consider the environmental reputation of firms within the sectors, considering the relative environmental impact among polluting sectors as an indication of a higher commitment to climate transition. Conversely, the alternative hypothesis asserts that investors, in their financial decisions, disregard the environmental reputation of firms within the sectors and do not consider the relative environmental impact among polluting sectors as a sign of higher commitment to climate transition.

We posit that there is a positive correlation between a firm's E Score and its stock price response to climate-related events, implying that companies with higher Environmental scores will exhibit stronger relative performance, and a high environmental reputation, in response to climate-related events. To test our second hypothesis, after calculating the cumulative abnormal returns of the stocks in our sample, we will empirically test whether among the selected sectors if a difference in stock performances exists w.r.t. a reputation environmental index within the selected sectors.

To conclude, we will provide insights through a sentiment analysis on individuals' perceptions and consciousness of climate-related events to check the alignment with investors' reactions to climate-related events. This leads to the formulation of our third research question and its associated hypotheses: what is the perception of individuals before and after the selected events on climate change issues? In particular, what are the factors that can impact this perception? How does this perception compare with the perception of investors? A first hypothesis may suggest that individuals' perceptions of climate change impacts align with the views of investors and financial markets. Conversely, individuals harbour strong and negative perceptions of climate change impacts, which are not in line with the perspectives of investors and financial markets.

Applying sentiment analysis to a large sample of random tweets, we want to compare daily pre- and post-event sentiment by estimating the correlation between this sentiment indicator used to generate a perception index and the performance of stocks in the event window. Given the priory quasi-exogenous nature of the climate-related events to investor behaviour, what we expect to find is a general positive correlation between sentiment and market performance. Conversely, we expect to find a negative sentiment in those areas where the companies that produce the most emissions also provide the most jobs to the community. Thus, the aim is to provide an indicator that estimates the differences in perceptions between generic individuals and sophisticated investors.

In order to conduct the entire analysis, we used financial data, such as the prices and relative daily returns of each stock in our sample and the S&P 500 as a market benchmark index. Moreover, we retrieve environmental performance data, such as GHG Emissions, E Score as an environmental reputation variable, and control variables for each firm, such as market capitalisation (USD), total revenues (USD), sector, and industry. Finally, for the sentiment analysis, we obtained, via query, a sample of daily tweets from users from the US and categorised these by state, city and occupation to assess the impact of heterogeneity on perceptions of climate change.

The results of our study try to shed light on the intricate relationship between financial market performances and climate-related events, trying to improve our understanding of the impact of environmental and social risks on the financial market performance of firms and provide insights into the role of reputation risks in shaping investor perception and behaviour. Moreover, the growing frequency and severity of extreme weather events have made the risks of climate change to our communities highly visible. These have led to a surge in climate activism by young people, demanding international action to limit CO2 emissions. Aligned with previous literature results, our study confirms, exploiting a new and unique data set and a cutting-edge sentiment methodology, that this wave of climate activism and climate-related events notably impacts investor behaviour and the market performances of companies with significant carbon emissions and different environmental reputations.

Firstly, our findings indicate a negative correlation between these events and the polluting sectors' financial performance compared to the green ones. This suggests that climate events have a disproportionately more significant impact on the financial performance of companies in polluting sectors. Secondly, we discovered that investors use E Scores to make investment decisions, making it a reputation indicator for firms, even though it is not necessarily correlated with GHG Emissions. Finally, through sentiment analysis, we observed a positive and significant correlation between firms' financial market performances and individuals' sentiments about climate change in the state where polluting companies are based. These findings highlight the need for companies to prioritize sustainability and climate-friendly practices to mitigate risks associated with climate events and enhance their reputation and appeal to investors.

The rest of the paper is structured as follows: Section 2 provides a literature review on the impact of natural disasters on the financial market performance of firms within the five sectors object of this study, including the impact of reputation risks, the role of environmental activism and the link between environmental performances and financial markets. Section 3 outlines the research design, data description and methodology, including a description of the event-study methodology. Section 4 presents the study's results and analyses the impact of climate-related on the financial market performance of firms within the five sectors object of study. Section 5 extends the analysis to the sentiment analysis, considering the role of perception and public attention to climate-related events. Finally, Section 6 concludes the study and provides insights into the findings' implications for future research.

2 Related Literature

2.1 Overview of prior research on the impact of climate-related events on financial markets

Financial markets are becoming attuned to the risks posed by climate change, with particular attention rising on companies in carbon-intensive sectors. Our work contributes to three main strands of literature.

First, this paper adds insights and results to works that study the relation between financial market performances and firms' environmental performance. Theoretical studies, such as those by Pastor et al., (2021) and Pedersen et al., (2021), incorporate environmental preferences. For instance, Pastor et al., (2021) reveal that brown assets experience lower returns when there are unexpected positive shifts in environmental preferences, despite overperforming the market. As a result, these companies are often subject to a carbon premium, reflecting investors' recognition of carbon risk (Jung et al., 2018; Guastella et al., 2022). The presence of this carbon premium highlights the consideration of climate risks in medium-term investment strategies and highlights the use of information on greenhouse gas (GHG) emissions in investment decisions (Bolton et al., 2021; Ilhan et al., 2021; Guastella et al., 2022).

In our study, we want to add new elements analyzing the impact of climate-related events on stock performances, taking into account emissions performances and environmental score indexes showing the impact of perception on stock cumulative abnormal returns. Our research is distinguished by the utilization of a unique dataset, encompassing a diverse range of climate-related events, enabling a comprehensive understanding of the interplay between environmental factors and financial markets.

Second, we shed light on the relationship and the magnitude of climate reputation risk faced by a company. Many studies argue that this relationship is determined by three key factors: exposure, specific events, and changes in investor perception during climate-sensitive events. Companies in stigmatized sectors with high GHG emissions are considered most exposed to the risks associated with transitioning to a low-carbon economy (Bolton et al., 2021; Ilhan et al., 2021). If investors consistently react to sector stigmatization, companies' exposure to climate transition risk should be reflected in abnormally low stock returns compared to the benchmark (Engle et al., 2020; Rogova et al., 2020). Companies in these sectors may also face additional risks if they engage in active social media communication around climate-related topics, which may signal their exposure to climate-related risks (Albarrak et al., 2019; Bank et al., 2019). The occurrence of specific events that draw public attention to climate change and the responsibility of significant polluters, such as the US government's withdrawal from the Paris Agreement in 2016 and climate strikes (Berkman et al., 2019; Fan et al., 2020), can result in abnormal returns for companies in stigmatized sectors as investors reassess their exposure to climate-related risks (Ilhan et al., 2021). The change in investor perception of a company's exposure to climate reputation risk during climate-sensitive events is a crucial determinant of a firm's financial performance. Companies that are significant polluters may face additional risk if they attempt to create legitimacy during these events, as this may appear incongruent with the heightened public attention on climate change and the responsibility of significant polluters (Behrendt et al., 2018; Bolton et al., 2021). How a company communicates and handles its exposure to climate-related risks can significantly impact its reputation, stock performance, and overall financial performance (Ilhan et al., 2021; Bank et al., 2019). Moreover, climate-related global strikes and natural disasters, often the result of human activity, heighten public awareness of the effects of climate change and can further exacerbate the risks posed by climate reputation risk (Engle et al., 2020). For instance, the media's coverage of natural disasters, such as hurricanes and wildfires, can influence public opinion and investor perception of a company's exposure to climate risks (Barakat et al., 2019; Vanstone et al., 2019). These events can result in abnormally low stock returns for companies in stigmatized sectors as investors reassess their exposure to climate-related risks (Bolton et al., 2021).

In this context, our work aims to add new insights by measuring stock performances in order to check if investors consider the environmental reputation of the firms within the sectors as the relative impact on the environment, also among polluting sectors, as a sign of higher commitment to climate transition. To do this, we use the reputation indicator, the environmental score, commonly used nowadays as an investment tool to select stocks based on environmental engagement, controlling for its correlation with environmental variables and the sector of belonging.

Third, we study the relationship between social expectations, perception, and financial performance that is intertwined with reputation and climate transition. In their work, Czinkota et al. (2014) conclude that reputation refers to a company's relative position compared to its competitors, while legitimacy refers to conformity with laws, rules, and social norms (Czinkota et al.,2014). For Guastella et al. (2022), adhering to minimum standards can improve a company's reputation, while violating these standards can have the opposite effect. Legitimate actions and communications can enhance a company's reputation, while illegitimate actions or communications can harm it (Guastella et al., 2022). This part of the literature gave ample space for official announcements' impact. Various factors shape investors' perception of the risk posed by climate change, including official announcements and the media's coverage of these announcements (Barakat et al., 2019; StrauB et al., 2018) and different works have shown that mainstream media sentiment can impact stock prices (Behrendt et al., 2018; Vanstone et al., 2019), indicating how news is communicated to the market may influence stock prices. Among others, for what concern the investor's perception and climate-relate event, Bourdeau-Brien and Kryzanowski (2017) examine the effect of natural disasters on financial markets and analyze the influence of significant catastrophes on the investment risk behaviour of individuals through an examination of municipal bond transactions in the United States. Their results demonstrate a statistically and economically substantial increase in risk aversion at the local level, thereby supporting the hypothesis that natural disasters profoundly impact investors' risk attitudes. In another study, Balvers et al. (2017) investigate the impact of temperature shocks on the cost of equity in their study. They assess whether uncertain fluctuations in temperature and have systematic effects on cash flows can be considered a priced risk factor under the Arbitrage Pricing Theory (APT), leading to higher expected returns. The study by Engle et al. (2020) proposes a dynamic investment strategy that seeks to mitigate potential risks posed by news about climate change. Their portfolios are constructed by creating a "climate" factor, which measures the extent of climate change coverage in The Wall Street Journal (WSJ) articles. This index is developed using text-based analysis and is determined by counting the number of articles related to climate change and measuring the overlap of these articles with a climate change glossary. The results demonstrate that coverage of climate news has been increasing over time, particularly during significant global climate events.

In order to study the relationship between social expectations, social perception, and financial performance that is intertwined with reputation and climate transition, we propose a sentiment analysis based on a sample of social network text retrieved from Twitter in which we provide the level of perception of climate change of the population to check if the investor sentiment is more aligned with social sentiment of climate change in the time frame of our study and to analyze the correlation between this perception index and our environmental, reputational variable.

In conclusion, the perception of a company's exposure to climate reputation risk can significantly impact its financial performance and is shaped by various factors, including the exposure of the firm, specific events drawing public attention to climate change, and how the company communicates and handles its exposure to climate-related risks. To mitigate these risks, companies must proactively reduce their GHG emissions and engage in effective climate-related communications that align with changing societal norms and expectations.

2.2 Discussion of event-study methodology and its application in the field

The event-study methodology is a widely-used and well-established analytical tool in finance and economics (J. Brown et al., 1985; Fama et al., 1992; Angrist and Pischke 2009; Bodie et al., 2011). It aims to assess the impact of a specific event or news on the stock prices of a particular firm or market sector. For example, in analysing the impact of climate-related events on financial markets, an event-study methodology has been employed to quantify the impact of specific news or events related to climate change on the stock prices of firms or sectors (Hjort et al., 2016; Guastella et al., 2022).

In the field of finance and economics, the event-study methodology has been used to analyse a variety of events, including mergers and acquisitions (J. Brown et al., 1985), earnings announcements (Ball et al., 1968), regulatory changes (Jensen, 1978), and other market-moving events. This methodology involves selecting a specific event, determining the event window, selecting a comparison group of firms, and calculating abnormal returns around the event.

The application of the event-study methodology in analysing climate-related events in financial markets has received increasing attention in recent years, especially as the global conversation around climate change and its effects has become more prominent (IPCC 2014). Researchers have used event-study methodology to examine the impact of climate-related news, such as the release of the Intergovernmental Panel on Climate Change (IPCC) reports (IPCC 2014), on the stock prices of firms or sectors (Guastella et al., 2022).

In analysing the five sectors in question (automobiles, transportation, fossil fuel, financials, and renewable energy), an event-study methodology can be used to assess the impact of climate-related events on the stock prices of firms within each sector. This approach can help to quantify the market's reaction to specific events and provide valuable insights into the financial markets' perception of the risks and opportunities associated with climate change.

It is worth considering the impact of climate-related global strikes and natural disasters, which are often the result of human activity, on the financial performance of polluting firms. In addition, these events heighten public awareness of the effects of climate change, further exacerbating the risks posed by climate reputation risk. As such, companies in carbon-intensive sectors would be wise to proactively manage their exposure to these risks by reducing their GHG emissions and engaging in effective climate-related communications (Guastella et al., 2022).

In conclusion, an event-study methodology is essential for analyzing the impact of climate-related events on financial markets. Its application in the field has yielded valuable insights into the market's perception of the risks and opportunities associated with climate change. By combining our unique dataset and cutting-edge sentiment analysis methodology, we can contribute to a better understanding of the financial implications of climate-related events and provide new insights into the relationship between climate-related events and financial market performances.

2.3 Environmental Performances and Financial Markets

In the next paragraphs, we shed light on the relationship between environmental performances and financial markets, focusing on three key areas. We first examine studies related to the Environmental Pillar Score and CO2 emissions, followed by an exploration of the impact of oil prices on financial performances, and finally, an investigation into the role of reputation and transition risks in shaping investor perceptions and financial market outcomes.

2.3.1 Environmental Pillar Score and CO2 Emissions

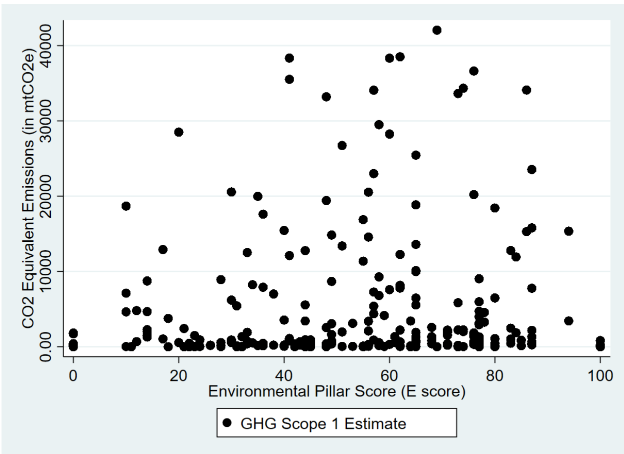
In recent years, there has been a growing interest in Environmental, Social, and Governance (ESG) indicators among investors as they seek to incorporate sustainability considerations into their investment decision-making processes. However, using ESG scores such as the E-Score, which aims to capture a company's environmental performance, has been subject to much debate in the academic and financial communities.

While high E-Scores can increase a company's reputation for sustainability, studies have found a low correlation between E-Scores and actual environmental metrics, such as CO2 emissions. (Boffo et al., 2020; OECD, 2022).

The OECD papers (Boffo and Patalano, 2020; OECD, 2022) on ESG ratings and climate transition provide valuable insights into the alignment of E pillar scores and environmental metrics. First, these works assess the correlation between E scores, which investors use to measure a company's environmental sustainability, and various environmental metrics, including carbon emissions. Second, these studies find that while E scores may be a valuable indicator of a company's reputation and perceived commitment to environmental sustainability, they are only sometimes well-aligned with actual environmental performance. E scores consider a wide range of factors, including economic and financial performance, which can result in a high score for a company even if its environmental performance is poor. In particular, the OECD report of 2022 (OECD, 2022) notes that the correlation between E scores and metrics such as carbon emissions remains low, indicating that E scores are not capturing the complete picture of a company's environmental impact, raising concerns about the reliability of E scores as a measure of environmental sustainability and highlights the need for additional metrics in the assessment of a company's environmental performance. From a technical perspective, as an investment tool, previous studies have demonstrated a limited ability to predict returns based on overall ESG ratings (Boffo and Patalano, 2020; Pedersen et al., 2021), and there exists mixed evidence when considering different ESG proxies (Hong at al., 2009; Bolton et al., 2021). Our contribution is to show the argument that ESG uncertainty and low reliability may influence not only the relationship between ESG performance and returns but also the perception and the financial choice of investors.

Overall, economic literature provides essential insights into the limitations of using E scores to measure environmental sustainability. First, E scores align with economic and financial performance rather than environmental performance (Venturini 2021; OECD 2022; Edmans 2023). Second, this lack of alignment is particularly concerning as it raises questions about the reliability of ESG scores in assessing a company's environmental impact, also from a forward-looking perspective (Cornell and Damodaran 2020).

Figure 1: Correlation CO2 Equivalent Emissions vs Environmental Pillar Score



Notes: Figure shows the linear correlation between the GHG Scope 1 CO2 Equivalent Emissions in mtCO2e and the Environmental pillar score. Paerson's correlation index = -0.00213.
Data Source: Bloomberg. Author elaborated the data on STATA and Python.

So, several challenges hamper using ESG (environmental, social, and governance) ratings and scores as benchmarks for investment decision-making. Firstly, limited comparability of scores due to diverse analytical approaches results in limited comparability of scores across significant providers. Secondly, there is a lack of transparency in methodology, criteria, and threshold values, with much of the information being labelled as proprietary. Furthermore, there is a factor of selection bias, with larger companies having more resources to implement and communicate ESG strategies and smaller companies lacking the ability to do so. The use of binary indicators also limits the scope of ESG metrics in measuring environmental performance and carbon emissions. Additionally, subjectivity in using qualitative questionnaires and judgement-based assessments can question the credibility of ESG scores and ratings (OECD 2022). This is further exacerbated by the proprietary nature of ESG rating methodologies (Boffo and Patalano 2020).

In light of what has been said, as shown in Figure 1 above, the selected sample for this study confirms a very low correlation between the chosen E scores and the CO2 emissions produced by the firms across Scope 1, Scope 2, and total emissions. Moreover, a slight negative correlation further reinforces the argument put forth thus far in this paragraph. So, an event-study approach is employed to examine if and to what extent the E scores can be considered a reliable index of environmental performance instead of simply serving as an indicator of environmental reputation. This examination sheds light on the crucial role that ESG data plays in investment analysis and decision-making, as transparent, consistent and comparable ESG data can help investors to make informed decisions that align with their sustainability goals.

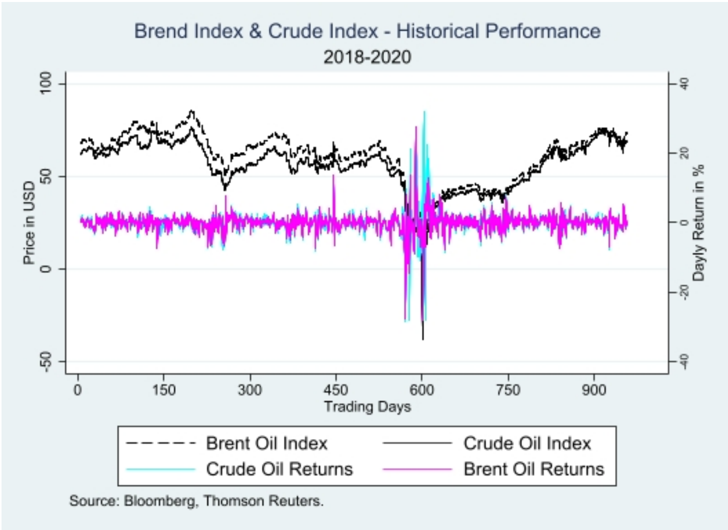
2.3.2 Impact of oil price on financial performances

In this sub-section, we examine the correlations between crude oil and financials, oil and fossil fuel, transportation, automobile, and renewable energy sectors. The impact of oil price shocks can vary across different sectors (Degiannakis et al., 2018), and the five sectors object of this study are no exception. This paper looks at the potential impacts of oil price shocks on the fossil fuel, transportation, auto, financial, and renewable energy sectors. Oil price shocks can directly impact the fossil fuel sector, as oil prices can significantly impact the profitability of oil and gas companies (Timilsina 2015). When oil prices increase, it can lead to higher profits for these companies as the cost of production remains relatively constant while the sale price for their products increases. Conversely, when oil prices decline, it can lead to lower profits for these companies, as the sale price for their products decreases while the cost of production remains relatively constant (Timilsina 2015). Second, in the transportation sector, oil price shocks can also impact it, as oil prices can affect the fuel cost for various transportation modes, such as cars, trucks, and aeroplanes. Therefore, increasing oil prices can lead to higher fuel costs, resulting in higher transportation costs for consumers and businesses. These, in turn, can impact the demand for transportation services and negatively affect the financial performance of companies in the sector (Nandha et al., 2009). Third, the auto sector can also be impacted by oil price shocks, as changes in oil prices can impact the demand for different types of vehicles. For example, higher oil prices can increase the demand for fuel-efficient vehicles, while lower oil prices can increase the demand for larger, less fuel-efficient vehicles (Degiannakis et al., 2018). As a result, changes in oil prices can impact auto companies' sales and financial performance and related industries, such as parts and equipment suppliers (Nandha et al., 2009; Degiannakis et al., 2018). Fourth, the financial sector can also be impacted by oil price shocks, as changes in oil prices can generally impact the financial performance of companies and individuals. For example, higher oil prices can increase inflation, resulting in higher interest rates and reduced consumer spending, potentially hurting the financial performance of companies in specific sectors, such as consumer goods and services. Conversely, lower oil prices can reduce inflation and increase consumer spending, which can boost the financial performance of companies in specific sectors, such as consumer goods and services. Finally, oil price shocks can also impact the renewable energy sector, as changes in oil prices can impact the demand for alternative energy sources. For example, higher oil prices can increase the demand for renewable energy sources, such as solar and wind, as consumers and businesses look for alternative energy sources less affected by oil price changes (Kyritsis et al., 2019). Conversely, lower oil prices can reduce the demand for renewable energy sources, as consumers and businesses may be less motivated to switch to alternative energy sources when oil prices are lower (Henriques et al., 2008; Kyritsis et al., 2019).

In conclusion, to summarise, there has been an increasing correlation between crude oil and financials in recent years, specifically among banks reliant on oil revenues. This positive and robust association between crude oil and the oil and fossil fuel industries can be attributed to shared factors that affect both, including supply and demand, geopolitical events, and environmental regulations. Conversely, the correlation between crude oil and transportation is moderately negative, as high oil prices increase fuel costs for shipping and reduce trade demand. The correlation between crude oil and the automobile sector is weakly negative, primarily due to high oil prices decreasing demand for cars, especially those with low fuel efficiency. On the other hand, the correlation between crude oil and the renewable energy sector is moderately positive, as high oil prices stimulate competition for renewable energy sources and promote investments in green technologies.

It is worth noting that the impact of oil price shocks on these sectors can be complex and multifaceted and can depend on a wide range of factors, such as macroeconomic conditions, the state of the global economy, geopolitical tensions, and other market-specific events.

Figure 2: Brend Oil Index and Crude Oil Index - Historical Performance



Notes: Figure shows the historical trend of Crude Oil index and Brent Oil index.
Data Source: Bloomberg; Elaboration of the authors.

Given the above, it could be helpful for the reader to present the trends of both Crude Oil and Brent Oil indices, emphasizing the substantial volatility of oil prices during the studied period. Figure 2 illustrates six prominent peaks within two medium-term cycles, indicating a minimal bias in the computation of abnormal returns based on different time window calculations.

2.3.3 Examination of the role of reputation and transition risks in shaping investor perceptions and financial market outcomes

Examining the role of reputation and transition risks in shaping investor perceptions and financial market outcomes will be addressed in this section. Understanding these two factors impact on the financial market is essential, as they can significantly influence investor behaviour and the overall market response to climate-related events.

A company's reputation plays a crucial role in shaping investor perceptions and can impact the financial market outcomes of climate-related events. Companies with a strong reputation are generally perceived as more trustworthy and responsible, increasing investor confidence and leading to more favourable financial market outcomes (Trotta et al., 2016). On the other hand, companies with a weaker reputation may face challenges in attracting investment and may experience adverse financial market outcomes due to climate-related events (Lorena et al. 2018).

Transition risks, or the risks associated with transitioning to a low-carbon economy, can also significantly shape investor perceptions and financial market outcomes. These risks can arise from policy changes, technological advancements, and shifts in consumer preferences, among other factors (Bohringer et al., 2013). Companies that are better equipped to manage these risks and adapt to the changing market conditions are more likely to experience buoyant financial market outcomes, while those unable to manage these risks effectively may face negative outcomes (Weber et al., 2020; Battiston et al., 2021).

In conclusion, examining the role of reputation and transition risks in shaping investor perceptions and financial market outcomes is essential for understanding the financial market response to climate-related events. Companies with solid reputations and the ability to effectively manage transition risks are more likely to experience positive financial market outcomes. In contrast, those with weaker reputations or inadequate risk management strategies may face challenges.

3 Data and Methodology

This section offers a thorough overview of the climate-related events, the data sources, the sample selection procedure and the descriptive statistics of the datasets. Additionally, it provides an in-depth examination of the event-study methodology used to analyze the financial market impact of climate-related events. This section concludes with an exhaustive explanation of the models utilized for data analysis and hypothesis testing, highlighting the techniques and methods employed to account for potential confounding factors.

3.1 Overview of the climate-related events analyzed in the study

The current study analyses eight significant climate-related events that occurred between 2019 and 2021 and their impact on financial market performance. The events selected for analysis include speeches by climate activist Greta Thunberg at the United Nations Climate Action Summit and the World Economic Forum, two major oil industry events resulting in fires on cargo ships, two significant oil spills, and two major global climate strikes. These events were chosen for the analysis as they represent various climate-related incidents with an impact on financial market performance. The description and the reported characteristic of these events provide a comprehensive understanding of the relationship between climate-related events, financial market outcomes and the role that reputation and transition risks play in shaping investor perceptions and market outcomes. The rationale for the choice of each event will be presented in the following three sub-sections.

3.1.1 Greta Thunberg's speeches

In this study, we have selected two pivotal speeches among climate-related events to examine their impact on stock returns. The first event is the speech delivered by Greta Thunberg at the United Nations Climate Action Summit on September 23rd, 2019, entitled "How Dare You!". This speech has garnered widespread attention due to its emotive and powerful message calling for immediate action to address the pressing issue of climate change. The second event is the appearance of Greta Thunberg at the World Economic Forum in Davos, Switzerland, on January 21st, 2020. Greta Thunberg addressed a large audience of influential individuals from the global business and political community. We selected these two events due to their prominence and the broad reach of their message, which has resonated with people worldwide.

More precisely, two main factors give the rationale for choosing these two events. First, the temporal distance from other similar minor events could affect either the estimation period or the event period of our event study. Second, the level of media resonance the event had. Greta Thunberg's speech in September 2019, "How dare you", was reported by major international newspapers and broadcasters, rising to the top of the most relevant speeches by the number of views on YouTube. The speech at United Nations features five times in the top 10 search results on the portal, achieving 29.3 million cumulative views across the five videos. Applying the same rationale, the second event selected is Greta Thunberg's speech in Davos at the Word Economic Forum. First, other possible significant and climate-related events have not interfered with the event. Second, the media resonance of the event is high, both due to the objective number of views on YouTube (more than four million) of the videos on the official channels of the major international broadcasters and the high political involvement of the speech, which was also the subject of a distant debate with the then US president, Donald Trump. Here below, Table 1 shows the list of the top six Greta Thunberg's Speeches by number of views, including the two we selected for our work.

Table 1: Greta Thunberg's Speeches by number of views on YouTube

Greta Tundhberg's Speech	Number of Views
UN Climate Action Summit (2019)	over 6.7 million
World Economic Forum (2020)	over 4.4 million
COP26 climate summit (2021)	over 3.9 million
European Parliament (2019)	over 2.1 million
World Economic Forum (2019)	over 1.8 million
Global Climate Strike (2019)	over 1.6 million

Notes: Table 1 shows Greta Tundhberg's Speeches by a number of views on YouTube. Source: YouTube.

3.1.2 Global Climate Strikes

The global climate strikes, also known as Fridays for Future, is a youth-led movement calling for action on climate change. The movement has gained widespread attention and participation, with young activists worldwide taking to the streets to demand immediate action from their governments. The impact of these strikes on the public consciousness has been substantial, raising awareness about the urgency of the climate crisis and inspiring many to take action themselves (Marris, 2019). However, for investors, participation in such events could pose reputational risks, as public sentiment towards companies that contribute to climate change may shift towards negative sentiment (Ramelli et al., 2021). This risk could result in decreased investment opportunities, as the perception of transition and reputational risks associated with fossil fuel industries may grow. In light of these events, firms and investors must be vigilant in considering the long-term impacts of their actions and investments on the environment and their reputation. That said, we used two events of this kind.

First, on September 25th, 2020, the strikes were scheduled in over 3,500 locations across more than 150 countries, attracting thousands of participants and drawing attention to the urgent need for action to fight climate change. The strike was partly digital, reflecting the need for social distancing measures in the context of the COVID-19 pandemic.

Second, on March 19th, 2021, the seventh global climate strike was held in over 800 locations across more than 50 countries, attracting thousands of participants and raising awareness about the issue. This strike was partly online and was organized under the hashtag #NoMoreEmptyPromises, reflecting the growing frustration with the lack of progress in addressing climate change. So, also for the Global Climate Strikes, the two main factors for the choice of these two events are the magnitude and the media coverage. Both of the strikes have been the two biggest strikes among the others in the time frame of the analysis in terms of participation and locations involved. For this reason, we'll show in the next sections how these events have highlighted the critical role of public pressure in driving action on climate change and have the potential to influence the reputation risks companies and investors face in the transition to a low-carbon economy.

3.1.3 Industry-Related Natural Disasters

Natural disasters can significantly impact the financial market performance of firms within different sectors due to the perception of transition and reputational risks associated with these events. In addition, these events can cause direct disruptions in the production and delivery of commodities and oil-related products, leading to decreased investor confidence and reduced stock returns. Therefore, this study seeks to analyze the four natural disasters that occurred within the oil and transportation sectors with a reasonably high impact on the global supply chain. On January 3rd, 2019, an oil industry event occurred with disastrous consequences when a fire broke out on the Yantian Express off Bermuda, resulting in the burning of 198 containers. Second, a similar event took place on March 12th, 2019, when the roll-on/roll-off ship of the Grimaldi group, Grande America, caught fire in the Bay of Biscay near Finisterre, Brittany. Third, in July 2020, another significant event occurred in the oil industry with the MV Wakashio oil spill in south Mauritius.

This environmental disaster had far-reaching consequences, causing significant harm to the local ecosystem and wildlife. Fourth, on May 25th, 2021, another oil industry event occurred, with the X-Press Pearl Shank in the Indian Ocean off Colombo, Sri Lanka. This event resulted in an oil spill, causing significant environmental damage and threatening local marine life. These events highlight the importance of addressing the impact of human activities on the environment, particularly in the oil industry.

Concerning the rationale for the choice, these four events are the only four events in the period of our analysis that represent industry-related natural disasters that significantly impacted the global supply chain and the economic activities of firms within the oil and transportation sectors. The events also caused direct disruptions in the production and delivery of commodities and oil-related products. Furthermore, the events varied in nature and severity, ranging from container fires to oil spills, thus allowing for a comprehensive analysis of how different natural disasters could affect firms' financial performance. Moreover, like Greta's speeches and the Global Climate Strikes, these four events have been selected for their high media resonance and distance from the other climate-related events: reported events received extensive international media coverage and are insulated from the possible influence of other similar events that could have increased the

Table 2: List of Climate-related Events

Date	Type	Description
03/01/19	Human disaster	198 containers go up in smoke in fire on 'Yantian Express' off Bermuda
10/03/19	Human disaster	A roll-on/roll-off ship of the Grimaldi group starts to catch fire off Finistère (Brittany)
23/09/19	Climate Speech	United Nations Climate Action Summit, Greta Thunberg's speech "*How Dare You!*"
21/01/20	Climate Speech	Greta Thunberg's speech at the World Economic Forum
25/07/20	Human disaster	MV Wakashio oil spill in south Mauritius, since July 2020
25/09/20	Global Climate Strike	3,500 locations across more than 150 countries, climing for the urgent need to fight climate change
19/03/21	Global Climate Strike	The seventh global climate strike held in more than 50 countries
02/06/21	Human disaster	X-Press 'Pearl' in the end swallowed on 2 June by the Indian Ocean off Colombo, Sri Lanka

Notes: Table 2 shows the eight climate-related events used in this work listed by date in the time period considered for this study.

level of bias of the event study. For example, in terms of media resonance, all of these events show a high level of views on Google. First, Yantian Express fire had about 1.05 million views on the first page of results of Google, the Grande America fire had about 1.3 million, The MV Wakashio oil spill had about 2.6 million views on the first page of results, and the X-Press Pearl Shank had about 1.9 million views in the first page of results.

3.2 Description of data sources and sample selection

This study collected a comprehensive dataset from various sources. More precisely, Bloomberg and Thomson Reuters for financial data and environmental performances, OECD for the Environmental Performance Index (EPI), Google, Wikipedia, and YouTube to retrieve information about climate-related events in terms of views and media coverage, as shown in the previous sub-sections. The data collected spanned from January 1st, 2019, to December 31st, 2021, and cover a sample of 5 sectors, including transportation, automobiles, fossil fuels, financials, and renewable energy, with a total of 84, 59, 84, 242, and 12 companies, respectively (See Appendix A.1 for the complete list of companies) selected with respect their market capitalization. In addition, the company data comprised variables such as company name, sector, country of domicile, market capitalization in USD, and GICS Industry Name.

The justification of the 5 sectors is the following. The fossil fuel, transportation, and automotive sectors, often termed as 'brown' sectors, traditionally have high carbon footprints and are more likely to be negatively impacted by environmental events, regulations, and shifts towards a low-carbon economy. On the other hand, the renewable energy sector represents 'green' firms that are typically beneficiaries of these same shifts. This contrast can give the opportunity to see if there is and how relevant the possible impact of nature-related financial risks is. Lastly, natural disasters, which are becoming more frequent and severe due to climate change, can affect banks and other financial institutions through their loan portfolios. When clients, particularly those in high-risk geographical areas or sectors, experience losses due to such events, it increases credit risk for banks. Moreover, financial institutions are also exposed to transition risks arising from the process of adjustment to a low-carbon economy. For instance, Greta Thunberg's speeches and similar activism increase public and regulatory pressure for transitioning away from fossil fuels, potentially devaluing investments and loans in those sectors.

In addition to the financial data, the study also collected event data, including the event's date, event type (speech, industry-related event or global strike), and an event ID for each has been assigned for the sake of clarity in our analysis. This level of information is essential in analyzing the impact of climate-related events on the financial performance of companies in the selected sectors. Finally, to avoid biases relative to different sizes and to make the comparison among the firms easy, the sample selection for this study was based on market capitalization. As a result, the data collected was comprehensive and relevant to the research question, providing a solid foundation for analyzing and discussing the key findings.

Concerning the sources, we utilize YouTube to visualize events to aid in selecting which events to include in the analysis and Wikipedia to obtain relevant information on strikes and natural disasters. Environmental performance data was also collected, including GHG scope 1, GHG scope 2, and GHG scope 1-2 estimates, disclosure score, and environmental score. In addition, we used financial data for each company, so the daily closing price for each and the S&P 500 market index was chosen as the benchmark for the market.

Table 3 summarises descriptive statistics for the main different variables in the dataset. It shows each

Table 3: Descriptive Statistics

	Mean	SD	Min	Max	N
Trading Days					957
Firms					481
Sectors					5
Market Cap in USD (Billions)	31.75	55.63	0.543	721.61	481
S&P 500 Index	3167.45	526.00	2237.40	4528.79	957
Crude Oil Index	55.57	13.07	-37.63	76.41	957
Brent Oil Index	60.91	13.57	0.00	86.29	957
GHG Emissions - Scope 1	4769.96	16535.41	0.00	197760	481
GHG Emissions - Scope 2	749.76	2948.19	0.00	36540	481
GHG Emissions - Scope 1 + 2	5519.71	18850.68	0.00	209200	481
Environmental Pillar Score	51.76	25.36	0.00	100.00	477
E Score by Category					477
- Green	78.96	7.1588	66	100	159
- Grey	51.03	9.6292	33	65	159
- Brown	22.63	7.2145	0	32	159
Firms Returns	0.00018	0.0250	-3.755011	3.79123	450,096
Abnormal Returns	0.00164	0.0226	-0.2558	0.3140	42,328
Cumulative Abnormal Returns	0.180702	0.12771	-0.6949	1.713394	3,848

Notes: Table 3 shows the descriptive statistics of the dataset used in this work. Trading days are all the trading days in the time period of the analysis. All the variables are retrieved from Bloomberg. Firm returns, abnormal returns and cumulative abnormal returns are calculated by the authors. *Source*: Bloomberg; the authors processed the data with STATA and Python.

variable's mean, standard deviation, minimum, maximum, and N (number of observations). The first three variables indicate the dataset's number of trading days, firms, and sectors. The following four variables, market capitalization, S&P 500 index, Crude Oil Index, and Brent Oil Index, provide information about the financial market conditions during the sample period. The next three variables represent greenhouse gas (GHG) emissions, including Scope 1, Scope 2 (indirect emissions from purchased electricity, heat, and steam), and Scope 1+2 (total own emissions).

We retrieved data on emissions based on the categories provided by the GHG Protocol[2] and the Environmental Protection Agency(EPA[3]) about GHG emissions inventory. Scope 1 emissions are direct emissions from sources that are owned or controlled by an organization, such as, for example, fuel combustion in boilers, furnaces or vehicles. Scope 2 emissions are indirect emissions from the generation of electricity, steam, heat and cooling purchased or acquired by an organization from a utility provider. Finally, Scope 3 represents all other indirect GHG emissions that come from sources not owned or controlled by the organization but related to the organization's activities. These include emissions from the production of raw materials, transportation of goods and services, and the use and disposal of the organisation's products and services. These last kinds of emissions are not taken into account, given the low level of available data in our sample.

To conclude, the last two collected variables provide information about the environmental performance of the firms in the sample.

The Environmental Pillar Score represents the overall environmental performance of the firms. In particular, the E score is part of an ESG (Environmental,Social and Governance) score, which measures a company's performance on environmental, social and governance issues (OECD 2022). The E score evaluates explicitly how a company manages its environmental impact, such as its carbon footprint, waste management, resource efficiency and biodiversity (Boffo et al., 2020). Rating platforms may have different criteria and methods for calculating the E score. The heterogeneity of E scores can affect investors' decisions and results in different ways. Some studies have found that higher E scores are not necessarily associated with higher returns or lower risks, or with environmental impacts. For example, one study found that higher E scores are correlated with negative alpha, meaning that such securities are overbought and overpriced.

At the same time, the E Score-Category provides the breakdown of the E score into three categories -

[2] https://ghgprotocol.org/
[3] https://www.epa.gov/greeningepa/greenhouse-gases-epa

Green, Grey, and Brown. Table 4 shows the level of greenhouse gas (GHG) emissions and environmental pillar scores of companies, categorized by their E score (Brown, Green, or Grey). The mean, maximum, and minimum values for Scope 1 and Scope 2 GHG emissions are reported, along with the mean, maximum, and minimum values for the Environmental Pillar Score. The Brown category has the highest mean GHG emissions and the lowest mean Environmental Pillar Score. In contrast, the Green category has the lowest mean GHG emissions and the highest mean Environmental Pillar Score. The Grey category falls between the Brown and Green categories for GHG emissions and Environmental Pillar Score.

Table 4: Level of emissions by E score Category

	Brown	Green	Grey
GHG Emissions - Scope 1			
Mean	16352.88	10683.91	15275.25
Max	141,360	197,760	87,440
Min	1.63	1.15	0
GHG Emissions - Scope 2			
Mean	3029.27	1068.29	1627.89
Max	36,540	15,300	27,440
Min	10	68	33
Environmental Pillar Score			
Mean	22.62	78.97	51.03
Max	32	100	65
Min	10	68	33

Notes: Table 4 shows the GHG Emissions (mean, max and min) for each of the three E score category. The category are built on the level of the E score: Green if the company has an E score above 66, Grey if the company has an E score below 66 and above 33; Brown if a company has an E score below 33. *Source*: Bloomberg; the authors processed the data.

Additionally, it is worth noting that while brown companies, on average, have higher levels of GHG emissions than green companies, the maximum level of emissions is actually shown by green companies. Conversely, the minimum level of emissions is lower for green companies than for brown or grey companies. This fact highlights the heterogeneity within each E score category. Further, it underscores the importance of looking beyond the average emissions values when examining the relationship between a company's environmental performance and its stock price reaction to climate-related events.

Finally, the table also reports the calculated daily firms' returns, the abnormal returns and the cumulative abnormal returns.

3.3 Event-Study Methodology

The event-study methodology is a widely used approach for assessing the impact of an event on a financial market. This methodology involves the collection and analysis of data related to the event in question, and the comparison of this data to the performance of the market or a specific asset or group of assets before and after the event. The main goal of an event study is to determine whether a particular event has had a statistically significant effect on the financial market. This is accomplished by comparing the average abnormal return (AR) of a stock or group of stocks around the event to the expected return, which is calculated based on past performances in a period, named *estimation window*, without the event.

Moreover, it is typically used to analyze the impact of specific events such as mergers and acquisitions, earnings announcements, and natural disasters, and it is considered a valuable tool for understanding the relationship between events and financial market performance and for making informed investment decisions based on this understanding. In terms of practicalities, the event-study methodology is typically divided into several stages, including event identification, estimation of the standard returns, calculation of the abnormal returns and cumulative abnormal returns, and hypothesis testing to determine the statistical significance of the results. However, the methodology also involves several potential pitfalls, including the need for sufficient data and a well-defined event window, the difficulty of controlling for other events that may affect the financial market, and the need for appropriate statistical analysis techniques to minimize the risk of false positives or false negatives.

The first step in the event study methodology is to calculate returns for each company. Returns are calculated using the following equation:

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}} \tag{1}$$

where R_t is the return at time t, P_t is the price of the stock at time t, and P_{t-1} is the price of the stock at time $t-1$.

The next step is to calculate normal returns, which represent the expected returns of a stock in the absence of any external events, during the estimation window period. The estimation window is a period before and distant from the event window. The equation for normal returns is:

$$SR_{i,t} = \alpha_i + \beta_i R_{m,t} + \epsilon_{i,t} \tag{2}$$

where, at the firm level, we estimate the parameters α and β in Eq. (2). The market alpha α_i measures the active return of a stock compared to the benchmark. In contrast, the market beta β_i indicates the average movement of the stock returns w.r.t. the benchmark. By utilizing each firm's estimated market alpha and beta, we calculate the expected stock returns using the conditional expectation $E(SR_{i,t}|R_{m,t})$ and then compute AR as described in Eq. (3).

$$AR_{i,t} = SR_{i,t} - E(SR_{i,t} \mid R_{m,t}) \tag{3}$$

where $SR_{i,t}$ is the return at time t for stock i, and $R_{m,t}$ is the market return at time t of the index chosen as market benchmark.

Finally, to obtain the cumulative abnormal return (CAR) we calculate the sum of all abnormal returns over the event window. The equation for CAR is:

$$CAR_{i,t} = \sum_{t=1}^{T} AR_{i,t} \tag{4}$$

where $CAR_{i,t}$ is the cumulative abnormal return of firm i at time t, and $AR_{i,t}$ is the abnormal return of firm i on day t. The sum is taken from the first day of the event window up to day T.

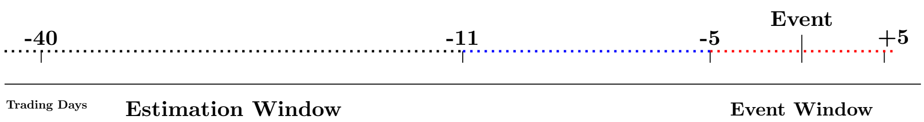
3.4 Empirical Methods

As said in the previous subsection, an event study typically tries to examine return behaviour for a sample of firms experiencing a common type of event. In this case, the initial sample consists of 8 observations of events and speeches over the period 1st of January 2018 and 30th December 2021. Data of share prices for the estimation period and event period is obtained for the individual stocks together with the Market Index, the S&P 500 used as the benchmark. The S&P500 has been chosen as the reference benchmark for our study as it comprises a significant number of indexed companies that report information on their emissions (IEA 2020), and different EGS providers calculate the Environmental Pillar Score. The estimation period runs for 30 days, starting 10 days before every single climate-related event. We chose to carry out the study on a subsample of the MSCI ACWI Index, on a sample of 492 firms, for the five selected sectors: Financials, Fossil Fuel, Automobiles, Transportation and Renewable Energy, selected by market capitalisation in USD.

This study sets out to evaluate the impact of three significant kinds of events on stock returns - namely, four natural disasters caused by human activities, two speeches delivered by Greta Thunberg, and two global climate strikes. A total of 8 events (disasters, strikes and speeches) are analyzed in this research, covering the period from January 2018 to December 2021. The effect of each event on stock returns was estimated through an event-study methodology, with a market model used to calculate α and β for the firm's estimated market, as described in the previous subsection. The regression equation parameters were obtained by conducting a simple regression analysis, with the estimation period defined as [-40, -11] and the event period as [-5, +5] for each of the eight events (see Figure 3). When investors use information efficiently, events may affect the stock returns, but their systematic effect should disappear within days (Naeem et al. 2020; Strong 1989), and in our study, the event window has been chosen as [-5, +5], the interval of trading days.

The selection of an appropriate event window is crucial for our empirical study. It is necessary to balance the need for a short event window to avoid confounding events with the need for a longer window to allow sufficient time for markets to reflect the impact of climate-related events on stock returns. Applying a similar methodology to the one provided by Ramelli et. al (Ramelli et al., 2021), we set up our event window on the number of daily tweets, using the number of daily Tweets in the US related to climate change in the considered event period. On average, the public attention to the selected climate-related events is higher around five days before and five days after (see Table 12 for a number of interactions in the event-window of Greta Thunberg's speech "*How dare you!*"). Given that, an appropriate and standardised event window for our study is from five days before the event up to five trading days after, in which public attention, on average for all eight events, was at a relatively high level.

Figure 3: Timeline used for event study



The following part of this section presents the methodological approach of the paper. The target variable is the Cumulative Abnormal Returns (CAR) observed for firm i in the event window, for each event. Building on the three hypotheses highlighted in the Section 1.4, equation (a) represents our baseline regression model where CAR_i^5, the cumulative abnormal returns, is the dependent variable and it is explained by our main key independent variable, $Escore_i$ in order to see the effects of this environmental reputation score. In equation (b) we also include the categorical independent variables $Sector_i$. The β_j coefficients are the regression coefficients which show the effect of each independent variable on the dependent variable. The constant term β_0 is the expected value of the dependent variable when all the independent variables are equal to zero. The $Sector_i$, $Size_i$, $EmissionScore_i$ variables represent categorical variables, indicating the sector of the company, the size of the company and the level of GHG Emissions Scope 1 and Scope 2, while the $Escore_i$ is a continuous variable between 0 and 100, and it is used also to set up the Environmental Pillar score category, Green, Grey and Brown, respectively. Finally, ϵ_i,t represents the error term, which accounts for the variability in the dependent variable that is not explained by the independent variables. All three groups of events are expected to display their effects on financial markets during the days following the event itself. As shown below, equation (a) represents our baseline model that takes into account only correlation with the E score, while equation (b) takes into account also the sectoral correlation with the impact event on stock performances. Equation (c) is the equation that takes into account also the correlation with the Environmental Pillar Score Categories and the size categorical variable in order to quantify the effects on a polluting company but with a high level of environmental reputation, measured from the E score.

$$(a)\ CAR_i^5 = \beta_0 + \beta_1 Escore_i + \epsilon_{i,t} \tag{5}$$

$$(b)\ CAR_i^5 = \beta_0 + \beta_1 Escore_i + \beta_2 Sector_i + \epsilon_{i,t} \tag{6}$$

$$(c)\ CAR_i^5 = \beta_0 + \beta_1 Escore_i + \beta_2 Sector_i + \beta_3 Size_i + \epsilon_{i,t} \tag{7}$$

In these equations, CAR_i represents the cumulative abnormal returns for firm i. The other variables are as follows: β_0 is the intercept term, β_1 is the coefficient for the critical variable $Escore_i$, β_2 is the dummy variable indicating the sector of the firm showing the relative effect of being in a polluting sector, β_3 is the coefficient for the dummy variable indicating the size of the company base on the market capitalisation in USD, β_i is the coefficient for control variables on the single the stock i, $\epsilon_{i,t}$ is the error term for stock i at time t.

$$(d)\ CAR_i^5 = \beta_0 + \beta_1 Escore_i + \beta_2 Sector_i + \beta_3 Size_i + \beta\Gamma_i^{'} + \epsilon_{i,t} \tag{8}$$

Finally, in equation (d) $\Gamma_i^{'}$, a vector of accounting variables (e.g., market capitalization, size, profitability, and country) is added.

That said, to estimate the equations reported above, we use a statistical linear regression model to examine the impact of the various variables on our outcome of interest. However, fixed effects - factors that are not directly observable but still influence the outcome - may exist and can vary across different groups or levels of observation (Allison 2009; Brüderl and Ludwig 2015). We use an absorbing technique to control for multiple levels of fixed effects, which we implement through the STATA software package called reghdfe. In our example, when studying the relationship between the E score and the Cumulative Abnormal returns, fixed effects such as, for example, sector, size, country, and emission category must be considered. Absorbing multiple levels of fixed effects has several advantages, such as removing potential unobserved confounding variables, increasing the efficiency and precision of estimates, and handling complex hierarchical structures and heterogeneous slopes. However, it may also have some drawbacks, such as potentially excluding parts of the sample that do not vary within groups, imposing strong assumptions about the nature and distribution of fixed effects (Allison 2009; Bruderl et al., 2015).

To conclude this section and introduce the findings of this work, the scope of the methodology presented so far is to determine the potential level of investor awareness of a company's or industry's responsibility toward climate change. This awareness would allow investors to differentiate companies for their investment decisions based on their environmental impacts. That said, the purpose of the next part of the paper is to show whether investors are already aware of the environmental materiality of financial market activity or whether there is still a greater focus on financial materiality only (i.e., profits and balance sheet). This second hypothesis would represent evidence that investors still need to consider the climate risks their investment choices face fully.

4 Results

4.1 Presentation of the results from the event-study analysis

This section explores the correlation between stock price performance and firms' E score during climate-related events. Our analysis employs Eq. (a) to calculate cumulative abnormal returns $CAR_i(t1, t2)$ for the market model over an 11-day window, as described in Section 2. We used the E Score index at the firm level and another control variable at the country-sector or firm levels.

Table 5 presents the primary findings of our study, which examines the average impact of all the Climate-related events on stock price reactions. We estimate Eq. (a)-(b)-(c)-(d) to compute the 11-day cumulative abnormal returns calculated with the market model for E score measures, including both the event, sector and firm levels fixed effects. Columns 1 and 2 present results for the E score at the event and sector level, while columns 3 and 4 report findings for the E score at the firm level. Specifications 5 and 6 also control for firm-level characteristics, and Specification 4 adds sector and E score fixed effects. We report standard deviation based on robust standard errors and use ***, **, and * to indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

The E Score coefficient is significant in all four models (indicated by the asterisks), meaning a statistically significant relationship exists between a firm's E Score and its CAR^5. E score categories, in model five are still significant, indicating a negative relative impact on firms with a low level of E Score (indicated as *Brown* in the output table). The sector coefficients are significant in all models but not all sectors. For example, the Automobiles coefficient is always significant at the 0.05 level. Fossil Fuels and Transportation are strongly significant at 0.01 level in all the model specifications. Conversely, the financial sector seems to be not statistically different from a green sector like renewable energy. The E Score-Category coefficients are significant in some models but not others. For example, in Model 5, the Brown coefficient is significant at the 0.05 level, while the Grey coefficient is not significant at the 0.05 level but only at the 0.10 level. This suggests that firms with lower E Scores may experience larger CAR^5 declines following negative events with respect to the firms with high E scores. The constant term is not significant in all models, but only in models 4, 5 and 6, and its magnitude varies depending on the specific model. The constant represents the average CAR^5 for firms with a zero E Score and operating in the baseline sector (i.e., the omitted sector). The R-squared and adjusted R-squared values suggest that the models explain between 19% and 23% of the variation in CAR^5, depending on the specific model. This indicates that there may be other factors not

Table 5: Regression - All Events

Dependent Variable:	CAR^5	CAR^5	CAR^5	CAR^5	CAR^5	CAR^5
E Score	0.00023*	0.00041***	0.0003**	0.00029**		
	(0.000)	(0.000)	(0.000)	(0.000)		
Sector						
Automobiles				-0.064**	-0.069**	-0.068**
				(0.027)	(0.032)	(0.032)
Financials				-0.0185	-0.017	-0.0183
				(0.027)	(0.023)	(0.023)
Energy - Fossil Fuels				-0.061***	-0.058**	-0.064**
				(0.021)	(0.027)	(0.027)
Transportation				-0.078***	-0.088***	-0.083***
				(0.021)	(0.027)	(0.027)
E Score Category						
Brown					-0.022**	-0.015
					(0.009)	(0.010)
Grey					-0.014*	-0.008
					(0.008)	(0.008)
Constant	0.005	-0.003	0.0014	0.068***	0.098***	0.095***
	(0.007)	(0.007)	(0.007)	(0.020)	(0.027)	(0.027)
Event FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	No	Yes	Yes	No	No	No
Size FE	No	No	Yes	Yes	No	Yes
E Score Category FE	No	No	No	No	Yes	Yes
Observations	3816	3816	3816	3816	3816	3816
R^2	0.192	0.208	0.215	0.215	0.217	0.225
Adjusted R^2	0.187	0.201	0.207	0.207	0.209	0.216

Robust Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Table 5 shows the output of the linear regression that absorbs for fixed-effects. The standard deviation in parenthesis is robust. The coefficients of sectoral dummy represent the relative effect of being in a polluting sector with respect to being in a green sector. *Source*: Bloomberg; the authors processed the data with STATA.

included in the model that also influence CAR^5, but this model is still able to explain part of the dependent variable, given also the low, but significant, level of coefficients.

Specifications 3 and 4 in Table 5 display outcomes obtained using the measure of E Score and the fixed effects at the firm level, revealing a strong positive impact of E score on the 5-day cumulative abnormal returns. Overall, the findings indicate that all eight climate-related events taken together, on average, adversely affected the stock prices of firms in high-carbon sectors relative to the green sector. To conclude, results in Table 5 provide a first conservative estimate of the market effects of all of these climate-related events.

So, considering all of the events, a positive and statistically significant relationship exists between the E score and cumulative abnormal returns (CAR) across different model specifications. This suggests that firms with higher E scores exhibit better stock price performance during climate-related events. Moreover, the sector-specific impacts reveal that, compared to green sectors, polluting sectors such as Automobiles, Energy - Fossil Fuels, and Transportation have negative and statistically significant coefficients, indicating that these sectors tend to underperform in terms of stock price reactions during climate-related events. Third, when accounting for E Score categories (Brown and Grey), both categories show negative and statistically significant coefficients in Specification 5, suggesting that firms classified as Brown and Grey tend to have lower stock price performance compared to Green firms. However, in Specification 6, only the Brown category remains statistically significant. Fourth, the various specifications demonstrate that the relationship between the E score and stock price performance is robust across different models, considering an event, sector, firm-

Table 6: Regression - Industry-Related Natural Disasters

Dependent Variable:	CAR^5	CAR^5	CAR^5	CAR^5	CAR^5	CAR^5
E Score	0.0004**	0.001***	0.000349*	0.00034*		
	(0.0002)	(0.0002)	(0.00022)	(0.00022)		
Sector						
Automobiles				-0.097**	-0.107**	-0.104**
				(0.038)	(0.048)	(0.046)
Financials				-0.015	-0.0121	-0.0122
				(0.052)	(0.035)	(0.035)
Energy - Fossil Fuels				-0.038	-0.032	-0.044
				(0.031)	(0.043)	(0.040)
Transportation				-0.090***	-0.108**	-0.095**
				(0.032)	(0.043)	(0.041)
E Score Category						
Brown					-0.034**	-0.018
					(0.015)	(0.015)
Grey					-0.015	-0.001
					(0.014)	(0.014)
Constant	0.040***	0.031***	0.043***	0.105***	0.144***	0.135***
	(0.011)	(0.012)	(0.012)	(0.029)	(0.043)	(0.041)
Event FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	No	Yes	Yes	No	No	No
Size FE	No	No	Yes	Yes	No	Yes
E Score Category FE	No	No	No	No	Yes	Yes
Observations	1908	1908	1908	1908	1908	1908
R^2	0.116	0.169	0.199	0.199	0.172	0.204
Adjusted R^2	0.111	0.160	0.187	0.187	0.161	0.192

Robust Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Table 6 shows the linear regression output that absorbs for fixed-effets. The standard deviation in parenthesis is robust. The coefficients of the sectoral dummy represent the relative effect of being in a polluting sector with respect to being in a green sector. *Source*: Bloomberg; the authors processed the data with STATA.

level fixed effects, and firm-level characteristics.

Table 6 presents the primary findings of our study, which examines the average impact of all industry-related natural disasters on stock price reactions. We estimate Eq. (a)-(b)-(c)-(d) to compute the 11-day cumulative abnormal returns calculated with the market model for E score measures, including both the event, sector and firm levels fixed effects. Columns 1 and 2 present results for the E score at the event and sector level, while columns 3 and 4 report findings for the E score at the firm level. Specifications 5 and 6 also control for firm-level characteristics, and Specification 4 adds sector and E score fixed effects. We report standard deviation based on robust standard errors and use ***, **, and * to indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Differently for the results of all events calculated together, here, the E score is still statistically significant for specifications (1) and (2), but the magnitude is lower. Moreover, the E score is not significant when sector FE is applied, and the sectoral effects are stronger and more significant for automobiles and the transportation sector but not for fossil fuel and financials. This last result also holds for specification (6).

So, concerning this specific type of event, firms with higher E scores generally experience better stock price performance during industry-related natural disasters, but this relationship is sensitive to model specification. Sectors like automobiles and Transportation tend to underperform compared to green sectors, while financials and energy-fossil fuels show no statistically significant relationship with CAR. There is a positive and statistically significant relationship between the E score and cumulative abnormal returns (CAR) in specifications one, two, three, four and five. This suggests that firms with higher E scores tend to exhibit

Table 7: Regression - Greta Thundberg's speeches

Dependent Variable:	CAR^5	CAR^5	CAR^5	CAR^5	CAR^5	CAR^5
E Score	0.001**	0.0012***	0.00046**	0.00046**		
	(0.0002)	(0.000184)	(0.00022)	(0.00022)		
Sector						
Automobiles				-0.020	-0.016	-0.016
				(0.048)	(0.061)	(0.060)
Financials				-0.039	-0.018	-0.018
				(0.051)	(0.052)	(0.051)
Energy - Fossil Fuels				-0.022	-0.017	-0.018
				(0.044)	(0.056)	(0.057)
Transportation				-0.024	-0.024	-0.022
				(0.043)	(0.056)	(0.055)
E Score Category						
Brown					-0.029**	-0.027**
					(0.012)	(0.013)
Grey					-0.009	-0.008
					(0.013)	(0.012)
Constant	-0.032***	-0.034***	-0.033***	-0.011	0.020	0.019
	(0.010)	(0.009)	(0.010)	(0.044)	(0.056)	(0.055)
Event FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	No	Yes	Yes	No	No	No
Size FE	No	No	Yes	Yes	No	Yes
E Score Category FE	No	No	No	No	Yes	Yes
Observations	954	954	954	954	954	954
R^2	0.144	0.146	0.147	0.147	0.142	0.144
Adjusted R^2	0.139	0.130	0.127	0.127	0.126	0.122

Robust Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Table 7 shows the linear regression output that absorbs fixed effects. The standard deviation in parenthesis is robust. The coefficients of sectoral dummy represent the relative effect of being in a polluting sector with respect to being in a green sector. *Source*: Bloomberg; the authors processed the data with STATA.

better stock price performance during industry-related natural disasters. However, the relationship becomes statistically insignificant in the sixth specification. The various specifications demonstrate that the relationship between the E score and stock price performance during industry-related natural disasters is sensitive to the inclusion of different fixed effects and firm-level characteristics.

In order to find the impacts of the two speeches of Greta Thundberg, Table 7 presents the primary findings of our study, which examines the average impact of these two events on stock price reactions. We estimate Eq. (a)-(b)-(c)-(d) to compute the 11-day cumulative abnormal returns calculated with the market model for E score measures, including both the event, sector and firm levels fixed effects. Columns 1 and 2 present results for the E score at the event and sector level, while columns 3 and 4 report findings for the E score at the firm level. Specifications 5 and 6 also control for firm-level characteristics, and Specification 4 adds sector and E score fixed effects. We report standard deviation based on robust standard errors and use ***, **, and * to indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Differently for the results of previous kinds of events calculated together, here the E score is always statistically significant for specifications (1) and (2), but the magnitude is still low. But the E score is always statistically significant also, sector FE is applied, as a sign of the importance and the impact of being seen as green by the investors when social climate events happen. This last result also holds for specification (6).

Therefore, for Greta Thundberg's speeches, the E Score has a positive and statistically significant relationship with cumulative abnormal returns (CAR) in the first four specifications. Moreover, also in specifications five and six, the Brown category has a negative and statistically significant coefficient, suggesting that brown firms tend to have lower stock price performance compared to green firms during events related to Greta Thunberg's speeches. This suggests that firms with higher E scores tend to exhibit better stock price performance during events related to Greta Thunberg's speeches. Conversely, in terms of sector-specific impacts, none of the sectors (Automobiles, Financials, Energy - Fossil Fuels, and Transportation) shows a statistically significant relationship with CAR in any of the specifications. This indicates that sector membership does not seem to have a clear impact on stock price reactions during events related to Greta Thunberg's speeches.

Table 8: Regression - Global Climate Strike

Dependent Variable:	CAR^5	CAR^5	CAR^5	CAR^5	CAR^5	CAR^5
E Score	-0.000325	-0.00002	0.0001	0.000057		
	(0.000)	(0.000)	(0.000)	(0.000)		
Sector						
Automobiles				-0.040	-0.048	-0.049
				(0.041)	(0.042)	(0.042)
Financials				-0.005	-0.009	-0.009
				(0.026)	(0.22)	(0.22)
Energy - Fossil Fuels				-0.143***	-0.150***	-0.148***
				(0.021)	(0.021)	(0.021)
Transportation				-0.108***	-0.113***	-0.119***
				(0.020)	(0.021)	(0.021)
E Score Category						
Brown					0.010	0.004
					(0.015)	(0.014)
Grey					-0.017	-0.021*
					(0.011)	(0.012)
Constant	-0.026**	-0.041***	-0.045***	0.073***	0.085***	0.090***
	(0.012)	(0.012)	(0.012)	(0.020)	(0.022)	(0.021)
Event FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	No	Yes	Yes	No	No	No
Size FE	No	No	Yes	Yes	No	Yes
E Score Category FE	No	No	No	No	Yes	Yes
Observations	954	954	954	954	954	954
R^2	0.036	0.165	0.178	0.178	0.159	0.174
Adjusted R^2	0.031	0.150	0.158	0.158	0.143	0.153

Robust Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Table 8 shows the linear regression output that absorbs fixed effects. The standard deviation in parenthesis is robust. The coefficients of sectoral dummy represent the relative effect of being in a polluting sector with respect to being in a green sector. *Source*: Bloomberg; the authors processed the data with STATA.

Table 8 presents the outcomes of our linear regression analysis, which utilizes a fixed-effect model to explore the Global Climate Strike's impact on the 5-day cumulative abnormal returns (CAR^5) of firms across various sectors and environmental performance categories. The table enumerates the coefficients of our independent variables, encompassing E Score, sector, and E Score category, alongside their corresponding statistical significance.

The results indicate that the Global Climate Strike exerted a negative, albeit statistically insignificant, influence on the CAR^5 of firms within the Energy-Fossil Fuels and Transportation sectors. Meanwhile, the strike's impact on firms in the Automobiles and Financial sectors proved negligible. Furthermore, our analysis found that firms with higher E Scores did not significantly affect CAR^5 post-strike, while firms with lower E Scores experienced a downturn in CAR^5.

Despite the R-squared values suggesting that our model accounts for only a marginal portion of the variation in the dependent variable, the overall findings still provide valuable insights. Specifically, they shed light on how Global Climate Strikes influence the stock returns of firms across different sectors and varying levels of environmental performance. Our results reveal that while such strikes do not seem to directly impact investor consideration of environmental reputation indices, they do broadly affect sectors known for higher pollution.

In conclusion, our examination of global climate strike impacts on stock price reactions reveals that the E Score does not statistically correlate with cumulative abnormal returns (CAR) in the first four specifications. This indicates that the E Score doesn't seem to significantly influence stock price performance during global climate strike events. However, firms within the energy-fossil fuels and transportation sectors display poorer stock price performance relative to the green sector.

From the four tables presented, our primary conclusions regarding the correlation between stock price performance and firm E scores during climate-related events are as follows. Firstly, firms with higher E scores generally exhibit superior stock price performance during climate-related events. Secondly, on average, polluting sectors underperform when compared to the green sector. Thirdly, while our results collectively hold across all events, the E score's significance increases markedly when we specifically consider Greta Thundberg's speeches. This third point serves as the rationale for introducing Section 5. Lastly, our findings underscore the significance of environmental performance and its potential financial implications for firms during climate-related events, consistent with our initial hypothesis.

4.2 Robustness Checks

In this section, to statistically confirm our findings, we provide a robustness check to ensure the reliability of the findings described in the previous section. Specifically, we focus on i) the definition of the event window, and ii) controlling for the level of GHG emissions.

In Table 9, we estimate our model by using $[-3, +3]$ event window to calculate cumulative abnormal returns as dependent variables, maintaining the same estimation window. All previous results are confirmed, both when considering E scores at the event-sector level, in specifications 1 and 2, and at the size level, in specifications 3 and 4. In Table A.6 (Appendix A.2), we also included GHG Emission Scope 1 as a control and in Table A.7 (Appendix A.3), we used this variable itself as an independent variable instead of the E score. At the firm level, showing that emissions levels are not relevant in terms of magnitude and also not statistically significant for investor decisions, concluding that reputation matters more than the environmental impact itself at the firm and sectoral level.

Our main result, i.e., the importance of the E score as a reputational indicator in explaining the stock price performance around the climate-related events, holds after controlling for the emission score (Table A.6), the emission level (Table A.7)). In particular, the main implications of the robustness checks conducted to ensure the reliability of our findings can be summarized as follows. The results hold across different specifications when using a $[-3, +3]$ event window to calculate cumulative abnormal returns (CAR) as dependent variables. This suggests that the choice of event window does not significantly affect the conclusions drawn from the analysis. Then, E Score continues to be an essential factor in explaining stock price performance around climate-related events across various specifications. This confirms the significance of the E Score as a reputational indicator for investors. In the appendix, we include GHG Emission Scope 1 as a control variable (Table A.6) and also use it as an independent variable instead of the E Score (Table A.7). The results show that emission levels are not relevant in terms of magnitude and are not statistically significant for investor decisions. This indicates that reputation, as captured by the E Score, matters more than the environmental impact at the firm and sectoral levels. In conclusion, the robustness checks confirm the importance of the E Score as a reputational indicator in explaining stock price performance around climate-related events. Moreover, the findings hold even after controlling for the emission score and emission levels, suggesting that reputation matters more than the environmental impact on investor decisions.

4.3 Cross-country heterogeneity

After examining the robustness of our findings, we now turn our attention to cross-country heterogeneity in this section of our work, exploring the differences in our main results exploiting the fact that in some countries climate policy and environmental regulation play significant roles in influencing firm value.

Table 9: Regression - All Events

Dependent Variable:	CAR^3	CAR^3	CAR^3	CAR^3	CAR^3	CAR^3
E Score	0.000165*	0.0002532***	0.000154*	0.000142*		
	(0.0000866)	(0.000088)	(0.0001)	(0.0001)		
Sector						
Automobiles				-0.034*	-0.041*	-0.040
				(0.021)	(0.025)	(0.024)
Financials				0.027	0.024	-0.014
				(0.027)	(0.028)	(0.031)
Energy - Fossil Fuels				-0.031*	-0.031	-0.036*
				(0.016)	(0.021)	(0.020)
Transportation				-0.032**	-0.042**	-0.050**
				(0.016)	(0.021)	(0.020)
E Score Category						
Brown					-0.017***	-0.0125*
					(0.007)	(0.007)
Grey					-0.010**	-0.011
					(0.006)	(0.006)
Constant	0.002	-0.003	0.002	0.035**	0.058***	0.055***
	(0.005)	(0.005)	(0.005)	(0.016)	(0.021)	(0.021)
Event FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	No	Yes	Yes	No	No	No
Size FE	No	No	Yes	Yes	No	Yes
E Score Category FE	No	No	No	No	Yes	Yes
Observations	3816	3816	3816	3816	3816	3816
R^2	0.239	0.249	0.263	0.263	0.264	0.279
Adjusted R^2	0.234	0.242	0.255	0.255	0.258	0.271

Robust Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Table 9 shows the linear regression output that absorbs for fixed effects. The standard deviation in parenthesis is robust. The coefficients of sectoral dummy represent the relative effect of being in a polluting sector with respect to being in a green sector. *Source*: Bloomberg; the authors processed the data with STATA.

Given that our sample includes also firms located in Europe, we can explore the cross-country dimension of our main results. Previous literature recognizes climate policy and environmental regulation as major drivers of the price of carbon intensity on firm value (e.g., Bolton and M. Kacperczyk 2021; P.-H. Hsu, Li, and Tsou 2022, and Ramelli et al., 2021).

Following the methodology used by Ramelli et al. (Ramelli et al., 2021), in this section, we consider the Environmental Performance Index (EPI) (Wolf et al. 2022), a composite indicator that measures how close countries are to establish environmental policy targets[4]. These indicators approximating the sustainability performance of a country allow us to split our sample between firms of the five sectors domiciled in countries with high scores (e.g., Austria, Denmark, Finland, France, Germany, Great Britain, Luxembourg, Norway, and Switzerland are in the top quartile), and firms headquartered in countries with low scores (e.g. China, United States, Brazil, Saudi Arabia).

Table 10 reports the results of our main regressions by splitting the sample into firms located in countries with low (specifications from 1 to 3) and high levels of environmental indexes (specifications from 4 to 6). Although the magnitude of the effect is low in both sub-samples, both at the country-industry and firm levels, the market penalization for carbon-intensive sectors appears statistically significant only for the sub-sample of firms located in countries with high levels of environmental indexes. The documented cross-country heterogeneity highlights that markets' reactions to an intensification in climate activism are likely to differ not only on a firm's environmental profile but also on the environmental aspects related to the specific

[4]See the methodology and updated data at https://epi.yale.edu/epi-results/2022/component/epi.

country of a firm.

Table 10: Countries' Environmental Performance. - All Events

Dependent Variable:	Low EPI CAR^5	Low EPI CAR^5	Low EPI CAR^5	High EPI CAR^5	High EPI CAR^5	High EPI CAR^5
E Score	0.000143	0.0001	0.0001	0.001***	0.001**	0.001**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Sector						
Automobiles			-0.003			-0.121***
			(-0.07)			(2.94)
Financials			-0.0060			-0.112***
			(-0.32)			(-4.59)
Energy - Fossil Fuels			-0.028			-0.113***
			(-0.82)			(-4.36)
Transportation			-0.041			-0.145***
			(-1.19)			(-4.49)
Constant	-0.005	-0.004	0.026	-0.018*	-0.018	0.110***
	(-0.48)	(-0.38)	(0.031)	(-1.72)	(-1.40)	(4.61)
Event FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	No	Yes	Yes	No
Size FE	No	Yes	Yes	No	Yes	Yes
E Score Category FE	No	No	No	No	No	No
Observations	1112	1112	1112	1360	1360	1360
R^2	0.185	0.194	0.194	0.134	0.135	0.135
Adjusted R^2	0.161	0.166	0.166	0.110	0.106	0.106

Robust Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Table 10 reports estimation results of Eq. (1-2-3) market-model cumulative abnormal returns on E Score index. Specifications 1,2, and 3 (4,5 and 6) refer to countries with low (high) environmental performance. Countries with high levels of environmental performance are either above the 66th percentile of EPI (an indicator of environmental sustainability). All specifications include firm characteristics and country-fixed effects. Specifications 2 and 5 also include the size fixed effects based on the market capitalisation in USD. The t-statistics based on robust standard errors are shown in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% levels, respectively. *Source*: Bloomberg; the authors processed the data using STATA and Python.

The main findings are as follows. In countries with a high Environmental Performance Index (EPI), the E Score has a statistically significant positive impact on CAR^5, implying that firms with better environmental reputations in these countries experience better stock price performance during climate-related events. In contrast, for countries with low EPI, the E Score does not significantly affect CAR^5. For the high EPI countries, all sector coefficients (Automobiles, Financials, Energy - Fossil Fuels, and Transportation) are negative and statistically significant, indicating that firms in these sectors underperform compared to those in greener sectors. Moreover, the implications of these results may be noteworthy. First, high E scores for firms based in high EPI countries suggest they have less reputational risk, as their environmental performance is well-regarded and in line with their country's strong commitment to sustainability. Additionally, these firms may face lower transition risk since their operations are already aligned with domestic environmental regulations, making them better prepared for the shift towards a low-carbon economy.

5 Potential impact channels

5.1 Sentiment Analysis on individuals' perception of climate change: *How Dare you!* Case-Study

In order to provide an answer to our third research question of this work about the perception of individuals about climate change before and after a climate-related event, we select to analyse, among the other events, the most influential and seen: the Greta Thunberg Speech at the UN on the 23rd of September 2019. For this final part of the analysis, we select a sub-sample composed of the top 15 US-based companies w.r.t. the market capitalisation in the fossil fuel sector, and we retrieved a sample of 263,024 Tweets written by Twitter users for the 11-day event window. The 15 selected companies represent 58.71% of the total market capitalisation of our sample composed of 85 fossil fuel companies. We excluded all the firms that are not based in the US and that are out of the top 15 based on market capitalisation in USD.

Through this part of the analysis, we aim to provide insights into the financial market performances and the individuals' perceptions of this climate-related event. As said, the list contains 15 companies operating in different US states. To give a brief context of this sub-sample, starting from Arkansas State, Williams Company is of social but significant importance, providing employment opportunities, energy and wealth and contributing to the state's economy from a market capitalisation of 39.81 billion USD.

In Texas, several companies on the list are crucially important for the same reasons, including Kinder Morgan, Valero Energy, Pioneer Natural Resources, Occidental Ptl, and Exxon Mobil. These companies provide employment opportunities, contribute to the state's wealth, and could significantly impact the energy supply in this state and in the US overall[5]. Moreover and unfortunately, the majority of these companies, such as Exxon Mobil and Pioneer Natural Resources, have Brown E scores, indicating a lower performance in environmental practices and a low reputation environmental score. On the contrary, part of these companies presents good environmental scores. For example, Ohio has Marathon Petroleum in the Green E score category, indicating good ESG practices and contributing to the state's economy. In Oklahoma, Devon Energy operates, contributing to the state's economy, with an average E performance score above the sector's average. These companies have been selected because we think they are economically and socially necessary for their respective states, providing employment opportunities, contributing to their economies through the supply chain, and significantly impacting energy supply and demand. Table 11 below shows the list of the 15 companies, with the market cap, the domicile state and the E score category.

Table 11: Top 15 US Oil companies by Market Capitalisation

Company Name	Market Capitalisation in USD (Billion)	US state of domicile	E Score Category
EXXON MOBIL	455,86	Texas	Brown
CHEVRON	352,30	California	Grey
CONOCOPHILLIPS	161,89	Texas	Green
EOG RES	78,35	Texas	Brown
SCHLUMBERGER	71,54	Texas	Green
OCCIDENTAL PTL.	66,92	Texas	Grey
PIONEER NTRL.RES.	61,14	Texas	Grey
MARATHON PETROLEUM	56,63	Ohio	Green
PHILLIPS 66	50,13	Texas	Grey
DEVON ENERGY	49,77	Oklahoma	Grey
VALERO ENERGY	48,57	Texas	Grey
CHENIERE EN.	43,58	Texas	Grey
HESS	43,49	New York	Green
KINDER MORGAN	39,94	Texas	Green
WILLIAMS	39,81	Arkansas	Green

Notes: Market Capitalisation in billion of USD relative to 2021. *Source*: Bloomberg; the authors processed the data.

In order to justify our use of sentiment analysis, it is worthy to recall all the previous works that used

[5]The oil and gas production sector employed more than 190,000 people in Texas. Moreover, Texas boasts a processing capacity of 5.1 million barrels of crude oil per day. This substantial capacity represents more than 28% of the nation's total refining capability. Source: Texas Economic Development Corporation.

this kind of methodology to measure the impact of social networks and media.

In light of the above, using social network data has become common to understand the impact of social media communication strategies on financial markets. Scholars have leveraged Twitter as the primary source for conducting systematic sentiment analysis on multiple firms using text mining. Twitter-based analysis has proven effective in understanding the issuer's sentiment and predicting the volatility and performance of financial instruments. Twitter has also been used to analyze the financial impact of relevant announcements, such as the United States' withdrawal from the Paris Treaty and extreme weather events. Social media communication aims to create legitimacy and explain an organization's behaviour and strategy to fulfil its social contract. Recognizing business objectives is crucial to positively affect corporate activity, especially during jumpy and turbulent moments. The stigmatization of major polluters is an attempt to counter their legitimacy narration, which is expected to be more effective during periods of great attention toward climate-related topics. These sensitive events can alter how investor communication is assimilated in financial markets.

The use of social network data to understand the effect of social media communication strategies on financial markets is gaining popularity, as evidenced by several studies (Affuso and Lahtinen 2019; Fan et al., 2020). Among the social media platforms for this kind of work, Twitter is one of the most used, mainly when sentiment analysis is conducted systematically for multiple firms using text mining techniques (Karami et al. 2020). Twitter represents a non-mandatory communication form used by investors to gauge issuer sentiment and predict the volatility and performance of financial instruments (Albarrak et al., 2020; Behrendt et al., Behrendt and Schmidt 2018; Diaz-Rainey et al. 2021; Sóti et al. 2020).

In addition, the analysis of Twitter-based data has gained popularity for studying the financial impact of relevant announcements, such as the negative effect of the United States' withdrawal from the Paris Agreements (Berkman et al., 2019; Diaz-Rainey et al. 2021) or extreme weather events (Chang et al., 2018). Social media communication aims to create legitimacy by explaining an organization's behaviour and strategy to fulfil its social contract. This element, in turn, helps generate positive effects on corporate activity, particularly during turbulent periods (Burlea and Popa 2013). Significant polluters are often stigmatized to counter their legitimacy narrative or "myth-making" (Ferns et al., 2019), which is expected to be more effective during heightened attention to climate-related topics. Such sensitive events can influence investor perspectives and alter how announcements and communication are assimilated in financial markets (Yong and Laing 2021; Chahine and Malhotra 2018; Lee et al., 2018).

5.1.1 Data and Methodology

In this study, we utilize tweets as a means of gauging individual citizens' sentiments and perceptions pertaining to climate change. We employ Python and the *Twitter API Academic Research product track* to collect a data set consisting of 263,024 tweets, which we retrieve on a daily basis between 2019-09-18 and 2019-09-28, the event window for our event.

Through the *Twitter API Academic Research product track*, we've been able to retrieve tweets from each of the US states with complete information about the geographic location of the user, the self-declare origin of the user, the time of the creation of the Tweet, the self-description of the user, the geo-localisation from where the tweet has been written and finally name and username of the user. Following others' works on this field (Elbagir and Yang 2019; Ittoo et al., 2016; Macanovic 2022), to analyze the data and calculate the sentiment we adopt a dictionary-based method and utilize the nltk.sentiment.vader, a sentiment analysis tool provided by the Natural Language Toolkit (NLTK) library in Python [6].

We extract tweets containing specific keywords or hashtags, such as "*climate change*" "*#howdareyou*" "*climate*" "*Climate crisis*" "*environmental crisis*" "*Greta Tundberg*" "*Emissions*" and "*Climate policy*" among others (See Appendix A.4.1 for the complete list of keywords used in our query). These keywords were selected based on a training period focused on identifying the most commonly used terms related to climate change. Our aim is to use sentiment analysis to measure US citizens' perceptions of climate change during the event window for our selected climate-related event.

We only selected texts in English from individuals located in the US. Section A.4 in Appendix presents a methodological example of our query and how the sample is composed, including the number of positive

[6] For a complete explanation of this methodology, see https://www.nltk.org/

and negative tweets, the job self-description of the authors of the tweets, the sentiment average for each day and the sentiment average for each day for each US state, given the origin of Twitter users.

For what concern the methodology, as said before, we use the *nltk.sentiment.vader*, a sentiment analysis tool provided by the Natural Language Toolkit (NLTK) library in Python. It uses a lexicon-based approach to determine the sentiment of a piece of text. Specifically, it uses a lexicon (i.e., a dictionary) of words that have been previously annotated with their polarity (i.e., positive, negative, or neutral) and intensity scores. Human experts create the lexicon and contains many words and phrases, including slang and emoticons. The SentimentIntensityAnalyzer is a class in the *nltk.sentiment.vader module* that provides a simple interface for sentiment analysis using the VADER (Valence Aware Dictionary and sEntiment Reasoner) algorithm. This algorithm considers the intensity of the sentiment expressed by each word and combines heuristics into an overall sentiment score for the text (Elbagir and Yang 2019). The VADER algorithm uses a set of rules to analyze the sentiment of a text. These rules include the following:

- Punctuation: The presence of punctuation, such as exclamation marks, question marks, and periods can indicate the intensity of the sentiment expressed.
- Capitalization: Words that are fully capitalized can indicate an increase in the magnitude of the sentiment.
- Emoticons: Emoticons such as :-) and :-(can be used to convey sentiment and are included in the VADER lexicon.
- Intensifiers: Words such as ”very” and ”extremely” can increase the intensity of the sentiment expressed.
- Negations: Words such as ”not” and ”never” can negate the sentiment expressed by a word.

The VADER algorithm also uses a set of heuristics to handle specific cases, such as:

- Handling conjunctions: when multiple sentiments are expressed in a single sentence, VADER can use heuristics to determine how to combine them into an overall sentiment score.
- Handling amplifiers: VADER can use heuristics to determine the impact of words that amplify the sentiment of other words in the text.

Overall, the VADER algorithm is designed to handle the nuances of natural language and produce accurate sentiment scores for a wide range of text (Elbagir and Yang 2019; Ittoo et al., 2016; Macanovic 2022).

5.1.2 Descriptive Statistics and tweets interaction

Table 12 shows the number of interactions on social media with positive and negative sentiments for the 11 days of the event window from September 18th to September 28th, 2019. The table includes data for each day, including the number of tweets, retweets, likes, and comments that were categorized as having positive or negative sentiments, in order to include also the possible effect of the eco-chambers of the tweets. The table shows that on each day, there were more interactions with a negative than positive sentiment. The total number of interactions with a negative sentiment over the 11 days was 800.110, while the total number of interactions with a positive sentiment was 707.986. The total interaction for each tweet has been calculated as $tweet \times \#\ of\ retweets \times \#\ of\ likes$. It is worth saying that we excluded comments for each tweet for the calculation of interactions. Although comments may offer supplementary perspectives on user engagement, incorporating them into the total interaction calculation may yield minimal incremental value. Retweets and likes generally serve as more straightforward and unambiguous measures of endorsement or approval, rendering them better suited for our analysis of the eco-chambers.

We expanded our Twitter dataset to include additional user information beyond sentiment analysis. Specifically, we retrieved self-declared job titles from each user's description and identified climate activist users and related keywords (see Appendix for the complete list of jobs and the number of environmental activist users). The user's self-declared job descriptions provide valuable information regarding the characteristics of individuals expressing opinions on Climate change. We found that out of the 263.024 tweets in our sample, users provide 5.166 self-declared job titles, without the overlapping of other jobs description for the same user (see Table 13). These users represent a diverse range of professions, including finance, law, education, and healthcare, among others. Additionally, we identified 8.371 users in our sample who declared

Table 12: Number of Tweets interaction from retweets and likes by sentiment type

Date	# of interactions with a negative sentiment	# of interactions with a positive sentiment
18/09/19	58.921	51.243
19/09/19	65.695	56.093
20/09/19	79.523	72.785
21/09/19	92.988	93.455
22/09/19	64.807	69.461
23/09/19	83.735	82.451
24/09/19	125.963	81.364
25/09/19	76.262	69.197
26/09/19	55.246	52.059
27/09/19	55.272	49.953
28/09/19	41.698	29.925
Total	800.110	707.986

Notes: Table 12 shows the number of interactions for each tweet (from 18/09/19 to 28/09/19) for each of the US states, respectively by type of sentiment, negative and positive, including the interactions based on retweets, likes and comments. Interactions are calculated as the sum of Tweet * Number of Retweets * Number of Likes. *Source*: Twitter API Academic Research product track; the authors processed the data.

themselves to be climate activists or used a related sequence of keywords such as "fight climate change" and "against global warming" in their self-description (see Table A.9 in Appendix for the list of the number of *activist* type in our sample). This sub-sample of climate activists provides an opportunity to explore the intersection between perceptions of financial performances and climate change activism in that US state in which social conditions can be linked with the economic performances of firms based in that state. We believe that this additional information will enrich our analysis and provide a more nuanced understanding of public sentiment towards climate change.

Table 13: Top 80 most frequent types of Jobs on users' description

Job	#	Job	#	Job	#	Job	#
writer	545	researcher	91	painter	19	soldier	7
teacher	298	singer	79	accountant	16	stylist	7
artist	278	doctor	60	environmental scientist	15	videographer	7
professor	221	chef	58	psychologist	15	carpenter	7
engineer	217	nurse	58	surgeon	14	publicist	7
photographer	212	analyst	58	firefighter	13	social media manager	7
coach	196	historian	54	graphic designer	13	software developer	7
editor	193	filmmaker	50	illustrator	13	detective	7
scientist	188	trainer	48	paralegal	13	financial advisor	6
entrepreneur	184	athlete	39	counselor	13	electrician	6
reporter	179	developer	35	social worker	12	environmental advocate	6
journalist	178	dancer	35	anthropologist	12	sociologist	5
consultant	149	gardener	33	project manager	12	art director	5
executive	132	judge	27	policy advisor	10	recruiter	5
manager	123	librarian	26	political scientist	10	marketing manager	5
designer	122	therapist	25	dietitian	9	pharmacist	5
lawyer	115	publisher	23	paramedic	9	fundraiser	5
actor	112	composer	22	prosecutor	8	program manager	5
architect	111	software engineer	19	creative director	8	climate scientist	4
musician	104	programmer	19	political analyst	8	content manager	4

Source: Twitter API Academic Research product track; the authors processed the data using Python package nktl.

For concern, the level of the sentiment, Table 14 presents the US daily sentiment for each day in the event window. The table includes the date and the corresponding daily sentiment level. The sentiment level is represented as a decimal number ranging from -1 to 1, where a negative number indicates a negative sentiment and a positive number indicates a positive sentiment. The sentiment analysis was conducted on a daily basis for the event window, which is a specific period of time analyzed in the study. The table provides insight into how the sentiment level fluctuated over the event window and can be used to analyze the effect of events or news on the sentiment level.

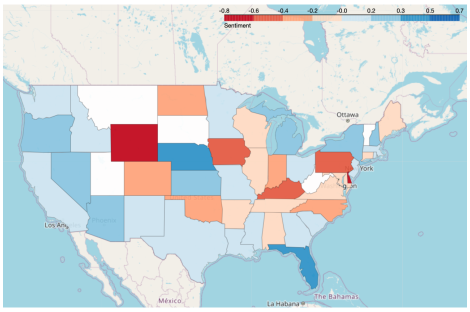
Table 14: US daily sentiment for each day in the event window

Date	Daily Sentiment level
2019-09-18	0,080817
2019-09-19	0,056001
2019-09-20	0,102401
2019-09-21	0,11896
2019-09-22	0,102277
2019-09-23	0,081561
2019-09-24	-0,08909
2019-09-25	0,081914
2019-09-26	0,101089
2019-09-27	0,100708
2019-09-28	0,000682

Notes: Table 14 shows the level of the sentiment concerning climate change of the tweets sample for each day (from 2019-09-18 to 2019-09-28) for each of the US state with available data. *Source*: Twitter API Academic Research product track; the authors processed the data.

Three figures are presented in this study, each representing a map of the United States on different days, highlighting changes in sentiment for climate change towards a specific event. The first figure, Figure 4, displays the sentiment map of the US the day before the event, where gradient colours indicate negative sentiment in red and positive sentiment in blue. As it is possible to note, the main sentiment is slightly positive or neutral as a sign of the robustness of this study, given the absence of the particular sentiment for the speech the day before it. Figure 5 displays the sentiment map of the US on the day of the speech, and Figure 6 represents the sentiment map of the US the day after the speech.

Figure 4: Average Sentiment for Climate Change - By US States - One day Before



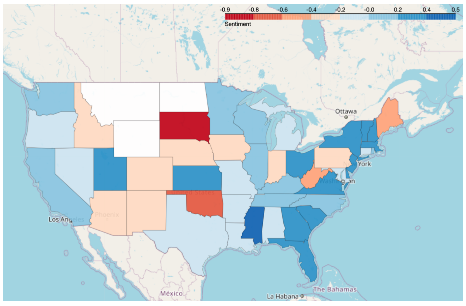
Source: *Data: Twitter API Academic Research product track; Figures: elaboration of the authors. Sentiment analysis followed the nltk methodology. Map of the US state has been retrieved from* `https://github.com/python-visualization/folium/blob/main/examples/data/us-states.json`*. Gradient colors from red to blue indicate: Red a strong negative sentiment; Blue a strong positive sentiment.*

Changes in sentiment are evident before and after the event, particularly in US states where fossil fuel companies provide employment, which has a significant social and economic impact on society, such as Texas, Ohio, Arkansas, and California. The gradient colors in these areas show a shift in sentiment, indicating that the event has had an impact on public perceptions of issues related to Fossil Fuel companies.

5.1.3 Methodology and sentiment results

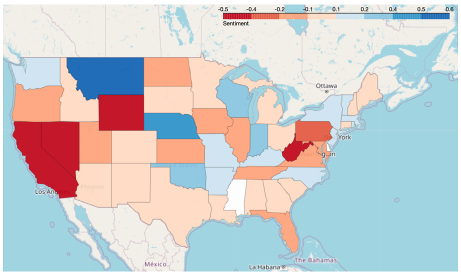
To see the relationship between the sentiments just derived from our algorithm presented in the previous section, we regress in two different equations, both the average US sentiment and the sentiments of the US states where the 15 firms are based using the abnormal returns obtained for the selected event as the

Figure 5: Average Sentiment for Climate Change - By US States - Day of the speech



Source: *Data: Twitter API Academic Research product track; Figures: elaboration of the authors. Sentiment analysis followed the nltk methodology. Map of the US state has been retrieved from* [*https://github.com/python-visualization/folium/blob/main/examples/data/us-states.json*](https://github.com/python-visualization/folium/blob/main/examples/data/us-states.json)*. Gradient colors from red to blue indicate: Red a strong negative sentiment; Blue a strong positive sentiment.*

Figure 6: Average Sentiment for Climate Change - By US States - One day after



Source: *Data: Twitter API Academic Research product track; Figures: elaboration of the authors. Sentiment analysis followed the nltk methodology. Map of the US state has been retrieved from* [*https://github.com/python-visualization/folium/blob/main/examples/data/us-states.json*](https://github.com/python-visualization/folium/blob/main/examples/data/us-states.json)*. Gradient colours from red to blue indicate Red, a strong negative sentiment; Blue, a strong positive sentiment.*

dependent variable, always considering a [-5;+5] window. Equation 9 below represents how the US sentiment variable enters our equation in our OLS regression model:

$$Abnormal\ Returns_{it} = \beta_0 + \beta_1\ (US\ sentiment)_{it} + \epsilon_{it} \tag{9}$$

Moreover, equation 10 below represents how the sentiment variables enter our equation in our OLS regression model:

$$\begin{aligned} Abnormal\ Returns_{it} = \beta_0 &+ \beta_1\ (Texas\ sentiment)_{it} + \beta_2 (California\ sentiment)_{it} + \\ &+ \beta_3\ (Ohaio\ sentiment)_{it} + \beta_4\ (Arkansas\ sentiment)_{it} + \\ &+ \beta_5\ (New\ York\ sentiment)_{it} + \epsilon_{it} \end{aligned} \tag{10}$$

where $Abnormal\ Returns_{it}$ represents the abnormal returns calculated for the eleven days of our event window, β_0 represents the intercept of our model, while the β_j coefficients represent all the coefficients of our sentiment independent variable. ϵ_{it} is the error term.

Table 15 shows the result from Equation 9. This outcome primarily substantiates two key aspects. Firstly, in general, it highlights the impact of Greta's speeches on individual sentiment related to climate change, which significantly impacts abnormal returns. Secondly, it demonstrates that when factoring in the average sentiment of all US states concerning climate change and evaluating the net effect of Greta's denunciation speech using the [-1;+5] window, sentiment negatively impacts the abnormal returns of fossil fuel companies. This consequently reaffirms the previously established notion that companies operating in pollution-intensive sectors are already subject, on average, to a considerable degree of reputational risk.

Now, in order to verify whether similar dynamics persist when considering only the sentiment of individuals living in the states where the fossil fuel companies are located, we present the regression results specified in Equation 10 in the following table.

Table 15: OLS Regression - Sentiment Analysis Fossil Fuel Top15 firms

Dependent Variable	Entire Event Window Abnormal Returns	From the day before Abnormal Returns	From the day after Abnormal Returns
US sentiment	-0.007	-0.174***	-0.506*
	(0.069)	(0.050)	(0.273)
Constant	0.007**	0.008***	0.022*
	(0.003)	(0.002)	(0.012)
Observations	150	90	60
R^2	0.070	0.506	0.545
Adjusted R^2	-0.034	0.406	0.390

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Table 15 shows a linear regression. Dependent variable: abnormal returns for the event window (from 2019-09-18 to 2019-09-28), for the period that starts the day before the event (from 2019-09-22 to 2019-09-28), and for the period that starts the day after the event (from 2019-09-224 to 2019-09-28) for the top15 Fossil Fuel firms by Market Capitalisation based in a US state. *Source*: Twitter API Academic Research product track and Bloomberg; the authors processed the data.

Table 16: OLS Regression - Sentiment Analysis Fossil Fuel Top15 firms

Dependent Variable	Entire Event Window Abnormal Returns	From the day before Abnormal Returns	From the day after Abnormal Returns
Texas Sentiment	0.085***	0.324***	0.093***
	(0.025)	(0.056)	(0.033)
California Sentiment	-0.00011	0.035***	0.543
	(0.013)	(0.009)	(0.335)
Ohaio Sentiment	0.105***	0.305***	0.096
	(0.019)	(0.052)	(0.080)
Arkansas Sentiment	0.046***	0.185***	0.0115
	(0.012)	(0.031)	(0.0113)
New York Sentiment	-0.162***	-0.088**	-0.124***
	(0.048)	(0.035)	(0.044)
Constant	0.027***	0.012*	-0.004
	(0.010)	(0.006)	(0.003)
Observations	150	90	60
R^2	0.305	0.626	0.675
Adjusted R^2	0.204	0.524	0.544

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Table 16 shows a linear regression. Dependent variable: abnormal returns for the event window (from 2019-09-18 to 2019-09-28), for the period that starts the day before the event (from 2019-09-22 to 2019-09-28), and for the period that starts the day after the event (from 2019-09-224 to 2019-09-28) for the top15 Fossil Fuel firms by Market Capitalisation based in a US state. *Source*: Twitter API Academic Research product track and Bloomberg; the authors processed the data.

Table 16 presents a regression analysis of sentiment analysis for the top 15 fossil fuel companies, with abnormal returns as the dependent variable. The table displays the coefficients of the independent variables, including Texas, California, Ohio, Arkansas, and New York sentiment, for the entire event window, the day before, and the day after the speech, respectively. The results show that Texas sentiment has a significant and positive effect on abnormal returns for the entire event window, the day before, and the day after the speech, with coefficients of 0.085, 0.324, and 0.093, respectively, all at a statistically significant level of 1%. The findings indicate that changes in sentiment towards fossil fuel companies in Texas have a strong impact on the abnormal returns during the event. The regression analysis also reveals that California sentiment has a significant and positive effect on abnormal returns the day before and a significant and negative effect on abnormal returns the day after the speech. However, the coefficients are not significant for the entire event window. The results also show that Ohio sentiment has a significant and positive effect on abnormal returns for the entire event window and the day before the speech, with coefficients of 0.105 and 0.305, respectively, at a statistically significant level of 1%. The coefficient for the day after the speech is not significant. Moreover, Arkansas sentiment has a significant and positive effect on abnormal returns for the entire event window and the day before the speech, with coefficients of 0.046 and 0.185, respectively, at a statistically significant level of 1%. Finally, the table shows that New York sentiment has a significant and negative effect on abnormal returns for the entire event window and the day before the speech, with coefficients of -0.162 and -0.088, respectively, at a statistically significant level of 1% and 5%. The R-squared values of the regression analysis indicate that the model has a good fit, with values of 0.305, 0.626, and 0.675 for the entire event window, the day before, and the day after the speech, respectively.

From an economic perspective, the results presented in Table 16 suggest that regional sentiment towards the top 15 fossil fuel companies has considerable implications for their financial performance, as measured by abnormal returns. Therefore, these results emphasize the importance of sentiment in driving the financial outcomes of the fossil fuel industry in the short term, particularly during events like the speech.

The positive and significant relationship between Texas, California, Ohio, and Arkansas sentiment and abnormal returns indicates that when sentiment in these states is favourable towards the fossil fuel industry, it tends to boost the financial performance of the top 15 fossil fuel companies. This may be because positive sentiment can influence investors' expectations, which in turn may lead to increased investment, driving up stock prices and abnormal returns.

On the other hand, the results for New York suggest that sentiment dynamics in this state may be more complex, as positive sentiment before the speech might be linked to positive expectations, while negative sentiment after the speech could reflect disappointment or a change in outlook. This highlights the potential for regional sentiment to play a crucial role in shaping investor perceptions and the financial performance of the fossil fuel industry.

Moreover, from a political economy perspective, New York and Texas, for example, have distinct political and cultural orientations, with New York generally leaning more liberal and Texas more conservative. As a result, individuals in New York may be more inclined to support policies to mitigate climate change and promote sustainable practices, thus making them more sensitive to climate change issues. In contrast, individuals in Texas, with its strong ties to the oil and gas industry, as shown by the number of fossil fuel companies based in this state, may not view climate change with the same level of concern, leading to a lower sensitivity to the issue.

On the other side, these findings underscore the importance of understanding regional differences in sentiment towards the fossil fuel industry and incorporating such insights into strategic decision-making, risk management, and communication efforts. For instance, companies and policymakers could tailor their messaging and policies to address sentiment shifts in different regions to navigate the financial implications of these changes better. Additionally, investors may want to consider regional sentiment dynamics when making investment decisions in the fossil fuel industry, as these factors can have a substantial impact on stock performance and risk exposure.

6 Conclusions

In recent years, the increasing concerns about the future effects of global warming have given rise to an unprecedented wave of environmental activism, especially by young people. In this paper, we study whether and how this call for bolder climate actions is influencing financial markets.

By analyzing the stock prices of a large sample of big firms, selected by market cap in 5 different sectors, automobile, fossil fuels, transportation, financials and renewable energy, around the occurrence of eight different climate-related events between 2019 and 2021, we provide evidence of a significant relative loss in stock performances for carbon-intensive firms. This stock-price penalty persists on average for all the selected events. In this study, to summarise, we examine several potential determinants of firm performance in relation to climate-related events. First, we find that the impact is more substantial for companies with lower environmental scores, as measured by the environmental reputation index utilized in our analysis. Additionally, firms in polluting sectors underperform compared to those in the green sector, which serves as our benchmark. We also observe that companies headquartered in countries with high Environmental Performance Index (EPI) values tend to outperform those with lower EPI scores. This could be attributed to their reduced exposure to potential future regulatory tightening or an indirect reputational effect associated with the country's environmental performance. Lastly, we conduct a sentiment analysis to investigate the correlation between individual attitudes towards climate change and the abnormal stock returns observed during the event window of Greta Thunberg's "How Dare You?" speech at the United Nations on September 23, 2019, for the top 15 fossil fuel companies based in a U.S. state. Our findings reveal a strong positive correlation between residents' sentiments in the state where these companies are located and their perceptions of climate change.

In terms of methodology, the basic idea of our event study is to compare the abnormal returns of a stock or portfolio during the event window with a market benchmark to capture the event's impact on the security's performance. To implement the event study analysis, we used a market model to estimate α β for each stock. First, we estimated these market model parameters using ordinary least squares (OLS) regression. Then, the abnormal returns are calculated as the difference between the actual returns of the security and the expected returns estimated by the market model.

Our key variable, the cumulative abnormal return, is calculated as the cumulative sum of the abnormal returns in the event window. Our hypothesis testing framework is based on the t-statistic, which measures the significance of the estimated abnormal returns. We used a one-tailed test with a significance level of 5% to test the hypothesis that the abnormal returns are negative during the event window, indicating that climate-related events negatively impact financial market performance. The event window is defined as the period from five days before the event day to the next 5 trading days. Given the aim of our analysis, we controlled for the impact of the control portfolio to capture the market-wide factors that might affect the cumulative abnormal returns of the stocks.

In the final section of this work, we provide an extension of our analysis about the cumulative abnormal returns based on the sentiment analysis of a sample of 263 thousand daily tweets from US users related to climate change and the eight climate-related events to check the possible correlation between the individuals' perception of climate change and financial market performances.

That said, we also are conscious that this study, at the moment, presents some issues and limitations. First, one limitation of this study is the limited time frame for the analysis, which will only cover the period of the events being studied. Additionally, the study focuses on the financial market performance of firms in response to natural disasters and climate-related events. Therefore, it does not consider other factors that may impact financial market performance, such as macroeconomic conditions or changes in the regulatory environment (see Section 2.3.2 for an overview of the possible impacts of the volatility in the oil market in the considered time span).

Another limitation is that this study only focuses on the impact of natural disasters and climate-related events on the financial market performance of firms in the five selected sectors. As a result, further research is needed to understand the impact of these events on the broader economy and society as a whole.

Third, the study relies on the availability of the data for the authors, which may not capture the full extent of the impact of natural disasters and climate-related events on the financial market performance of firms. Despite these limitations, we think that this study provides valuable insights into the relationship between natural disasters and climate-related events, financial market performance, and investor perception.

Finally, individuals' sentiments can be influenced by various factors, including political narratives and marketing strategies employed by companies. For example, individuals' sentiments about climate change may be shaped by political ideologies or marketing campaigns promoting the benefits of fossil fuels. Therefore, it is essential to consider the possible influence of these factors when interpreting sentiment analysis results. To better understand the transmission channels through which political and marketing influences affect individuals' perceptions, future research could analyze the language and themes used in political discourse and marketing materials related to fossil fuels and climate change. From a political economy perspective, such an analysis could provide valuable insights into the ways in which political and marketing messages shape public sentiment and attitudes towards climate change.

To conclude, our findings underscore the importance of companies prioritizing sustainable and climate-friendly practices to mitigate risks associated with climate events and enhance their reputation with investors. Firms in polluting sectors must address climate risks seriously and transition towards more sustainable and environmentally friendly practices. These efforts would not only help protect the environment but would also appeal to environmentally-conscious investors. The results of our study have implications for policymakers, investors, and firms, highlighting the need for strategies that promote sustainability and reduce climate-related risks in financial markets

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Appendix

A.1 List of all the companies in the dataset

Table A.1: List of companies - Transportation sector

Company Name	Market Cap.	Company Name	Market Cap.
UNITED PARCEL SER.B	145.22	CANADIAN PACIFIC RY.	68.64
UNION PACIFIC	122.13	CSX	61.43
CANADIAN NATIONAL RY.	81.14	NORFOLK SOUTHERN	53.05
CHINA TOURISM GROUP DUTY FREE 'A'	47.59	A P MOLLER MAERSK A	37.19
DEUTSCHE POST	44.1	DSV	31.48
FEDEX	41.73	OLD DOMINION FGT.LINES	30.25
MTR	27.22	TRANSURBAN GROUP STAPLED UNITS	26.14
KUEHNE UND NAGEL INTERNATIONAL	25.84	CENTRAL JAPAN RAILWAY	23.57
COSCO SHIPPING HDG.'H'	23.52	DELTA AIR LINES	22.23
SOUTHWEST AIRLINES	21.5	ADANI PORTS AND SEZ.	21.04
EAST JAPAN RAILWAY	20.33	ATLANTIA	18.52
HUNT JB TRANSPORT SVS.	17.56	AIR CHINA 'H'	17.41
AENA SME	17.33	EXPEDITOR INTL.OF WASH.	16.01
CHINA SOUTHERN AIRL.'H'	14.14	ZTO EXPRESS (CAYMAN) 'A' ADR 1:1	14.05
ADP	13.22	LOCALIZA RENT A CAR ON	12.32
CH ROBINSON WWD.	12.12	AMERCO	11.46
POSTE ITALIANE	11.39	SINGAPORE AIRLINES	10.81
WEST JAPAN RAILWAY	9.54	NIPPON YUSEN KK	9.13
EVERGREEN MARINE	9.05	GETLINK	8.71
SG HOLDINGS	8.67	INTERGLOBE AVIATION	8.25
DEUTSCHE LUFTHANSA	8.12	TFI INTERNATIONAL	7.73
KNIGHT-SWIFT TRSP.HDG. 'A'	7.66	GRUPO AEROPORTUARIO DEL PACIFICO	7.62
HANKYU HANSHIN HDG.	7.47	RUMO ON	7.38
TOKYU	7.12	MITSUI OSK LINES	7.11
QANTAS AIRWAYS	6.96	MISC BHD.	6.85
GRUPO AEROPORTUARIO DEL SURESTE B	6.76	YANG MING MAR.TRAN.	6.58
AUCKLAND INTL.AIRPORT	6.43	KINTETSU GROUP HDG.	6.4
HMM	6.38	AGILITY PUB.WHSG.	6.32
WAN HAI LINES	5.98	KOREAN AIR LINES	5.98
CONTAINER CORP.OF INDIA	5.81	YAMATO HDG.	5.6
AIR CANADA VOTING AND VARIABLE VOTING	5.25	TAIWAN HIGH SPEED RAIL	4.87
CMPH.COCS. RODOVIARIAS ON	4.86	TOBU RAILWAY	4.8
JIANGSU EXPRESSWAY H	4.75	CHINA MERCHANTS PORT HOLDINGS	4.72
HYUNDAI GLOVIS	4.55	KEISEI ELEC.RAILWAY	4.54
KEIO	4.49	NIPPON EXPRESS HOLDINGS	4.48
SITC INTERNATIONAL HDG.	4.46	ODAKYU ELECTRIC RY.	4.42
AURIZON HOLDINGS	4.29	BANGKOK EXPRESSWAY AND METRO NVDR	3.74
BTS GROUP HOLDINGS NVDR	2.88	ZHEJIANG EXPRESSWAY H	2.83
BEJ.CAPI.ARPT.H	2.56	MALAYSIA AIRPORTS HDG.	2.14
HOTEL SHILLA	1.96	SHENZHEN INTERNATIONAL HOLDINGS	1.71
COSCO SHIPPING PORTS	1.7	CJ LOGISTICS	1.39
AIRPORTS OF THAILAND NVDR	27.63		

Notes: Table A.1 represents the list of all the selected firms in the Transportation sector. *Source*: Bloomberg; the authors processed the data using STATA and Python.

Table A.2: List of companies - Fossil Fuel sector

Company Name	Market Cap	Company Name	Market Cap
EXXON MOBIL	455.86	CHINA SHENHUA EN.CO.'H'	76.18
CHEVRON	352.3	SCHLUMBERGER	71.54
RELIANCE INDUSTRIES	207.56	CHINA PTL.& CHM. 'H'	67.1
SHELL	199.45	OCCIDENTAL PTL.	66.92
CONOCOPHILLIPS	161.89	CANADIAN NATURAL RES.	66.57
TOTALENERGIES	142.11	GAZPROM	65.69
PETROCHINA 'H'	121.98	PIONEER NTRL.RES.	61.14
EQUINOR	115.67	OC ROSNEFT	59.06
BP	100.76	MARATHON PETROLEUM	56.63
PETROLEO BRASILEIRO	84.07	NK LUKOIL	53.19
LUNDIN ENERGY	0.54326	PHILLIPS 66	50.13
ENBRIDGE	78.97	DEVON ENERGY	49.77
EOG RES.	78.35	VALERO ENERGY	48.57
ENI	46.63	SUNCOR ENERGY	46
TC ENERGY	44.17	CHENIERE EN.	43.58
HESS	43.49	KINDER MORGAN	39.94
WILLIAMS	39.81	CENOVUS ENERGY	38.56
IMPERIAL OIL	33.59	NESTE	33.31
HALLIBURTON	32.64	BAKER HUGHES A	27.47
DIAMONDBACK ENERGY	27.35	PTT NVDR	27.06
ONEOK	26.69	YANKUANG ENERGY GROUP COMPANY 'H'	24.14
COTERRA ENERGY	23.95	OIL & NATURAL GAS	20.43
ECOPETROL	20.43	REPSOL YPF	19.89
PTT EXPLORATION AND PRODUCTION NVDR	18.86	TOURMALINE OIL	18.49
PEMBINA PIPELINE	18.05	TENARIS	17.96
SANTOS	16.57	SNAM	15.1
OMV	14.8	TATNEFT	14.56
INPEX	14.04	SURGUTNEFTEGAS	12.58
SK	10.95	SK INNOVATION	10.93
ENEOS HOLDINGS	10.71	CHINA OILFIELD SVS.'H'	9.21
EMPRESAS COPEC	8.93	GALP ENERGIA SGPS	8.41
ADARO ENERGY INDONESIA	8.03	BHARAT PETROLEUM	7.99
UNITED TRACTORS	7.73	PLKNC.NAFTOWY ORLEN	7.33
S-OIL	6.97	IDEMITSU KOSAN	6.55
WASH.H SOUL PATSN.& CO.	6.47	POLISH OIL AND GAS	6.27
COSAN INDUSTRIA E COMERCIO ON	5.74	PETRO RIO ON	5.63
TUPRAS TKI.PEL.RFNE.	5.41	MOL MAGYAR OLAJ-ES GAZIPARI	4.91
KEYERA	4.55	ENAGAS	4.25
AMPOL	4.14	EXXARO RESOURCES	3.92
VIBRA ENERGIA ON	3.83	HD HYUNDAI	3.34
SURGUTNEFTEGAZ PREF.	3.29	PARKLAND	3.26
ULTRAPAR PARTICIPOES ON	2.71	DIALOG GROUP	2.28

Notes: Table A.2 represents the list of all the selected firms in the Fossi Fuel sector. *Source*: Bloomberg; the authors processed the data using STATA and Python.

Table A.3: List of companies - Automobile sector

Company Name	Market Cap	Company Name	Market Cap
AISIN	7.68	BMW	52.26
APTIV	24.53	BORGWARNER	8.86
ASTRA INTERNATIONAL	17.03	BRIDGESTONE	25.44
BAJAJ AUTO	12.9	BYD 'A'	83.15
CONTINENTAL	10.35	CUMMINS	34.51
DENSO	38.09	DONGFENG MOTOR GP.	4.02
EICHER MOTORS	12.44	FAURECIA	2.89
FERRARI	36.32	FORD MOTOR	53.31
FUYAO GLASS INDUSTRY GP. CO.	11.4	GEELY AUTOMOBILE HDG.	10.79
GENERAL MOTORS	55.19	GENUINE PARTS	25.25
GREAT WALL MOTOR CO.	27.81	GT CAPITAL HOLDINGS	1.53
GUANGZHOU AUTOMOBILE GP.	13.63	HANKOOK TIRE TECHNOLOGY	3.16
HERO MOTOCORP	6.43	HONDA MOTOR	40.7
HYUNDAI MOBIS	14.48	HYUNDAI MOTOR	24.58
ISUZU MOTORS	8.99	KIA CORPORATION	18.82
KOITO MANUFACTURING	4.51	KUMHO PETRO CHEMICAL	2.71
LEAR	8.22	LKQ	14.97
MAGNA INTL.	16.13	MAHINDRA and MAHINDRA	19.8
MARUTI SUZUKI INDIA	34.82	MAZDA MOTOR	4.17
MERCEDES-BENZ GROUP N	62.31	MINTH GROUP	2.28
NIO ADR 1:1	16.19	NISSAN MOTOR	13.18
PORSCHE AML.HLDG.PREF.	17.54	RENAULT	9.2
SAIC MOTOR	22.62	STANLEY ELECTRIC	2.89
STELLANTIS	42.51	SUBARU	11.85
SUMITOMO ELECTRIC IND.	8.16	SUZUKI MOTOR	16.04
TATA MOTORS	18	TESLA	721.61
TOYOTA MOTOR	224.2	VALEO	4.01
YAMAHA MOTOR	7.14	VOLKSWAGEN PREF.	76.13
WEICHAI POWER 'H'	10.51	YADEA GROUP HDG.	4.71

Notes: Table A.3 represents the list of all the selected firms in the Automobile sector. *Source*: Bloomberg; the authors processed the data using STATA and Python.

Table A.4: List of companies - Renewable Energy sector

Company Name	Market Cap
BALLARD PWR.SYS. (NAS)	1.66
DAQO NEW ENERGY ADR 1:5	3.45
SUNRUN	4.65
XJG.GOLDWIND SCTC. H	5.67
HANWHA SOLUTIONS	6.44
XINYI SOLAR HOLDINGS	9.13
FLAT GLASS GROUP H	9.31
PLUG POWER	9.31
SIEMENS GAMESA RENEWABLE ENERGY	12.15
SOLAREDGE TECHNOLOGIES	12.89
VESTAS WINDSYSTEMS	20.04
ENPHASE ENERGY	41.49

Notes: Table A.4 represents the list of all the selected firms in the Renewable Sector sector. *Source*: Bloomberg; the authors processed the data using STATA and Python.

Table A.5: I List of companies - Financial sector

Company Name	Market Cap	Company Name	Market Cap
360 DIGITECH ADR 1:2	1.58	ABU DHABI COML.BANK	17.31
3I GROUP	13.15	AGRICULTURAL BANK OF CHINA	132.34
ABN AMRO BANK	8.91	AKBANK	4.11
ABRDN	3.76	AL RAJHI BANK	92.59
ABSA GROUP	9.39	ALINMA BANK	19.85
ALLY FINANCIAL	8.5	ARAB NATIONAL BANK	12.87
AMERICAN EXPRESS	112.41	ASX	8.09
AMERIPRISE FINL.	33.77	AUS.AND NZ.BANKING GP.	48.29
AMUNDI (WI)	9.46	AXIS BANK	33.69
APOLLO GLOBAL MANAGEMENT	31.85	B3 BRASIL BOLSA BALCAO ON	16.2
BAJAJ FINANCE	51.52	BANCO BRADESCO ON	35.5
BANCO DE CHILE	9.21	BANCO DE CREDITO E INVERSION	4.69
BANCO DO BRASIL ON	20.84	BANCO SANTANDER	44.37
BANCO SANTANDER BRASIL UNITS	20.2	BANCO SANTANDER CHILE	6.73
BANCOLOMBIA PREF.	6.55	BANDHAN BANK	5.19
BANK ALBILAD	13.44	BANK ALJAZIRA	5.12
BANK CENTRAL ASIA	69.28	BANK HAPOALIM B M LTD.	12.71
BANK JAGO INDONESIA	4.29	BANK MANDIRI	30.57
BANK NEGARA INDONESIA	11.17	BANK OF AMERICA	290.25
BANK OF CHINA	116.62	BANK OF COMMS.	41.86
BANK OF MONTREAL	63.54	BANK OF NEW YORK MELLON	34.2
BANK OF NINGBO 'A'	22.64	BANK OF SHAI. 'A'	11.09
BANK OF THE PHILP.ISLE.	7.46	BANK POLSKA KASA OPIEKI	4.26
BANK RAKYAT INDONESIA	45.07	BANQUE SAUDI FRANSI	13.9
BARCLAYS	26.9	BBV.ARGENTARIA	31.44
BCO BTG PACTUAL UNT	19.7	BDO UNIBANK	9.62
BK.OF NOVA SCOTIA	57.92	BLACKROCK	100.71
BLACKSTONE	112.3	BNP PARIBAS	58.01
BOC AVIATION	4.8	BOC HONG KONG HOLDINGS	32.12
BOUBYAN BANK	9.79	BROOKFIELD ASSET MAN. (NYS)	65.91
CAIXABANK	26.37	CANADIAN IMP.BK.COM.	40.93
CAPITAL ONE FINL.	40.91	CAPITEC BANK	12.21
CARLYLE GROUP	10.4	CBOE GLOBAL MARKETS(BTS)	13.31
CHAILEASE HOLDING	7.36	CHANG HWA COML.BANK	5.42
CHARLES SCHWAB	152.13	CHINA CINDA ASSET MANAGEMENT 'H'	3.65
CHINA CITIC BANK 'H'	26.35	CHINA CON.BANK 'H'	141.01
CHINA EVERBRIGHT BK.'A'	19	CHINA GALAXY SECURITIES 'H'	9.57
CHINA INTL.CAP.'H'	16.17	CHINA MERCHANTS BANK 'A'	92.9
CHINA MINSHENG BANKING 'A'	18.52	CHOLAMANDALAM INV.and FIN.	7.15
CIMB GROUP HOLDINGS	12.33	CITIC	27.16
CITIC SECURITIES 'A'	32.95	CITIGROUP	89.35
CITIZENS FINANCIAL GROUP	20.31	CME GROUP	62.81
COML.INTL.BANK (EGYPT)	4.12	COMMERZBANK	10.33
COMMONWEALTH BK.OF AUS.	112.18	CONCORDIA FINANCIAL GP.	3.71
CREDICORP	11.45	CREDIT AGRICOLE	27.63
CREDIT SUISSE GROUP	10.44	CTBC FINL.HLDG.	12.46
DAIWA SECURITIES GROUP	6.06	DANSKE BANK	13.93
DBS GROUP HOLDINGS	61.56	DEUTSCHE BANK	20.2
DEUTSCHE BOERSE	31.38	DISCOUNT	6.98
DISCOVER FINANCIAL SVS.	28.86	DNB BANK	27.28
E SUN FINL.HLDG.	10.28	EMIRATES NBD	22.79
EQUITABLE HOLDINGS	11.63	ERSTE GROUP BANK	10.75
EURAZEO	4.56	EURONEXT	6.95
FAR EAST HORIZON	3.3	FIFTH THIRD BANCORP	24.69
FINECOBANK SPA	8.33	FIRST ABU DHABI BANK	52.04
FIRST CTZN.BCSH.A	12.82	FIRST FINANCIAL HOLDING	10.1
FIRST REPUBLIC BANK	21.98	FIRSTRAND	20.32
FRANKLIN RESOURCES	11.82	GF SECURITIES 'H'	13.13
GOLDMAN SACHS GP.	121.67	GPO FINANCE BANORTE	22.92

Notes: Table A.5 represents the first part of list of all the selected firms in the Financial sector. *Source*: Bloomberg; the authors processed the data using STATA and Python.

Table A.6: II List of companies - Financial sector

Company Name	Market Cap	Company Name	Market Cap
GRUPO FINANCIERO INBURSA SRIES 'O'	11.19	HAITONG SECURITIES COMPANY	12.84
HANA FINANCIAL GROUP	8.58	HANG SENG BANK	27.21
HARGREAVES LANSDOWN	4.16	HDFC ASSET MANAGEMENT COMPANY	5.36
HONG KONG EXS.& CLEAR.	34.69	HONG LEONG BANK	9.7
HONG LEONG FINL.GP.	4.61	HOUSING DEVELOPMENT FINANCE CORPORATION	52.98
HSBC HOLDINGS	102.33	HUA NAN FINANCIAL HDG.	8.93
HUATAI SECURITIES 'H'	13.86	HUNTINGTON BCSH.	21.8
IA FINANCIAL	5.96	ICICI BANK	76.85
INDUSTRIAL & COML.BK.OF CHINA 'A'	197.8	INDUSTRIAL BANK	43.14
ING GROEP	37.18	INTERCONTINENTAL EX.	53.99
INTESA SANPAOLO	35.96	INVESCO	7.01
ITAU UNIBANCO HOLDING PN	49.85	ITAUSA INVESTIMENTOS ITAU PN	17.27
JAPAN EXCHANGE GROUP	6.95	JAPAN POST BANK	24.88
JP MORGAN CHASE & CO.	369.74	JULIUS BAER GRUPPE	10.27
KB FINANCIAL GROUP	13.71	KBC GROUP	21.21
KEYCORP	16.89	KKR AND	42.46
KOMERCNI BANKA	5.46	KOTAK MAHINDRA BANK	45.44
KUWAIT FINANCE HOUSE	34.21	LEGAL & GENERAL	15.96
LEUMI LTD.	14.62	LLOYDS BANKING GROUP	32.22
LONDON STOCK EXCHANGE GROUP	48.8	M&T BANK	29.08
MACQUARIE GROUP	41.24	MALAYAN BANKING	21.89
MARKETAXESS HOLDINGS	9.2	MASRAF AL RAYAN	9.7
MEDIOBANCA BC.FIN	7.7	MEGA FINANCIAL HOLDING	12.92
METROPOLITAN BANK AND TRUST	4.01	MIRAE ASSET SECURITIES	4.01
MITSUBISHI UFJ FINL.GP.	61.82	MIZRAHI TEFAHOT LTD.	9.7
MIZUHO FINL.GP.	27.29	MORGAN STANLEY	141.16
MOSCOW EXCHANGE	3.17	MUANGTHAI CAPITAL ORS NVDR	2.04
NASDAQ	30.59	NATIONAL AUS.BANK	64.66
NATIONAL BANK OF CANADA	22.78	NATIONAL BANK OF KUWAIT	25.72
NEDBANK GROUP	6.25	NOAH HOLDINGS 'A' 2:1 ADR	.79797
NOMURA HDG.	10.37	NORDEA BANK	35.75
NORTHERN TRUST	17.65	OLD MUTUAL LIMITED	2.7
ONEX	4.43	ORIX	18.21
OTP BANK	6.1	OVERSEA-CHINESE BKG.	38.15
PARTNERS GROUP HOLDING	24.17	PING AN BANK 'A'	27.88
PKO BANK	6.77	PNC FINL.SVS.GP.	65.8
POSTAL SAVINGS BOC.'H'	49.34	PUBLIC BANK	18
QATAR ISLAMIC BANK	15.52	QATAR NATIONAL BANK	48.46
RAIFFEISEN BANK INTL.	4.55	RAYMOND JAMES FINL.	25.65
REGIONS FINL.NEW	20.42	REINET INVESTMENTS SCA	3.15
RESONA HOLDINGS	8.97	RIYAD BANK	28.58
ROYAL BANK OF CANADA	128.39	SBERBANK OF RUSSIA	44.58
SBI HDG.	4.88	SEI INVESTMENTS	7.24
SHAI.PUDONG DEV.BK. 'A'	27.52	SHANGHAI COMMERCIAL	6.35
SHINHAN FINL.GROUP	13.17	SHRIRAM TRANSPORT FINANCE COMPANY	4.19
SIGNATURE BANK	9.99	SINGAPORE EXCHANGE	6.38
SINOPAC FINL.HDG.	5.67	SKANDINAVISKA ENSKILDA BANKEN A	23.42
SOCIETE GENERALE	19.36	SRISAWAD CORPORATION NVDR	1.46
ST.JAMES'S PLACE ORD	6.72	STANDARD BANK GROUP	15.99
STANDARD CHARTERED	17.43	STATE BANK OF INDIA	61.86
STATE STREET	27.44	SUMITOMO MITSUI FINL.GP.	38.17
SUMITOMO MITSUI TST.HDG.	10.68	SVB FINANCIAL GROUP	13.84
SVENSKA HANDELSBANKEN A	18.69	SWEDBANK A	17.22
SYNCHRONY FINANCIAL	16.28	T ROWE PRICE GROUP	24.28
TAISHIN FINANCIAL HLDG.	5.01	TAIWAN COOP.FINL.HLDG.	10.92
THE SAUDI BRITISH BK.	23.45	THE SAUDI NATIONAL BANK	71.25
TKI.GARANTI BKSI.	5.29	TMX GROUP	5.41
TOKYO CENTURY	4.11	TORONTO-DOMINION BANK	116.82
TRUIST FINANCIAL	59.77	UBS GROUP	56.45
UNICREDIT	24.64	UNITED OVERSEAS BANK	32.09
US BANCORP	63.69	WELLS FARGO & CO	175.81
WESTPAC BANKING	53.81	WOORI FINANCIAL GROUP	6.05
YUANTA FINANCIAL HDG.	7.62		

Notes: Table A.6 represents the second part of the list of all the selected firms in the Financial sector. *Source*: Bloomberg; the authors processed the data using STATA and Python.

A.2 Robustness Check - I

Table A.7: Robustness check regression - All Events

Dependent Variable:	CAR^5	CAR^5	CAR^5	CAR^5	CAR^5	CAR^5
E Score	0.00023*	0.00039***	0.00024*	0.00024*		
	(1.87)	(3.10)	(1.78)	(1.78)		
GHG Emissions Scope 1	-0.00000	-0.00000	-0.00000***	-0.00000***	-0.00000	-0.000001***
	(-0.31)	(-1.28)	(-3.43)	(-3.43)	(-1.31)	(-3.57)
Sector						
Automobiles				-0.063**	-0.069**	-0.067**
				(-2.33)	(-2.14)	(-2.10)
Financials				-0.018		
				(-0.47)		
Energy - Fossil Fuels				-0.052**	-0.054**	-0.055**
				(-2.47)	(-1.98)	(-2.05)
Transportation				-0.075***	-0.087***	-0.078***
				(-3.61)	(-3.23)	(-2.95)
E Score Category						
Brown					-0.021**	-0.011
					(-2.30)	(-1.13)
Grey					-0.014	-0.005
					(-1.64)	(-0.58)
Constant	0.006	-0.000	0.011	0.071***	0.098***	0.093***
	(0.84)	(-0.07)	(-1.46)	(3.57)	(3.59)	(3.46)
Event FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	No	Yes	Yes	No	No	No
Size FE	No	No	Yes	Yes	No	Yes
E Score Category FE	No	No	No	No	Yes	Yes
Observations	1384	1384	1384	1384	1296	1296
R^2	0.192	0.209	0.220	0.220	0.218	0.230
Adjusted R^2	0.187	0.201	0.211	0.211	0.210	0.221

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Table A.7 reports estimation results of Eq. (1-2-3) market-model cumulative abnormal returns on E Score index controlling also for GHG Emissions Scope 1. All specifications includes firm characteristics and sector fixed effects. Specifications 2 and 5 include also the size fixed effects based on the market capitalisation in USD. The t-statistics based on robust standard errors; t-statistics are shown in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. *Source*: Bloomberg; the authors processed the data using STATA and Python.

A.3 Robustness Check - II

Table A.8: Robustness check regression - All Events

Dependent Variable:	CAR^5	CAR^5	CAR^5	CAR^5	CAR^5	CAR^5
GHG Emissions Scope 1	-0.000	-0.000	-0.000***	-0.000***	-0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(-1.31)	(-3.57)
Sector						
Automobiles				-0.073***	-0.069**	-0.067**
				(0.020)	(-2.14)	(-2.10)
Financials				-0.065***		
				(0.019)		
Energy - Fossil Fuels				-0.049**	-0.054**	-0.055**
				(0.020)	(-1.98)	(-2.05)
Transportation				-0.073***	-0.087***	-0.078***
				(0.019)	(-3.23)	(2.95)
E Score Category						
Brown					-0.021**	-0.011
					(-2.30)	(-1.13)
Grey					-0.014	-0.005
					(-1.64)	(-0.58)
Constant	0.018***	0.019***	0.020***	0.083***	0.098***	0.093***
	(0.002)	(0.002)	(0.002)	(0.019)	(3.59)	(3.46)
Event FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	No	Yes	Yes	No	No	No
Size FE	No	No	Yes	Yes	No	Yes
E Score Category FE	No	No	No	No	Yes	Yes
Observations	3936	3936	3936	3936	1296	1296
R^2	0.140	0.150	0.158	0.158	0.218	0.230
Adjusted R^2	0.138	0.148	0.155	0.155	0.210	0.221

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Table A.8 reports estimation results of Eq. (1-2-3) market-model cumulative abnormal returns on GHG Emissions Scope 1. All specifications includes firm characteristics and sector fixed effects. Specifications 2 and 5 include also the size fixed effects based on the market capitalisation in USD. The t-statistics based on robust standard errors; standard errors are shown in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. *Source*: Bloomberg; the authors processed the data using STATA and Python.

A.4 Sentiment Analysis

A.4.1 Complete list of keywords

The query has been set on these list of keywords:
"*Climate*" OR "*Emissions*" OR "*Global warming*" OR "*Sustainability*" OR "*Environment*" OR "*Renewable energy*" OR "*Net zero emissions*" OR "*Green energy*" OR "*Climate change impacts*" OR "*Climate policy*" OR "*Climate justice*" OR "*Climate action*" OR "*Climate solutions*" OR "*Climate adaptation*" OR "*Climate mitigation*" OR "*Climate strikes*" OR "*Climate activism*" OR "*#ClimateChange*" OR "*#GlobalWarming*" OR "*#ClimateAction*" OR "*#ClimateCrisis*" OR "*#ClimateJustice*" OR "*#NetZero*" OR "*#Renewables*" OR "*#ClimateGoals*" OR "*#ClimateSolutions*" OR "*#ClimateStrikes*" OR "*#Greenpeace*" OR "*#ZeroEmissions*" OR "*#ActOnClimate*"

A.4.2 Complete list of jobs used for the query on users' description

- Political careers: political analyst, political scientist, political consultant, lobbyist, campaign manager, policy advisor, government affairs specialist, political strategist, political campaign manager, public affairs specialist, political researcher, government relations manager.

- Environmental careers: environmental analyst, environmental scientist, sustainability analyst, climate change analyst, environmental advocate, environmental policy specialist, sustainability manager, green policy advisor.
- General careers: programmer, developer, engineer, analyst, scientist, teacher, nurse, doctor, lawyer, judge, police officer, firefighter, soldier, architect, designer, artist, journalist, reporter, editor, publisher, photographer, filmmaker, musician, dancer, actor, athlete, coach, trainer, chef, entrepreneur, executive, manager, consultant, marketing professional, salesperson, customer service representative, HR professional, accountant.
- Marketing careers: marketing professional, content manager, copywriter, public relations specialist, social media manager, event coordinator, fundraiser, recruiter, hr manager, hr assistant, hr coordinator, training and development manager, talent acquisition specialist, payroll specialist, compensation analyst, benefits administrator, employee relations specialist, recruiting coordinator, sales manager, product manager, market research analyst, brand manager, media buyer, digital marketer, advertising manager, publicist, promotions coordinator, creative director.
- Design and IT careers: graphic designer, mobile developer, front end developer, back end developer, full stack developer, devops engineer, cloud engineer, network administrator, system administrator, security analyst, help desk technician, technical writer, solutions architect, database administrator, software developer, systems analyst, information security analyst, web developer, business development manager, quality assurance analyst, motion graphics designer, animator, illustrator.
- Entertainment, media and research careers: audio engineer, music producer, sound designer, film editor, makeup artist, stylist, costume designer, production designer, set designer, production manager, stage manager, theater director, dance choreographer, actor, singer, composer, writer, proofreader, librarian, museum curator, archivist, historian.
- Healthcare careers: nutritionist, dietitian, physical therapist, occupational therapist, speech therapist, optometrist, orthodontist, dentist, veterinarian, pharmacist, nurse, doctor, surgeon, physician assistant, emergency medical technician, paramedic.
- Legal careers: law enforcement officer, detective, criminal investigator, prosecutor, public defender, judge, lawyer, paralegal, legal assistant, court reporter, notary public.
- Financial careers: bank teller, loan officer, financial advisor, investment banker, insurance agent, real estate agent, property manager.
- Construction and maintenance careers: construction worker, carpenter, electrician, plumber, painter, landscaper, gardener, roofer, bricklayer.

A.4.3 Complete list of environmental activities used for the query on users' description

- activist
- campaigner
- community organizer
- environmentalist
- grassroots organizer
- human rights activist
- non-profit worker
- political organizer
- social justice advocate
- social worker
- sustainability specialist
- wildlife conservationist

- environmental scientist
- environmental policy analyst
- environmental lawyer
- climate justice activist
- green energy specialist
- sustainable development expert
- human rights lawyer
- social justice campaigner
- environmental health advocate
- animal rights activist
- environmental educator
- environmental justice advocate
- environmental journalist
- environmental campaign coordinator
- environmental program manager
- environmental engineer
- climate change activist

A.4.4 User's description - Type of self-declared activistis

Table A.9: Top 20 most frequent types of Environmental Activist self-description on users' description

Type of Activist	#
activist	650
environmentalist	92
campaigner	44
environmental scientist	30
environmental journalist	26
animal rights activist	26
social worker	24
human rights activist	18
human rights lawyer	16
environmental engineer	14
social justice advocate	14
community organizer	12
climate justice activist	10
environmental lawyer	10
political organizer	6
wildlife conservationist	2
environmental educator	2

Notes: Table A.9 shows the type of self-description based on the list of possible definition of environmental activists. *Source*: Twitter API Academic Research product track; the authors processed the data through Python code.

A.4.5 Methodological Example

Here an example abouth the Python code that has been used to obtain the sentiment score:

from nltk.sentiment.vader **import** SentimentIntensityAnalyzer

Create an instance of the SentimentIntensityAnalyzer

analyzer = SentimentIntensityAnalyzer()

Use the `polarity_scores()` method to get sentiment scores for a text string:

`sentiment_scores()` = analyzer.`polarity_scores()`("*I love this product! It's amazing*")

Print the sentiment scores

print `sentiment_scores`

here the output for a single sentence: {'neg': 0.0, 'neu': 0.333, 'pos': 0.667, 'compound': 0.7351}

A.4.6 Textual Example

"Despite the rainy weather, I had a great time at the park with my friends."
The lexicon-based sentiment analysis approach would break down this sentence into individual words and look up each word in a sentiment lexicon to determine its polarity and intensity score.

For example:
Despite: negative polarity, high intensity
rainy: negative polarity, low intensity
weather: neutral polarity, low intensity
great: positive polarity, high intensity
time: neutral polarity, low intensity
park: neutral polarity, low intensity
friends: positive polarity, low intensity

Based on these individual words' polarity and intensity scores, the sentiment analysis algorithm would then calculate an overall sentiment score for the sentence. In this case, the algorithm would likely classify the sentence as having a positive sentiment, despite the negative word "rainy".

Table A.10: Level of the sentiment for each US state in the event-window

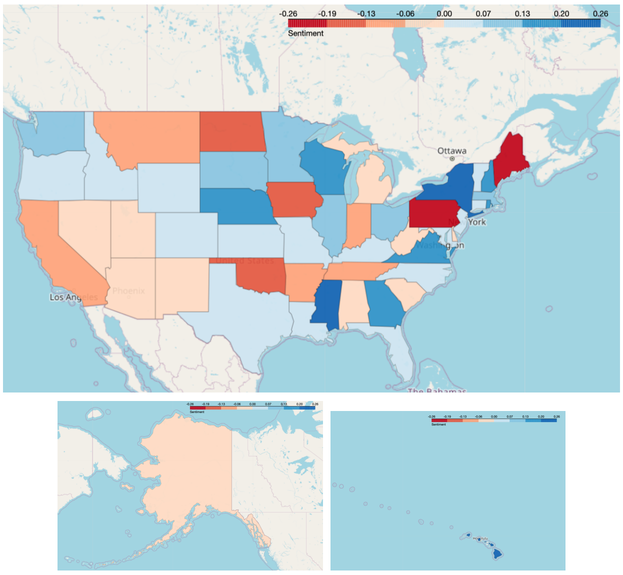
	Sentiment level for each day of the event-window										
State	2019-09-18	2019-09-19	2019-09-20	2019-09-21	2019-09-22	2019-09-23	2019-09-24	2019-09-25	2019-09-26	2019-09-27	2019-09-28
AK	-0.20	-0.54	0.11	0.02	0.72		0.64	-0.86	0.68	-0.23	0.30
AL	0.07	0.08	-0.05	0.04	-0.09	-0.07	-0.04	-0.31	-0.18	-0.19	0.18
AR	-0.39	0.02	0.10	0.13	-0.05	-0.17	0.12	-0.18	0.24	-0.14	-0.39
AZ	0.12	-0.30	-0.13	-0.14	0.25	-0.25	-0.06	0.11	0.04	0.08	-0.00
CA	0.01	-0.05	-0.06	0.10	0.14	0.10	-0.42	-0.02	0.04	-0.02	-0.02
CO	0.36	0.31	-0.16	0.16	-0.32	-0.25	0.00	0.00	0.31	0.16	0.22
CT	0.12	0.35	0.26	0.01	-0.12	-0.04	0.06	-0.10	0.11	-0.58	0.16
DC	0.12	0.12	0.14	0.08	0.23	-0.02	0.16	0.20	0.32	0.04	0.02
DE		-0.63	-0.15		-0.76	0.33		0.06	0.71	0.26	
FFL	0.01	-0.07	0.12	0.11	0.35	0.18	-0.14	-0.01	-0.16	0.04	0.36
GA	0.50	-0.21	0.41	0.44	0.03	0.20	-0.07	-0.14	0.14	0.12	0.30
HI	0.04	0.39	-0.11	-0.09	0.22	0.46	-0.04	0.20	0.46	0.67	-0.10
IA	0.34	-0.23	-0.13	0.05	-0.55	-0.24	-0.20	0.05	-0.66	0.07	0.38
ID	0.49	0.66	0.00	0.06	0.14	-0.36	-0.03	0.46	0.29	-0.15	-0.54
IL	0.45	-0.10	-0.02	0.13	-0.09	0.09	-0.11	0.10	0.24	0.50	-0.50
IN	0.17	0.08	-0.12	-0.27	-0.29	-0.22	0.26	0.02	0.62	-0.10	0.41
KS	0.60	0.20	-0.20	-0.04	0.17	0.17	-0.13	0.13	-0.41	0.14	-0.40
KY	-0.09	0.68	0.14	0.55	-0.40	0.13	0.08	0.07	-0.14	0.67	-0.24
LA	-0.20	-0.08	0.15	-0.02	0.00	-0.11	-0.04	0.43	0.28	-0.09	0.82
MA	0.47	-0.29	0.17	0.08	0.05	0.19	0.15	0.21	0.07	0.21	0.12
MD	0.13	0.18	0.01	0.10	-0.18	-0.04	-0.16	0.22	-0.05	0.04	-0.11
ME	-0.34	0.00	0.01	-0.77	-0.13	-0.53	-0.04	-0.36	-0.38	-0.27	0.11
MMI	0.04	0.12	0.20	-0.38	0.17	-0.16	-0.04	-0.36	-0.29	0.41	0.12
MN	0.32	0.06	0.17	0.01	0.11	0.13	0.06	0.10	-0.09	0.21	0.09
MO	-0.08	0.01	0.06	0.12	-0.01	-0.11	0.15	-0.19	-0.22	0.07	-0.18
MS	0.17		0.49	0.02	0.05	0.54		-0.12	0.50	0.46	
MT	0.12	-0.19	0.15	0.27			0.50	-0.62	0	-0.75	0
NA	0.03	0.01	-0.04	-0.07	-0.04	0.00	-0.06	0.08	-0.01	0.03	-0.04
NC	0.24	0.11	-0.11	-0.11	-0.22	0.04	0.13	0.18	-0.07	0.15	0.12
ND		-0.24		0.09	-0.29		-0.14	0.36	-0.61	-0.25	
NE	0.61	0.69	-0.03	0.28	0.50	-0.36	0.44	0.35	0.09	0.41	-0.11
NH	0.18	0.38	0.37	0.32	0.29	0.17	-0.00	0.06	0.10	-0.01	0.18
NJ	0.11	-0.15	0.07	0.30	0.09	0.24	0.14	-0.00	-0.27	0.10	0.09
NM	-0.40	0.12	0.41	0.48	0.00	-0.23	0.02	0.05	-0.26	0.33	-0.07
NNV	0.31	0.05	-0.43	-0.18	0.26	-0.13	-0.41	-0.04	-0.22	-0.06	0.06
NY	0.06	0.14	0.19	0.28	0.21	0.21	0.19	0.15	0.16	0.28	0.16
OH	0.43	0.24	0.09	0.22	0.07	0.29	0.03	0.10	-0.17	0.16	0.07
OK	-0.37	-0.10	0.08	0.01	-0.33	-0.76	0.28	0.12	-0.24	-0.12	0.10
OR	0.33	0.25	0.27	-0.09	0.28	-0.11	-0.17	0.13	-0.03	0.16	0.29
PA	0.17	0.32	0.06	-0.13	-0.42	-0.28	-0.34	0.17	-0.03	-0.34	-0.72
PR	-0.76	0.14	0.20	0.28		0.33	-0.32	0.21	-0.12		0.00
RI		0.25	0.28		-0.01	0.11	0.13	0.40	0.16	0.00	0.00
SC	0.05	0.01	-0.19	-0.17	0.10	0.28	0.06	0.18	0.19	-0.12	0.40
SD			-0.16	-0.07		-0.95	0.05	0.79	0.22	0.12	
TN	0.10	-0.28	-0.14	-0.06	-0.07	0.17	-0.16	-0.11	-0.10	-0.04	-0.04
TX	-0.07	0.10	0.01	-0.01	0.14	-0.14	-0.02	-0.01	0.05	-0.05	0.19
UT	0.15	-0.00	0.24	-0.02		0.17	-0.17	-0.30	-0.13	-0.46	-0.15
VA	-0.23	0.11	0.54	0.24	-0.13	0.17	-0.14	-0.17	0.35	0.17	0.10
VT	0.89	-0.23	-0.16	-0.02		0.28	0.16	-0.25		0.74	-0.27
WA	0.18	0.20	0.17	0.21	0.11	0.06	0.13	-0.00	0.01	-0.10	-0.11
WI	0.33	0.22	0.07	-0.30	-0.17	0.06	0.30	0.05	0.12	0.09	0.20
WV	0.03	0.02	0.00	-0.01		-0.44	-0.51	0.54	0.38	-0.30	-0.01
WY				0.79	-0.68		-0.49	0.23	0.41		

Notes: Table A.9 shows the level of sentiment for each US state (from 18th September 2019 to 28th September 2019) for each day of the event-window. *Source*: Twitter API Academic Research product track; the authors processed the data through Python code.

A.4.7 Averege sentiment of the US states during the entire event-window

Here below the map of the average sentiment of the US states for the entire event-window. The sentiment average has been calculated for each of the day of the event-window, from the 18th September 2019 to 28th September 2019, for all the US states with available tweets on this time period.

Figure A.1: Average Sentiment for Climate Change - By US States



Source: *Data: Twitter API Academic Research product track; Figures: elaboration of the authors. Sentiment analysis followed the nltk methodology. Map of the US state has been retrieved from* [*https://github.com/python-visualization/folium/blob/main/examples/data/us-states.json*](https://github.com/python-visualization/folium/blob/main/examples/data/us-states.json).

A.4.8 Sentiment per US state during the event-window

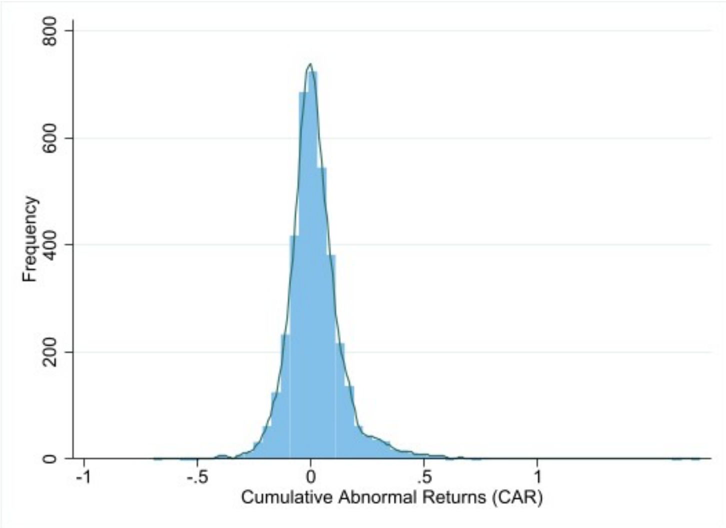
Here below the list of the average sentiment for each of the US states for the entire event-window. The sentiment average has been calculated for each of the day of the event-window, from the 18th September 2019 to 28th September 2019, for all the US states with available tweets on this time period.

Table A.11: Level of the sentiment for each US state in the event-window

US state	Level of sentiment	US state	Level of sentiment
AK	-0,05356	NC	0,03045
AL	-0,04287	ND	-0,19198
AR	-0,09149	NE	0,152413
AZ	-0,02069	NH	0,179732
CA	-0,08856	NJ	0,059663
CO	0,059517	NM	-0,04517
CT	0,061145	NV	-0,05272
DC	0,134985	NY	0,19846
DE	-0,01395	OH	0,127835
FL	0,049219	OK	-0,18336
GA	0,164532	OR	0,047872
HI	0,203405	PA	-0,23063
IA	-0,189	PR	-0,05628
ID	0,040052	RI	0,188921
IL	0,08723	SC	-0,00494
IN	-0,07897	SD	0,09329
KS	0,009311	TN	-0,07266
KY	0,063634	TX	0,006713
LA	0,020627	UT	-0,04646
MA	0,108534	VA	0,144801
MD	0,030817	VT	0,013189
ME	-0,25861	WA	0,091065
MI	-0,00038	WI	0,135125
MN	0,108613	WV	-0,03044
MO	0,003516	WY	0,043351
NA	-0,01593		

Notes: Table A.11 shows the level of sentiment for each US state (from 18th September 2019 to 28th September 2019). *Source*: Twitter API Academic Research product track; the authors processed the data through Python code.

Figure A.2: Distribution of Cumulative Abnormal Returns - All the events



Notes: Figure shows the distribution of the Cumulative Abnormal Returns for all the events for each firm of the sample. Data Source: Bloomberg; Elaboration of the authors.

Figure A.3: Distribution of Cumulative Abnormal Returns - Greta's speech "How dare you?"

Notes: Figure shows the distribution of the Cumulative Abnormal Returns for the event for each firm of the sample. Data Source: Bloomberg; Elaboration of the authors.

Taxation, health system endowment and institutional quality: 'social media' perceptions across Europe

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Abstract

In this paper we analyse how health system endowment and the quality of institutions impact perceptions towards taxation. We conduct a sentiment analysis of Twitter users' tweets to determine whether the impact of the Covid-19 health emergency has modified the attitudes of the citizens towards taxation in the four largest European countries: France, Germany, Italy and Spain. We use a difference-in-differences estimation strategy, comparing the average sentiments of individual tweets regarding taxation in different European NUTS-2 regions, before and after the spread of the Covid-19 pandemic. Our results highlight that in regions characterised by higher health system endowment people adopted more positive attitudes towards taxation with respect to those living in regions with low levels of health system endowment over the period -. In addition, we show how higher quality institutions led to more positive perceptions in relative and absolute terms, suggesting a greater predisposition for a more progressive tax system.

Keywords: Taxation; Sentiment Analysis; Tax compliance; Health System Endowment; Quality of Institutions; Covid-19 Crisis.

JEL classification: H26, H51, D04, C81.

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1 Introduction and Literature Review

The deep global recession caused by the Covid-19 pandemic health emergency has triggered all world economies. One relevant area of the debate regarding the consequences of this recent economic crisis is focused on the need to introduce additional taxation and to implement higher degrees of income redistribution. However, announcements by different European governments on the potential need for an introduction of wealth taxation to support low income citizens after the pandemic crisis split public opinion.[1]

Several factors have driven taxation over the long run in history. Limberg and Seelkopf (2022), analysing the historical drivers of wealth taxation, find out that recurrent taxes on net wealth are more recent than other progressive taxes. They demonstrate that also in the past net wealth tax was mainly used as an "emergency tax" when countries faced massive economic contractions. In history, also, wars required new taxes to finance the conflict and the associated debt (Walter and Emmenegger, 2021) or as a tool to balance the sacrifice between citizens (Scheve and Stasavage, 2012).

Public health faced unprecedented challenges in its efforts to contain the spread of the Covid-19 pandemic. Although essentially all health systems were unprepared for the emergency, there were considerable differences across and within countries. Rodriguez-Pose and Burlina (2021) find that excess mortality in the first six months of the pandemic was mainly concentrated in regions characterised by 'underfunded' health care systems.

In this vein, we investigate how much the quality of health system endowments during a recession triggered by a health crisis affect attitudes towards taxation. To do so, we used Eurostat data on the number of physicians per 100,000 inhabitants in NUTS-2 regions as a proxy for health system endowment quality[2], which may be considered as a proxy for public good provision of health care (Selway, 2021).

We construct our methodology to measure the level of sentiment towards taxation on Twitter as a proxy of citizens' perceptions. This allows us to investigate whether the Covid-19 pandemic and the subsequent economic crisis is modifying citizens' perspectives regarding taxation in the four largest European countries by conducting a sentiment analysis of French, German, Italian and Spanish users' tweets. From an empirical perspective, social media provides a unique space in which sentiments can be compared and updated. Twitter, for example, has become a valuable resource for analysing social trends, financial performance (Yu, 2013) and major political events (Rill et al. 2014). Kusen and Strembeck (2018) observed that these topics emerged earlier on Twitter than Google trends, showing a greater predisposition of Twitter users to express their opinions through the social network promptly. Khedr et al. (2017) built a predictive model of financial news and historical stock market prices based on sentiment analysis. More recently, Angelico et al. (2021) employed textual data and machine learning techniques to construct new real-time measures of consumers' inflation expectations based on Italians' tweets.

A recent stream of literature agrees that tax compliance (taxpayers' decision to pay tax regularly and in time) and its opposite, tax evasion, do not result from cost–benefit analyses but are determined by multiple personal and subjective factors, such as personal values, social norms and attitudes towards public institutions (Torgler, 2003). Braithwaite (2003) suggests that taxpayers are pushed to pay taxes by different motivations. While some may choose to comply based on commitments to the community, others may opt for tax evasion as a sort of game with the state. For this reason, economic psychology emphasise the context in which taxpayers trust state authorities, and other

[1] In particular, we refer to the political debate that took place in the following countries: Italy, France, Spain, Belgium and Portugal.

[2] This is one of the few measures of healthcare system quality at a granular level in Europe. While at an aggregate (country) level there are many measures of health system endowment quality, at a granular level (as well as homogeneously across European states) there are fewer.

variables, such as knowledge, attitudes, moral appeals, fairness and democracy, gain importance in addition to those considered in mainstream economic studies (Kirchler et al., 2007). Recessions inevitably lead to a contraction of income and involuntary unemployment, which may impact the prevalent views regarding the welfare state (Heinemann, 2011). Moreover, evidence suggests that greater individual participation in allocation and decision processes, together with a judgement on the role of government on expenditures and on the redistribution mechanism, will encourage an increased level of compliance. Casal et al. (2016) determine that tax compliance is significantly higher when citizens participate on contributions.

Higher institutional quality leads to a smaller shadow economy (Torgler and Schneider, 2009). To this aim, it is important to focus on the public's perceived institutional quality. To the best of our knowledge, we are the first to provide an empirical assessment of the role of health system endowment as a proxy of public good provision and a measure of perceived public expenditure efficiency that can lead citizens towards a higher degree of tax compliance[3].

We apply a difference-in-differences (DID) estimation strategy, comparing the average sentiment towards taxation as expressed by tweets in several European NUTS-2 regions[4], before and after the spread of Covid-19. Our findings highlight how, after March , people who live in regions characterised by a higher health system endowment became more favourable towards taxation.

These results are robust to the use of regional fixed effects that account for both the observable and unobservable characteristics of each NUTS-2 region. In addition, to confirm the validity of our identification strategy, we control for a full set of regional controls covering various dimensions, including geography, demographics and socio-economic context, among others. Following Durante et al. (2021), we integrate the controls into the model by interacting them with a pre-/post-pandemic dummy variable. Heterogeneity analyses show that the relation is more pronounced in areas characterised by high quality institutions as measured by the European Quality of Government Index (EQI). In contrast, it is not evident in areas where the quality of institutions is low.

Government quality is defined as the impartiality and efficiency of the public institutions through which the output of government is organised (Rothstein and Teorell, 2008). The quality of government has an impact on both social outcomes and public attitudes towards welfare policies. We stress that citizens are more favourable towards taxation in regions characterised by a high EQI score. This result is consistent with existing literature investigating the relationship between institutional quality, impartiality, corruption and taxation. For instance, Svallfors (2013) deeply analyses public perceptions of government impartiality and efficiency, finding that such perceptions influence attitudes towards taxes and social spending differently.

Ricciuti et al. (2018) analyse the long-run impact of political institutions, distinguishing between the accountability and transparency of fiscal institutions (impartiality) and effectiveness in extracting revenue, determining that the effect of political institutions on tax collection is substantial, for both income tax and total tax revenue. Developing robust tax systems that are effective, efficient and equitable is essential for sustaining legitimate and effective states with resilient fiscal social contracts and responsive tax morale (Brock, 2014). Corruption facilitates the spread of the informal sector, eroding the potential tax base (Schneider and Denste, 2000). In addition, it is well-known in the literature that the diffusion of corruption at different levels of government fosters increased tax evasion, damaging the culture of compliance (Aghion et al., 2016). The influence justifies the

[3]The choice of using health system endowment as representative of public good provision finds its root in what citizens have learnt after the diffusion of Covid-19 disease. While higher-quality hospitals have been associated with lower mortality rates, socioeconomically disadvantaged groups that obtain health care from lower-quality facilities have reported higher degrees of illness and death (Azar et al., 2020 ; Alsan et al., 2021). People may have thus perceived as prominent lesson emerging from the COVID-19 pandemic the need of the introduction of an integrated health system as a "universal public good" that may help in reducing the impact of a health disease.

[4]The Nomenclature of Territorial Units for Statistics (NUTS) classification is a system for dividing up the territory of the European Union for the application of regional policies. NUTS-1 corresponds to major socio-economic regions, while NUTS-2 indicates basic regions.

negative relationship between corruption and taxation that corruption has on tax compliance. To this aim, as suggested by Baum et al. (2017), strengthening institutions should be considered as a way to increase tax compliance.

We test the validity of our results using various robustness tests. First, we repeat our analysis by randomly allocating the number of physicians per 100,000 inhabitants across NUTS-2 regions, finding no effect. Following Guiso et al. (2017), we also replicate the model using alternative measures of health system endowment, namely, dummy variables based on the quartiles of the distribution interacted with the post-pandemic dummy. The main results remain broadly confirmed both by considering also retweets, by removing extreme values from the sample and without considering tweets with potentially biased hashtags. Moreover, we demonstrate that the results are not driven by pre-existing favourable attitudes towards taxation in regions with high health system endowment.

This paper is organised as follows. Section 2 shows the data and the descriptive statistics; Section 3 presents the identification strategy; Section 4 conducts the empirical analysis, detailing the placebo tests and the robustness checks applied; and Section 5 presents the policy implications and concludes.

2 Data and Descriptive Statistics

Social media has notably increased its impact on communication and the rapid and broad spread of news in the past decade. For instance, Chadwick (2011) illustrates how humanity is moving from a traditional 'news cycle'—dominated by journalists and professional sources—to a more complex 'information cycle'—integrating ordinary people into the on-going construction and contestation of news.

The debate on taxation is not an exception. Opinions and 'sentiments' on this topic clearly emerge within the social media app Twitter. This social network has 152 million users that communicate and discuss whatever they like within a 'tweet' (a short text of 280 characters or less). These expressions reflect individuals' thoughts and feelings regarding a multitude of concerns, such as taxation perception (Durán-Vaca and Ballesteros-Ricaurte, 2020) and carbon taxation (Zhang et al., 2021).

As for Covid-19-related issues, Chen et al. (2020) create a Twitter data set, demonstrating that the amount of data available grew significantly as the pandemic continues to run its course. Basiri et al. (2021) find that the sentiment in individuals' tweets is correlated to news and events that occur in their countries, such as the number of newly infected cases, recoveries and deaths. We measure the evolution of citizens' attitudes towards taxation using a sentiment analysis approach. Before introducing how our sentiment analysis is computed and presenting the results, it will be useful to briefly examine the differences between tax compliance behaviour and attitudes.

2.1 Tax compliance behaviour and tax compliance attitude

Tax compliance is the opposite of tax avoidance and tax evasion (Simon and Clinton, 2002). It is a measure of behaviour that can be influenced by different factors, both economic (such as the level of actual income, tax rate, tax benefits, tax audits, audit probabilities, fines and penalties) and non-economic (for example the willingness to pay for public provision, public education and tax morale)[5].

Individuals' behaviour regarding tax payment is not always consistent with their declared attitudes. This attitude–behaviour relationship is indeed rather weak, as suggested by an extensive body of research dating back to the 1930s (Liska, 1974). On the other hand, studies on taxation

[5]For a complete discussion on this alternative framework, please see Smith and Stalans (1991) and Barbuta-Misu (2011).

claim that citizens' tax-paying behaviour is measured by the intrinsic motivation to comply called the tax morale (Cummings et al., 2009). Tax morale depends on other (non)economic factors, such as concern for others, the individuals' perception regarding the significance of their actions, tax-payers' concern regarding general social welfare and social reciprocity and trust in the government (Alm et al., 2010). For instance, a more recent empirical study examines the relationships between taxation attitudes and behaviours to demonstrate that tax attitudes do not significantly predict tax behaviour (Guerra and Harrington, 2018).

In presenting this social media sentiment analysis, we are indirectly measuring the evolution of citizens' attitudes towards taxation.

2.2 Attitude towards taxation and Twitter

Tweets are collected as a proxy of individual citizens' sentiments and perceptions regarding taxation. We retrieve tweets on a weekly basis, for the period 2018–2022, using Python through the Twitter API Academic Research product track,[6] obtaining a dataset composed by 61,351 tweets. Data from Twitter are analysed using a dictionary-based method. To compute our sentiment analysis, we use the TwitteR package for the R programming language (Gentry, 2013; Philander and Zhong, 2016). Using the searchTwitter function, it is possible to capture any tweet containing specified keywords or hashtags. Tweets are retrieved using these parameters: country of origin of authors' tweet, the language of the country and the following keywords and hashtags: *property tax, taxes, spread, progressive taxation, public debt, fiscal equity, #taxtherich and inheritance tax.*[7]

Sentiment clustering is constructed by classifying tweet texts using positive and negative words from a sentiment lexicon, as in Philander and Zhong (2016). The words are scored following the scoring methods for classifying positive and negative words following Hu and Liu's (2004) work. As for the sentiment lexicon, a variety of methods and dictionaries attribute sentiments to the opinions, emotions or exclamations in a text. We choose the 'Bing' library, provided by Bing Liu and collaborators, which includes lexicons based on single words. These words (from many different languages, such as Italian, French, Spanish and German are only associated to negative or positive categories in a binary ('yes'/'no') fashion. We did not attribute to the words a rate for their degree of negativity or positivity but along the line of Philander and Zhong we only calculate an average sentiment score for each tweet. In formal terms, the average score is defined as follows:

$$AverageScore_{rt} = \frac{(\sum_{i=1}^{n} Pos_{rit} - \sum_{i=1}^{n} Neg_{rit})}{n_{rt}} \quad (1)$$

The average sentiment classification at year t represents the difference between the sum of positive words appearing in each tweet (i), aggregated at the regional level (r) and negative words appearing in tweets (using the aforementioned criteria), divided by the total number of tweets. For every individual text, we consider the difference between negative and positive words. If $Pos - Neg > 0$, we attribute 1 to the tweet, indicating that it is positive; otherwise, a 0 is assigned.

Some examples demonstrating how the average sentiment is computed is presented in Appendix A, in addition to a more detailed explanation of the data cleaning process. Sentiment classification

[6] For further details, see https://developer.twitter.com/en/docs/twitter-api.

[7] The keywords we considered are a result of a training period regarding the most used keywords related to taxation. While both property taxes and inheritance taxes belong to the category of wealth taxes (Levinson, 2021; OECD, 2021), discussions on taxation in general are also included. The aim of the sentiment analysis is to measure the changes in citizens' perceptions regarding the need for the welfare state during the pandemic crisis. These criteria are applied in each of the relative countries' languages. For French and Spanish texts, we set a geographic filter to exclude opinions of individuals from South America, Belgium and African French-speaking countries from the sample. For example, a search for 'dette publique', the French translation of public debt, returns any tweet, by any Twitter user discussing this topic. We then selected only texts from individuals located in France. Every keyword has been retrieved in each source language also using different synonym. Table A.6 shows how the sample is composed with respect to the different keywords and the number positive and negative tweets at the hashtag level.

for each region (r) is computed as the ratio of overall positive tweets over the total tweets at time t. For region (r), if $PosTweets - NegTweets > 0$, with PosTweets indicating those with a score of 1 and NegTweets those with a score of 0, we attribute a positive average sentiment to r. Moreover, API Academic Research makes it possible for us to examine specific users' individual information, including tweet id, author id, text, geographical coordinates, location name (NUTS-2 region and city/town), author's username and author's bio. We then cluster tweets according to the regional origin of each author (at the NUTS-2 level of observation). Regional origin is determined by the Twitter API geographical reference, which is automatically provided by Twitter. We choose not to include retweets in our datasets.[8]

Table 1 presents the distribution of the number of tweets for each year, the average aggregate sentiment per country each year and the level of observation of the analysis. At the aggregate level, the average sentiment is positive for France, Germany and Spain throughout the entire period of consideration, whereas Italian tweets are always negative. We aggregate the individual tweets at NUTS-2 level for France, Italy and Spain, while NUTS-1 is used for Germany, as it is comparable to the NUTS-2 regions of other three countries.

Table 1: Reference sample, average sentiment of Twitter users, share of positive tweets per country per year and level of observations

Country	Year	Number of Tweets	Average Sentiment	Share of Positive Tweets	Level of Observations
France	2018	1151	Positive	69.64 %	NUTS-2
	2019	2936	Positive	70.73 %	NUTS-2
	2020	1554	Positive	56.62 %	NUTS-2
Germany	2018	559	Positive	51 %	NUTS-1
	2019	3382	Positive	50.5 %	NUTS-1
	2020	3098	Positive	54.41 %	NUTS-1
Italy	2018	2655	Negative	44.94 %	NUTS-2
	2019	11870	Negative	41.28 %	NUTS-2
	2020	11216	Negative	43.61 %	NUTS-2
Spain	2018	7525	Positive	63.20 %	NUTS-2
	2019	6622	Positive	61.36 %	NUTS-2
	2020	6242	Positive	59.03 %	NUTS-2

Notes: Table 1 shows the number of tweets for each year (from 2018 to) for each of the four countries studied (France, Germany, Spain and Italy), respectively by average sentiment, share of positive tweets and level of observations. *Source*: Twitter API Academic Research product track; the authors processed the data.

2.3 Taxation in four countries

By examining users' biographies, we can include some additional considerations on our sample.

Table 2 presents the composition of Twitter users that we considered in the study. The Italian sub-sample differs from the other three groups in the proportion of politicians, which is 11.47% for Italy and between 2.56% and 3% in the other three countries. There is also a pronounced difference in the number of entrepreneurs and managers between Italy, Spain, Germany and France. The number of students and retirees is low for all countries. The most striking information is that the majority of users attained a high level of education. This characteristic is more pronounced for German, French and Spanish users, while nearly half of Italian users hold a degree or a PhD. An important consequence of this finding is that we are considering a sample that is far more educated than the average in their countries.

[8]Retweets are reposted messages from other users. Despite their contribution to the engagement of a tweet, we decided not to include them in our sample to avoid repeatedly including a single opinion. However, in Appendix A we report the analysis also considering retweets. We also repeat the analysis by considering the Tweets associated to political related keywords as neutral, to avoid the risk of including the echo-chambers in our sample. Since the aim of our study is to investigate the variation of sentiments proxied by tweets across time, we do not distinguish between users' number of followers.

Despite the higher education that characterises our users, we can assume they provide externally valid measures. Tucker et al. (2018) illustrate why direct media studies provide externally valid measures of media consumption. Barberá (2014) demonstrates that Twitter is reliable for increasing the validity of contextual variables, as it is used in real time and in real life, without giving users any notion that they are being studied, which provides confidence in the external validity of the measure. However, the higher degree of education observed in our sample may also be a consequence of homophily. For instance, in a study focusing on the behaviour of scholars in Twitter, Bisbee et al. (2020) present robust evidence of how users tend to interact more frequently than by chance with those who are similar to themselves in terms of gender, ideology and position. Moreover, in their study on the political alignment of Twitter users, among other aspects, Hoang et al. (2013) demonstrate that both sentiment and political affiliation have effects on information sharing, though these effects differ for different types of users.

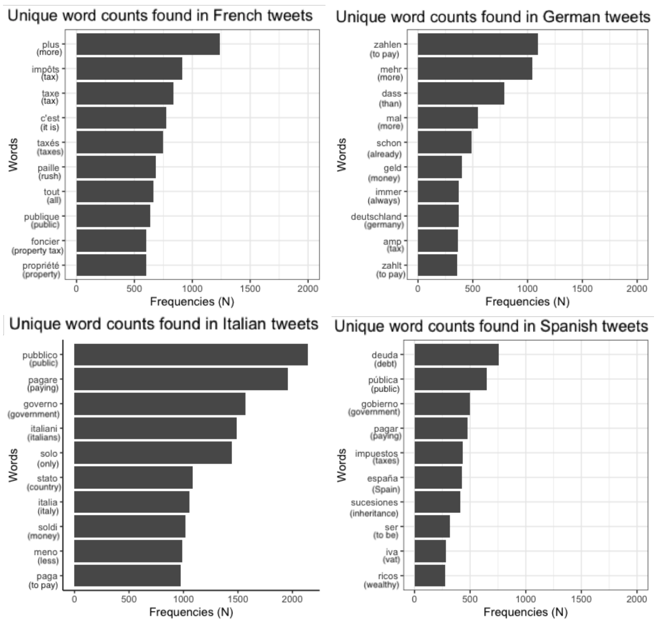
Table 2: Twitter users' most prevalent professional categories

	Italy	Spain	Germany	France
Jobs requiring a degree or PhD	47.41%	68.46%	80.35%	74.32%
Politician	11.47%	2.69%	2.56%	3.00%
Entrepreneur/Manager/Businessman	16.32%	23.85%	8.79%	10.54%
Student	0.44%	1.49%	0.18%	0.43%
Retired	0.99%	0.20%	0.37%	0.24%
Other	23.37%	3.31%	7.75%	11.47%
	100.00%	100.00%	100.00%	100.00%

Notes: Source: Twitter API Academic Research product track; Elaboration of the authors.

Fig. 1 illustrates the 10 most frequent words used in tweets from the four countries. Some words - "state", "debt", "pay", "government" - are common to all countries, but in different languages. Others - "wealthy", "money", "property" - are still related to the same topic, highlighting a common debate between countries when referencing taxation.

Figure 1: The 10 most frequent words in French tweets (top left panel), German tweets (top right panel), Italian tweets (bottom left panel), Spanish tweets (bottom right panel)



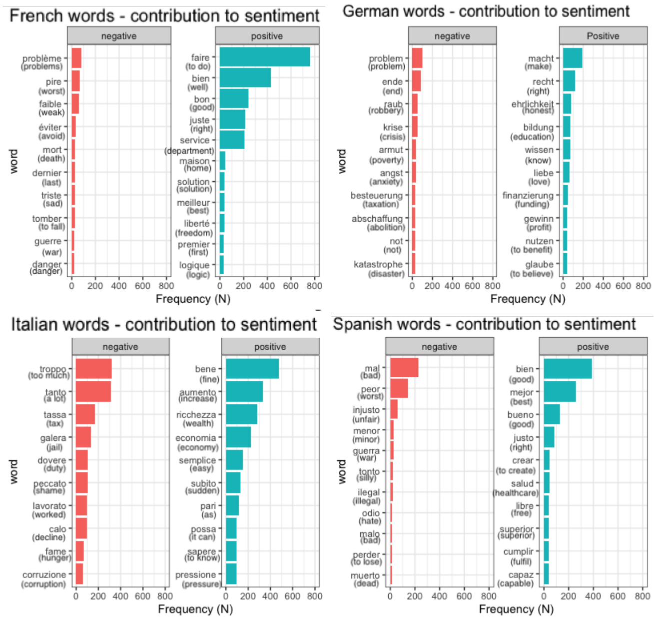
Source: *Twitter API Academic Research product track; Elaboration of the authors.*

Fig. 2 presents the frequency of the most used positive and negative words for France, Germany, Italy and Spain. Overall, positive sentiments predominate. While the difference is more pronounced for France and Spain, the gap is smaller for the other two countries. Notice that the statistics displayed in Table 1 refer to a sentiment analysis computed on the whole sample of the four countries. A more detailed empirical investigation is presented in Section 3, where we conduct NUTS-2 level and time fixed effects analyses.

Table 3 presents the descriptive statistics with respect to the variables included in the model. Four different groups of control variables are used in this study, the majority[9] of which are obtained from the Eurostat database (NUTS-2 level). Demographic controls include population, population density, the percentage of people with tertiary education, the percentage of people over 75 years of age and the number of women per 100 men. Geographic controls include latitude, ruggedness, area surface, distance from the coast and distance from Codogno, where the first outbreak of Covid-19 occurred in Europe in February . For the last variables, using Q-GIS software, we calculate the distance of each centroid of NUTS-2 regions from the coast and from Codogno, the European epicentre of the pandemic. This information has some limitations but, to the best of our knowledge, it is the most useful information for considering the spread of the pandemic for our period of analysis

[9] All the variables reported in Table 3 are obtained from Eurostat, except the EQI index, which is obtained from the European Quality of Government Institute at Gothenburg University and the distance from Codogno as well as from the coast, calculated by the authors using Q-GIS software.

Figure 2: Contribution to sentiment of the 10 most frequent words in French tweets (top left panel), German tweets (top right panel), Italian tweets (bottom left panel), Spanish tweets (bottom right panel)



Source: *Twitter API Academic Research product track; Elaboration of the authors.*

at such a granular level (NUTS-2). Indeed, we cannot use the speed at which the population was vaccinated, as our period of analysis unfortunately ends at the beginning of , the year in which vaccinations began in Europe. Regarding infections and tests, data are not available at such a granular level but only at the country level; however, Eurostat's supplementary weekly data include mortality rate, a time-varying variable that considers the difference between mortality rates in pre- and post-pandemic periods to account for excess mortality. We also account for some internet-related controls, including the number of households with internet access and the amount of time spent on social networks. We use per capita GDP, unemployment rate and high-tech employment rate as socio-economic variables. Finally, we consider the critical element of the quality of institutions, proxied by the EQI index.[10]

[10]The EQI index is a composite indicator based on three main dimensions of institutional quality, impartiality and corruption. Concerning the quality dimension, the index captures the quality of the public system as reported in specific individual level questions. The impartiality pillar is based on individual perceptions regarding the existence of advantages that some group(s) of people obtain within the public sector. Finally, the corruption dimension relies on both perceived and experienced corruption. The importance of the EQI is stressed by its uniqueness as sub-regional indicator of institutional quality. For further details, see https://www.gu.se/en/quality-government/qog-data/data-downloads/european-quality-of-government-index

Table 3: Descriptive statistics

Variables	Mean	Std.Dev.	Min	Max	Obs.
Positive tweets (%)	0.57	0.19	0	1	142
Physicians per 100,000 inhabitants (%) (NUTS-2)	390.52	74.54	259.75	629.07	142
EQI index (NUTS-2)	0.072	0.88	-2.09	1.31	142
Women per 100 men (NUTS-2)	104.73	2.34	99.2	109.3	142
Population, total (NUTS-2)	3,381,398	3,083,105	308,493	17,900,000	142
Population density (km^2) (NUTS-2)	296.17	608.80	25.7	4,289.8	142
Tertiary education, share (NUTS-2)	19.07	7.01	7.4	34.6	142
People over 75 years of age (%) (NUTS-2)	0.11	0.02	0.07	0.16	142
Mortality rate (NUTS-2)	0.01	0.002	0.01	0.017	142
Distance from the coast (km) (NUTS-2)	126.40	110.24	12.52	419.23	142
Latitude (NUTS-2)	45.30	4.90	28.34	54.18	142
Area (km^2) (NUTS-2)	22,784.45	18,091.28	399.81	94,217.59	142
Ruggedness (NUTS-2)	1.41	1.00	0.05	3.80	142
Distance from Codogno (km) (NUTS-2)	751.42	419.27	51.57	2,912.1	142
Social networks use (%) (NUTS-2)	48.52	7.59	30	63	142
Broadband(%) (NUTS-2)	87.45	5.37	74	97	142
Unemployment rate (20-64) (%) (NUTS-2)	9.02	4.75	2.3	21.2	142
GDP per capita (NUTS-2)	29,530.99	8,642.95	16,300	65,200	142
High tech employment (rate) (NUTS-2)	3.14	1.48	0.8	7.9	142

Notes: The authors directly extracted Twitter data, using Twitter's API Academic Research product track. The majority of the other variables used in the analysis are from Eurostat and relate to the pre-pandemic years (2018–) or, in the absence of data, to the last available year prior to the pandemic. The mortality rate variable is derived from Eurostat weekly data at the NUTS-2 level. For this and other variables, Eurostat provides data at the NUTS-2 level for all countries, except Germany, whose data are available only at the NUTS-1 level.

3 Identification Strategy

The role of the state and of its (in)efficiency in providing public goods is crucial for ensuring individuals' tax compliance. Cummings et al. (2009) use an experimental setting to demonstrate that cross-cultural differences in tax compliance behaviour find roots in individual perceptions of good governance.

Public health, a crucial determinant of government expenditure, is navigating unprecedented challenges in its efforts to control and to limit the spread Covid-19, with a sudden necessity to treat a large number of patients. Most countries and regions were unprepared to face the Covid-19 health emergency due to a lack of human and structural resources. Generally, the pandemic highlighted the un-preparedness of all health systems for managing the pandemic (Mauro and Giancotti, 2021). Different health system strengths may have led to different perceptions of the efficiency of public authorities, their adequacy to afford the emergency and gaps in satisfaction regarding how public money has been spent, leading to changes in citizens' attitudes towards taxation. We endeavour to investigate whether this also occurs in the post-pandemic scenario under consideration.

To determine the role of health system endowment in the evolution of attitudes towards taxation (Y), we estimate several versions of the following equation, where r denotes a NUTS-2 region in year t.

$$Y_{rt} = \beta\ (N^{o}Physicians_r \times Post_t) + \delta\ X_r \times Post_t + \eta\ Z_{rt} + \mu_r + \tau_t + \epsilon_{rt} \qquad (2)$$

where β is the coefficient of the interaction between the pandemic dummy variable ($Post_t$), which takes the value 1 in , and the $N^{o}Physicians_r$ variable, which varies at the NUTS-2 level. This coefficient captures the changes in attitudes towards taxation of individuals living in regions characterised by a high level of local health system endowment compared to those living in regions with low levels of local health system endowment in relative to .

X_r is a vector of time invariant variables defined at the regional level (at NUTS-1 or NUTS-2 levels of aggregation, depending on the available information) accounting for different demographic, geographic, internet-related and socio-economic characteristics.[11] These regional controls measured in the pre-pandemic period are interacted with the pandemic dummy ($Post_t$) to account for possible differences in the evolution of attitudes towards taxation associated to regional characteristics that might be correlated with the level of health system endowment.

The vector Z_{rt} includes the regional mortality rate, that is, a time-varying regional NUTS-2 characteristic that considers the impact of the pandemic. Finally, μ_c and τ_t are NUTS-2 region and time fixed effects respectively. μ_c controls for any time-invariant unobservable heterogeneity that could be correlated with both the attitude towards taxation and the health system endowment, while τ_t is the dummy that accounts for macroeconomic shocks that are common to all individuals.

The identification assumption that enables us to causally interpret β in Eq. (2) is that, conditional on controls, as well as regional time-varying controls Z_{rt} and regional fixed effects, the changes in attitudes towards taxation in in regions with a quality health system are not related to factors other than those we control for in the ($X_r \times Post_t$) interaction term. Moreover, we extensively test the robustness of our identification strategy, confirming that attitude towards taxation is not on a different trend in low versus high health system endowment regions in the pre-pandemic period (parallel trends assumption over the 2018– period) and we conduct a placebo test that supports our empirical results.

[11] Among other variables, demographic controls include population, population density, the percentage of people with tertiary education, the percentage of people over 75 years of age and the number of women per 100 men. Geographic controls refer to latitude, ruggedness, area surface, distance from the coast and distance from Codogno, where the first outbreak of Covid-19 occurred in Europe in February . Internet-related controls include the number of households with internet access and the amount of time spent on social networks. Socio-economic controls are per capita GDP, unemployment rate, high-tech employment rate and the EQI index. For further details, see Section 2.

Table 4: Impact of Covid-19 pandemic on the attitude towards taxation across regions with different health system endowment

Dep. Var: Positive tweets (%)	(1)	(2)	(3)	(4)	(5)	(6)
*N^o Physicians*Post*	0.1021**	0.0974**	0.0979**	0.0969**	0.0972**	0.0866**
	(0.0417)	(0.0420)	(0.0424)	(0.0428)	(0.0428)	(0.0402)
NUTS-2 FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
Demographic controls * Post		yes	yes	yes	yes	yes
Mortality rate (TV)			yes	yes	yes	yes
Geographic controls * Post				yes	yes	yes
Internet-related controls * Post					yes	yes
Socio-economic controls * Post						yes
Observations	142	142	142	142	142	142
R-square	0.7651	0.7754	0.7758	0.7961	0.7972	0.8080

Notes: The variable *N^o Physicians*Post* is the diff-in-diff interaction term between the number of physicians at NUTS-2 region level (2018) and the pandemic dummy. TV stands for time varying. Demographic controls include: population, percentage of graduates, percentage of over 75s, the number of women per 100 men, population density. Geographic controls include: latitude, ruggedness, area surface, distance from the coast and distance from Codogno. Internet related controls are the number of households with internet connection,as well as the amount of time spent on social network. Socio-economic controls include: GDP per capita, EQI index, unemployment rate and the share of high tech firms. Standard errors are clustered at NUTS-2 region level. * significant at 10%, ** significant at 5%, *** significant at 1%.

4 Empirical Results

Table 4 presents the estimates of the effects of the first wave of the Covid-19 pandemic on attitudes towards taxation in European regions with different levels of health system endowment.[12] As described in previous Sections, our sample consists of Italy, France, Germany and Spain.

The first column in Table 4 shows a specification without controls but including a full set of NUTS-2 and time fixed effects. Columns (2) to (6) present estimates that progressively include an increasingly wide set of controls. More specifically, demographic controls, geographic controls, internet-related controls and socio-economic controls (measured in , or in the last available year before the pandemic) enter the model interacted with the pandemic dummy variable (before/after the pandemic) to account for possible evolutions in attitudes towards taxation related to regional characteristics correlated with the number of physicians.[13]

For an aggregate interpretation of Table 4, the *N^o Physicians*Post* coefficient is significantly positive, suggesting that the pandemic raised aggregate positive tweets towards wealth redistribution, particularly in regions with a higher number of physicians. The coefficient is stable and significant (at a 5% level) between all specifications.[14] The coefficient of the most complete specification reported in Table 4 column (6) is 0.0866. This implies that the share of positive tweets towards taxation is 8.3 percentage points higher for those in regions with a very high number of physicians per thousand inhabitants (75th percentile) compared to those with a low number of physicians (25th percentile).[15]

To assess the stability of our results, referencing Guiso et al. (2017), we repeat the analysis

[12]Table A.12 in the Appendix replicates Table 4, presenting the coefficients of all control variables.

[13]Among other geographical controls, we include a geodetic distance between the centroids of each NUTS-2 region and the Italian pandemic epicentre (expressed in Km), as Italy was the first country in Europe where the Covid-19 pandemic broke out. However, since the pandemic resulted in many restrictions on people's movement, especially between different nations, we replicated all analyses using the distance of each NUTS-2 centroid from the national epicentre of the pandemic as a control and the results remain unchanged.

[14]The results remain significant even if region fixed effects are entered at the NUTS-1 level (instead of at the NUTS-2 level) and the N.°Physicians term is entered individually as control. The same is true if region fixed effects are not accounted for.

[15]The differential for positive tweets was calculated by multiplying the coefficient reported in Table 4 column (6) by the difference between the number of physicians per 100,000 inhabitants at the 75th and 25th percentile of the distribution. Thus, the number cited in the main text should be read as the difference in the dynamics of positive tweets in compared to between those living in regions with high and low health system endowment. Since the dependent variable, positive tweets, is a dummy (1 = positive tweet), the differential can be read in terms of percentage points.

using the interaction between the post-pandemic dummy and a dichotomous dummy variable as a dependent variable equal to 1 if the number of physicians is above the 75th percentile and 0 otherwise (see Appendix A, Table A.10).[16] Overall, the results remain the same.

To further explore the drivers of this result, we investigate whether the impact of the pandemic on perceptions towards taxation expressed via Twitter differ in regions with high or low level of institutional quality.[17] To capture the quality of institutions, we use data from the 2017 EQI from the European Quality of Government Institute at Gothenburg University, funded by the European Commission,[18] at the NUTS-2 level. This indicator, which is based on a large citizens' survey regarding the three dimensions, was first published in 2010 and then updated in 2013, 2017 and . The different versions of the indicator are strongly correlated with one another. As our research focuses on the time span 2018–, in this heterogeneous analysis we refer to the 2017 release.

In split sample, Table 5 presents the impact of the Covid-19 pandemic on attitudes towards taxation between regions with different health system endowment with low and high quality of institutions, respectively. Both specifications in the table are complete, including the full set of controls, as the main specification reported in column (6) of Table 4.

Table 5: Impact of the Covid-19 pandemic on attitudes towards taxation across regions with different health system endowment for different EQI

Dep. Var: Positive tweets (%)	low EQI (1)	high EQI (2)
N^o Physicians*Post	0.0136 (0.0328)	0.3193* (0.1593)
NUTS-2 FE	yes	yes
Year FE	yes	yes
Demographic controls * Post	yes	yes
Mortality rate (TV)	yes	yes
Geographic controls * Post	yes	yes
Internet-related controls * Post	yes	yes
Socio-economic controls * Post	yes	yes
Observations	72	70
R-squared	0.9416	0.8435

Notes: The variable N^o Physicians*Post is the difference-in-differences interaction term between the number of physicians at the NUTS-2 region level (2018) and the pandemic dummy. TV stands for time-varying. demographic controls, including population, percentage of graduates, percentage over age 75, the number of women per 100 men and population density. Geographic controls include latitude, ruggedness, area surface, distance from the coast and distance from Codogno. Internet-related controls are the number of households with internet access and the amount of time spent on social networks. Socio-economic controls include GDP per capita, EQI index, unemployment rate and the share of high-tech firms. Standard errors are clustered at the NUTS-2 region level. * significant at 10%, ** significant at 5%, *** significant at 1%.

[16] In addition, Table A.11 in the Appendix separately presents the coefficients of the dummy given by the interaction of the inclusion in each quartile of the distribution of the physicians per 100,000 inhabitants variable with the post-pandemic dummy. As shown, the regions in the first quartile (those with the lowest number of physicians per capita) in the post-pandemic period reduce the number of positive tweets regarding taxation, while those in the fourth quartile (regions with the highest number of physicians) increase positive tweets. The second and third quartiles around the median have no significant relationship.

[17] The EQI index is entered as a control in our main model. In particular, it is included in the specification considering the full set of controls (column (6) of Table 4).

[18] Please see https://www.gu.se/en/quality-government/qog-data/data-downloads/european-quality-of-government-index

Judging by both the significance and the magnitude of the coefficient reported in column (2) of Table 5, the investigated issue appears to be much stronger in the sub-sample of regions with high quality institutions compared to the overall sample, whereas there appears to be no significant effect in the sub-sample of regions with low quality institutions. In addition, the *N^o Physicians*Post* coefficient reported in column (2) of Table 5 is 0.319 and implies that the share of positive tweets towards taxation is 30.6 percentage points higher for those in regions with a high number of physicians per one hundred thousand inhabitants (75th percentile) compared to those with a low number of physicians (25th percentile). The effect of the pandemic appears to be more than threefold that found in our main specification (as indicated in column (6) of Table 4).[19] This difference may be explained by the fact that in regions with low quality of institutions people are less favourable to increasing taxation overall, since low quality institutions in the pre-pandemic period have a positive correlation with lower trust in them.[20] Consequently, people living in such areas tend to attribute less importance to health system performance in combating the pandemic in relation to taxation choices (as proxied by tweets), as institutions' poor reputations cannot be offset by the effect of approaches for curbing the pandemic. Conversely, where institutions are stronger, i.e. less corrupt, more impartial and of higher quality, individuals tend to be guided by the quality of the local health system (the most important issue at the time) in their choice of taxation and redistribution.

[19] This result seems to align with Bottasso et al. (2022), who find an increase in political trust in European regions with high quality institutions after the first pandemic wave compared to those with low quality institutions.

[20] Subsequently, the EQI index seems to be an appropriate indicator to capture this phenomenon, as it is a composite indicator that includes perceptions of institutions' corruption, quality and impartiality.

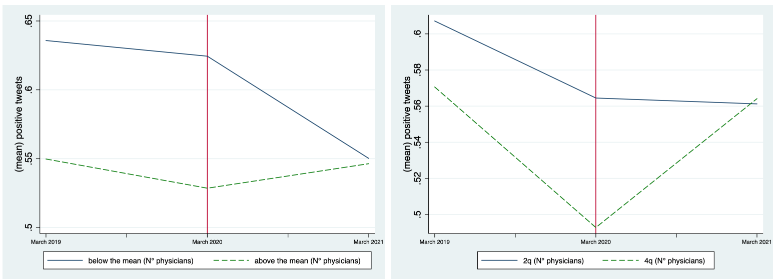
4.1 Parallel trends, placebo and robustness checks

We next run a battery of placebo and robustness checks to validate our empirical approach. Furthermore, we also investigate the validity of the parallel trend assumption.

Indeed, the DID research design and our identification strategy are valid under the assumption of a common trend in tweets regarding taxation between treatment and comparison groups before the outbreak of the Covid-19 pandemic. Since all regions in our study are considered 'treated' and what changes is the intensity of treatment, we separate the regions according to health system endowment. Thus, our treatment group includes regions within the four European countries analysed that have a number of physicians per 100,000 inhabitants above the aggregate average, whereas the control group includes regions that have a number of physicians per 100,000 inhabitants below the aggregate average.[21]

The graph on the left hand side of Fig. 3 presents the trend in pro-tax tweets weighted by the number of total tweets in a region for the period 2018 to . The blue line depicts the trend for the treatment group and the dashed green line depicts the trend for the control group. The graph on the right hand side in Fig. 4 investigates the same issue, assuming a different definition for treatment and control groups in which the treatment group includes those who are in the second quartile of the distribution regarding the number of physicians per 100,000 inhabitants, while the control group considers the fourth quartile. In both graphs of Fig. 4 the path of attitudes towards taxation in the pre-pandemic period, as proxied by the number of positive tweets over the total number of tweets related to the issue, is very similar for the treatment and control groups. What emerges demonstrates that the number of positive tweets from regions characterised by a number of physicians below the average decreased after the spread of the pandemic, while people adopted a more friendly attitude towards taxation where more physicians per 100,000 inhabitants are present. This result aligns with the findings of a consistent portion of the literature on tax compliance.

Figure 3: Parallel trend analysis



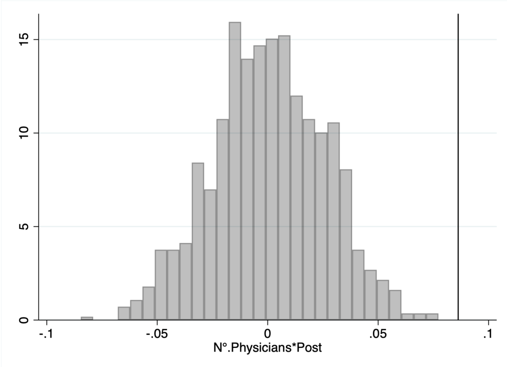
Notes: Mean number of physicians index for the pre-pandemic period (2018–), as well as quartiles of the distribution based on Eurostat 2018 and Twitter data.

As previously discussed, to further test the validity of our research design, we also perform a placebo analysis, randomly assigning the dependent variable of positive tweets towards taxation (%) across regions and keeping the number of treated and control regions constant. Fig. 4 presents the frequency of *N^o Physicians*Post* estimated coefficients obtained from replicating the specification in column (6) in Table 4, after randomly distributing the dependent variable. We replicated this placebo 1,000 times. As shown in Fig. 4, the largest number of estimated coefficients reveal a value of zero for our main independent variable, indicating that among 1,000 replicated placebo regressions, the value of the *N^o Physicians*Post* coefficient is not evident in the main analysis, represented by

[21] "Aggregate average" indicates the average regional health system endowment, considering all regions within the European countries included in the analysis.

the black vertical line. This placebo analysis provides further evidence supporting the validity of our results. Moreover, in Appendix A, we provide further evidence of the validity of our research design by testing any lack of balance among the controls (Table A.8) and assessing the stability of the results by excluding extreme values from the sample (Table A.9).

Figure 4: Random allocation of positive tweets (%) towards taxation across regions



Notes: The estimate reported in Fig. 4 is made by taking our main equation as the base equation. The dependent variable is the positive tweets variable (weighted on total tweets), while *N° Physicians*Post* is the difference-in-differences interaction term between the health system endowment index and the pandemic dummy, divided by one hundred to normalise the indicator. Controls include demographic controls (population, percentage of graduates, percentage over age 75, the number of women per 100 men and population density); geographic controls (latitude, ruggedness, area surface, distance from the coast and distance from Codogno); interne-related controls (the number of households with internet access and the amount of time spent on social networks); and socio-economic controls (GDP per capita, EQI index, the share of high-tech firms and the unemployment rate). The y-axis indicates the probability density function of the estimated coefficients. The black vertical line is placed in correspondence of the 'true' estimated value of the coefficient, reported in column (6) of Table 4. (N. Physicians*Post = 0.0866**).

5 Conclusions

Over the last decades, continuous and growing social and political discussions regarding the need for more redistributive policies have taken place in Western economies. In light of this debate, this article evaluates the impact of the Covid-19 pandemic and the consequent economic crisis on citizens' perceptions of taxation. We evaluate the role of the health system endowment in the four largest countries of the European Union: France, Germany, Italy and Spain. We apply a simple social sentiment analysis using different keywords related to the topic to measure Twitter users' perception and attitudes towards taxation.

To examine the mechanism of health system quality in this debate, we use a DID estimation strategy, comparing the average sentiment reported in tweets by individuals living in NUTS-2 regions with high/low levels of healthcare system endowments, before and after the spread of the Covid-19 pandemic.

Two results are worth noting. First, in regions characterised by a high number of physicians, citizens adopt more positive attitudes towards taxation with respect to the period before the spread of Covid-19. The ability to curb the pandemic with higher health care endowment seems to have been the real game changer with respect to citizens' propensity towards taxation. The COVID-19 health crisis with the consequent economic downturn may have caused the introduction of additional taxation *di per sè*, since several times in history additional taxes have been levied to face an emergent need of (extra) revenues (Limberg and Seelkopf, 2022). However, when new taxes are introduced as short-term measures they hardly remain part of long-term government fiscal policy tools. Second, this favourable attitude is more present for area with high quality of institutions, while it vanishes for those where the quality of institutions is low. Where institutions are stronger, more impartial and of higher quality, individuals' attitude towards taxation tend to be more sensitive to how healthcare expenditure is managed. This suggests that widespread support for public policies depends on the quality of the institutions in regions in which they are delivered.

In terms of policy implications, we highlight that efficient public expenditure as well as a higher health system endowment generates favourability towards redistributive policies in governments that are considered trustworthy. As Midgley (1999) suggests, social development offers an alternative perspective on redistribution, emphasising how resources are allocated and preferring social programmes that are investment-oriented, since they encourage economic participation and make a positive contribution to overall development. European economic and social challenges and pandemic recovery will require a certain degree of redistribution, which must be supported by citizens. To encourage support for these measures, positively framed information from government and policymakers should promote a positive public awareness of the ways in which public finances are employed. Moreover, it is crucial to couple a high quality of the health system endowment with an increase in the quality of institutions to encourage a stronger people's attitude towards taxation. In areas characterised by a low quality of institutions an improvement of the health system will probably not have a significant impact in terms of attitude towards taxation.

Future research could evaluate the effect of tax morale on the level of persistence in the degree of positive (negative) public opinion and perceptions of institutions.

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Appendix A

A.1 Sentiment analysis

To compute the level of sentiment, we first cleaned the data using the following steps:

- removing punctuation from textual data;
- erasing common words unable to express a sentiment;
- counting the positive and negative words in each tweet;
- generating the average sentiment for tweets computed at the regional level.

Tables A.1, A.2 and A.3 provide three examples of how a tweet of the sample was cleaned and classified as positive or negative. In particular, Tables A.2 and A.3 provide two demonstrations of how we treat a tweet that handles (double) negations in a random italian and french text respectively.

Table A.1: First example of the procedures applied to random tweets in the sample

Original Tweet	**English Translation**
XXX Un'altra bugia era quella della Patrimoniale #DiMaio lo ha ripetuto molte volte che non la faranno! il RDC non e diminuito #Romano deve smettere di raccontar #Bufale @NonelArena	XXX Another lie was the one about the wealth tax #DiMaio has repeated many times that they won't do it! the RDC (=basic income) is not diminished #Romano must stop telling #Lies #NonelArena @nonelarena
First Step: Removing punctuation from textual data	
XXX Un altra bugia era quella della Patrimoniale DiMaio lo ha ripetuto molte volte che non la faranno il RDC non e diminuito Romano deve smettere di raccontar Bufale NonelArena nonelarena	XXX another lie was the one about the wealth tax DiMaio has repeated many times that they won't do it the RDC is not diminished Romano must stop telling Lies NonelArena nonelarena
Second Step: Eliminating common words that did not express a sentiment	
bugia patrimoniale molte volte non faranno RDC non diminuito bufale	lie wealth taxation many times will not do it RDC not diminished hoax
Third step: Quantifying the ratio score	
bugia (=negative) patrimoniale molte volte non faranno non diminuito (=negative) bufale (=negative)	lie (=negative) wealth taxation many times will not do it not diminished (=negative) hoax (=negative)
Final step: Calculating the average sentiment of tweets at individual and regional levels	
	$Pos - Neg < 0.$ then the tweet is negative. If $Number\ of\ Pos\ Tweets - Number\ of\ Neg\ Tweets < 0$ holds true for all the tweets of a certain region, then we consider the average sentiment of that region negative (otherwise positive).

Table A.2: Second example of the procedures applied to random tweets in the sample

Original Tweet	**English Translation**
XXX non è un problema di aliquote è un problema di #evasori e in italia sono tanti a non pagare le tasse e tu ne sai qualcosa	XXX it is not a problem of tax rates it is a problem of #evaders and in Italy there are many (people) who do not pay taxes and you know something about that
First Step: Removing punctuation from textual data	
XXX non è un problema di aliquote è un problema di evasori e in italia sono tanti a non pagare le tasse e tu ne sai qualcosa	1) XXX it is not a problem of tax rates it is a problem of evaders and in Italy there are many people who do not pay taxes and you know something about that
Second Step: Eliminating common words that did not express a sentiment	
XXX non problema aliquote problema evasori italia tanti non pagare tasse ne sai qualcosa	XXX not problem tax rates problem evaders Italy many people not pay taxes know something about
Third step: Quantifying the ratio score	
XXX *non problema* (c(negative-1, negative+1)=0) aliquote problema(=negative) *evasori tanti*(=negative) *non pagare*(=negative) tasse ne sai qualcosa	XXX *not problem* (c(negative-1, negative+1)=0) tax rates problem(=negative) tax evaders(=negative) italy *lots of not paying* taxes(=negative) you know something about it
Final step: Calculating the average sentiment of tweets at individual and regional levels	
	$Pos - Neg < 0.$ then the tweet is negative. If $Number\ of\ Pos\ Tweets - Number\ of\ Neg\ Tweets < 0$ holds true for all the tweets of a certain region, then we consider the average sentiment of that region negative (otherwise positive).

Table A.3: Third example of the procedures applied to random tweets in the sample

Original Tweet	**English Translation**
XXX Rappelons qu'il y a 57% de taxes sur la facture EDF et que ces taxes comprennent aussi une taxe pour payer la retraite des agents EDF et Engie.... pas mal la France de la redistribution	XXX Remember that there are 57% taxes on the EDF bill and that these taxes also include a tax to pay the retirement of EDF and Engie agents.... not bad France of redistribution
First Step: Removing punctuation from textual data	
XXX qu il y a de taxes sur la facture EDF et que ces taxes comprennent aussi une taxe pour payer la retraite des agents EDF et Engie pas mal la France de la redistribution	XXX Remember that there are 57 taxes on the EDF bill and that these taxes also include a tax to pay the retirement of EDF and Engie agents not bad France of redistribution
Second Step: Eliminating common words that did not express a sentiment	
XXX taxes facture taxes comprennent aussi taxe payer retraite agents pas mal redistribution	XXX remember taxes bill taxes include tax pay retirement agents not bad redistribution
Third step: Quantifying the ratio score	
XXX taxes facture(=negative) taxes comprennent taxe payer (=negative) retraite agents *pas mal*(=positive) redistribution(=positive)	XXX Remember taxes bill(=negative) taxes include tax pay(=negative) retirement agents *not bad*(c(negative-1, negative+1)=0) redistribution(=positive)
Final step: Calculating the average sentiment of tweets at individual and regional levels	
	$Pos - Neg < 0.$ then the tweet is negative. If $Number\ of\ Pos\ Tweets - Number\ of\ Neg\ Tweets < 0$ holds true for all the tweets of a certain region, then we consider the average sentiment of that region negative (otherwise positive).

A.2 Retweets

To assess the robustness of our results, we also perform the analysis considering the number of retweets. Table A.4 illustrates the new composition of our sample per country per year. Column "Retweets (in %)" shows the number of Tweets that have been retweeted at least one time both in absolute and in percentage terms. Germany presents the highest number of retweets in percentage values, while Spanish tweets experience the lowest number of interactions. The last column displays how many time on average every tweets has been retweeted. In this case, France experience on average the lowest number of retweets while Italy has the highest.

Table A.4: Composition of reference sample (in terms of number of Tweets and retweets) and number of retweets considered.

Country	Year	Number of Tweets	Retweets (in %)	Number of Retweets (On average)
	2018	1151	102 (8.8)	6
France		2936	290 (9.8)	2.18
		1554	128 (8.2)	2.37
	2018	559	92 (16.45)	5.3
Germany		3382	260 (7.68)	4.83
		3098	237 (7.65)	7.45
	2018	2655	51 (1.92)	16.7
Italy		11870	360 (3)	6
		11216	260 (2.31)	5.24
	2018	7525	295 (3.92)	7.47
Spain		6622	156 (2.35)	7.18
		6242	27 (0.43)	5.42

Notes: Table A.4 shows the number of tweets for each year (from 2018 to) for each of the four countries studied (France, Germany, Spain and Italy), together with the number of retweets that composes the sample and the average time they have been retweeted. *Source*: Twitter API Academic Research product track; the authors processed the data.

Table A.5 replicates the results reported in Table 4 (main text), with the difference that for the purpose of creating the indicator of positive tweets (out of the total) we also considered all retweets and not only direct tweets. As evidenced by the sign and magnitude of the coefficients, the investigated relationship remains essentially unchanged. Regarding significance, the coefficients are always statistically significant (10%) except in column (6), where we consider the specification with the full set of controls. This may be somewhat a consequence of the fact that retweets require less commitment than tweets.

Table A.5: Impact of Covid-19 pandemic on the attitude towards taxation across regions with different health system endowment (retweets included in the analysis)

Dep. Var: Positive tweets (%)	(1)	(2)	(3)	(4)	(5)	(6)
*N^o Physicians*Post*	0.0934*	0.1108*	0.1146*	0.1293*	0.1231*	0.0973
	(0.0519)	(0.0643)	(0.0677)	(0.0663)	(0.0655)	(0.0603)
NUTS-2 FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
Demographic controls * Post		yes	yes	yes	yes	yes
Mortality rate (TV)			yes	yes	yes	yes
Geographic controls * Post				yes	yes	yes
Internet-related controls * Post					yes	yes
Socio-economic controls * Post						yes
Observations	142	142	142	142	142	142
R-square	0.6302	0.6406	0.6414	0.6789	0.6812	0.7085

Notes: The variable *N^o Physicians*Post* is the diff-in-diff interaction term between the number of physicians at NUTS-2 region level (2018) and the pandemic dummy. TV stands for time varying. Demographic controls include: population, percentage of graduates, percentage of over 75s, the number of women per 100 men, population density. Geographic controls include: latitude, ruggedness, area surface, distance from the coast and distance from Codogno. Internet related controls are the number of households with internet connection,as well as the amount of time spent on social network. Socio-economic controls include: GDP per capita, EQI index, unemployment rate and the share of high tech firms. Standard errors are clustered at NUTS-2 region level. * significant at 10%, ** significant at 5%, *** significant at 1%.

A.3 Hashtag composition - echo chambers

In this section we present the number of Tweets associated to each keyword and the composition of the sentiment of the sample for every country at the hashtag level (Table A.6). The aim of this analysis is to ensure that the keywords through which we have retrieved data do not lead to the formation of the so-called "echo-chambers",a phenomenon that occurs when choosen hashtags are biased. Not surprisingly, the only two keywords associated to a biased composition of the sample - in terms of an oriented debate exclusively in one of the two directions - are "fiscal equity" and "#taxtherich", that are the most political related keywords. We perform our analysis by considering the tweets associated to these two keywords as neutral and the results are still significant both in the specification without controls and with the full set of controls (Table A.7).[22]

Table A.6: Composition for each hashtag in the four countries of the sample.

Hashtag	Number of Tweets per country			
	France	Germany	Italy	Spain
taxes	2166	6555	12188	11980
	(62 % positive; 38 % negative)	(49 % positive; 51 % negative)	(37% positive; 63% negative)	(58% positive; 42 % negative)
spread	130	210	4512	130
	(65% positive; 35 % negative)	(72% positive; 28 % negative)	(37% positive; 63 % negative)	(80 % positive; 20% negative)
public debt	370	69	3283	1156
	(55 % positive; 45 % negative)	(37 % positive; 23 % negative)	(37 % positive; 63 % negative)	(63 % positive; 37 % negative)
fiscal equity	24	9	122	238
	(100% positive)	(65% positive; 35% negative)	(43 % positive; 57 % negative)	(50 % positive; 50 % negative)
#taxtherich	3	12	38	135
	(67 % positive; 33 % negative)	(100% negative)	(40 % positive; 60 % negative)	(100 % negative)
property tax	644	297	1000	95
	(72 % positive; 28 % negative)	(67 % positive; 33% negative)	(39 % positive; 61 % negative)	(25 % positive; 75 % negative)
progressive taxation	1177	34	2119	99
	(66% positive; 34% negative)	(28 % positive; 72 % negative)	(60% positive; 40 % negative)	(63% positive; 37 % negative)
inheritance tax	75	196	29	360
	(83 % positive; 17 % negative)	(57.5 % positive; 42,5 % negative)	(37,5 % positive; 62,5 % negative)	(55 % positive; 45 %negative)

Notes: Table A.6 shows the composition of the sample at the keywords level. The sum of the observations may be higher than the total number of Tweets presented in Table 1 because every tweet may contain more than one keywords.

[22]Results are available upon request.

Table A.7: Impact of Covid-19 pandemic on the attitude towards taxation across regions with different health system endowment (without "echo-chambers")

Dep. Var: Positive tweets (%)	(1)	(2)
*N°.Physicians*Post*	0.0857*	0.0938*
	(0.0461)	(0.0506)
NUTS-2 FE	yes	yes
Year FE	yes	yes
Demographic controls * Post		yes
Mortality rate (TV)		yes
Geographic controls * Post		yes
Internet-related controls * Post		yes
Socio-economic controls * Post		yes
Observations	142	142
R-squared	0.7660	0.8112

Notes: The variable N.°Physicians*Post is the diff-in-diff interaction term between the number of physicians at NUTS-2 region level (2018) and the pandemic dummy. TV stands for time varying. Demographic controls include: population, percentage of graduates, percentage of over 75s, the number of women per 100 men, population density. Geographic controls include: latitude, ruggedness, area surface, distance from the coast and distance from Codogno. Internet related controls are the number of households with internet connection,as well as the amount of time spent on social network. Socio-economic controls include: GDP per capita, EQI index, unemployment rate and the share of high tech firms. Standard errors are clustered at NUTS-2 region level. * significant at 10%, ** significant at 5%, *** significant at 1%.

A.4 Additional placebo and robustness checks

In this section, we provide some robustness checks to further test the validity of the model and our results. Table A.8 presents the first placebo test. Specifically, referencing Pei et al. (2019), we re-estimate our baseline model substituting the main variables used as controls in our analysis (one by one) as the dependent variable. In this way, we can assess any lack of balance among the variables used as controls; that is, if the balancing property holds, the interaction term of all coefficients should equal zero. As demonstrated by the coefficients reported in Table A.8, all main control variables used as dependent variables (placebo outcomes) do not indicate a connection with our *N°.Physicians*Post* interaction variable.

Table A.8: Test of main covariate balance

Dependent Variables:	Popul.	Elderly	Sex	Mortal.	Coast Dist.	Codogno Dist.	Unemp.	EQI	GDP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$4N°.Physicians*Post$	-816,812.3986	0.1672	0.1749	-0.0001	-23.9944	13.2086	-0.3895	-0.0258	-292.5764
	(558,453.6797)	(0.1078)	(0.5023)	(0.0002)	(20.2060)	(76.6073)	(0.4367)	(0.0989)	(682.5335)
NUTS-2 FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Demographic controls * Post	yes	yes	yes	yes	yes	yes	yes	yes	yes
Mortality rate (TV)	yes	yes	yes	yes	yes	yes	yes	yes	yes
Geographic controls * Post	yes	yes	yes	yes	yes	yes	yes	yes	yes
Internet-related controls * Post	yes	yes	yes	yes	yes	yes	yes	yes	yes
Socio-economic controls * Post	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	142	142	142	142	142	142	142	142	142

Notes: The variable *N.Physicians*Post* is the difference-in-differences interaction term between the number of physicians at the NUTS-2 region level (2018) and the pandemic dummy. TV stands for time-varying. Demographic controls include population, percentage of graduates, percentage over age 75, the number of women per 100 men and population density. Geographic controls include latitude, ruggedness, area surface, distance from the coast and distance from Codogno. Internet-related controls are the number of households with internet access and the amount of time spent on social networks. Socio-economic controls include GDP per capita, EQI index, unemployment rate and the share of high-tech firms. Standard errors are clustered at the NUTS-2 region level. * significant at 10%, ** significant at 5%, *** significant at 1%.

In Table A.9, we report some replications of our main specification (column (6), Table 4) repeated on some specific sub-samples. In column (1), we remove the top and bottom 1% of observations with the highest/lowest number of physicians per 100,000 inhabitants from the sample, in column (2), the 1% of observations with the highest/lowest GDP per capita and, finally, in column (3) the 1% of observations with the highest/lowest mortality rate.

As demonstrated by the estimated coefficients, the results remain substantially unchanged as well as statistically significant (5%). Thus, this robustness test again confirms the stability of our results.

Table A.9: Robustness check removing extreme values

Dep. Var: Positive tweets (%)	(1)	(2)	(3)
*N°.Physicians*Post*	0.0964**	0.0894**	0.0912**
	(0.0411)	(0.0410)	(0.0409)
NUTS-2 FE	yes	yes	yes
Year FE	yes	yes	yes
Demographic controls * Post	yes	yes	yes
Mortality rate (TV)	yes	yes	yes
Geographic controls * Post	yes	yes	yes
Internet-related controls * Post	yes	yes	yes
Socio-economic controls * Post	yes	yes	yes
Observations	138	138	136
R-squared	0.8100	0.8072	0.8127

Notes: The variable N.Physicians*Post is the difference-in-differences interaction term between the number of physicians at the NUTS-2 region level (2018) and the pandemic dummy. TV stands for time-varying. Demographic controls include population, percentage of graduates, percentage over age 75, the number of women per 100 men and population density. Geographic controls include latitude, ruggedness, area surface, distance from the coast and distance from Codogno. Internet-related controls are the number of households with internet access and the amount of time spent on social networks. Socio-economic controls include GDP per capita, EQI index, unemployment rate and the share of high-tech firms. Standard errors are clustered at the NUTS-2 region level. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table A.10 presents a supplementary robustness check. Following Guiso et al.(2017) we repeat our main analysis using as main independent variable the interaction between the post-pandemic dummy and a dichotomous variable, namely a dummy variable equal to 1 if the number of physicians (NUTS-2 level) is above the 75th percentile and 0 otherwise.

The specifications in columns (1)–(6) replicate the structure of our main table (Table 4, main text), progressively including a growing number of controls in the analysis. A joint interpretation of the several coefficients presented in Table A.10 indicate a robust and stable coefficient. The coefficient of the most complete specification shown in column (6) suggests that positive tweets increased by about 11% in regions with a very high number of physicians per 100,000 inhabitants compared to those with a medium to low number of physicians.

Table A.10: Robustness to alternative measure of health system endowment I

Dep. Var: Positive tweets (%)	(1)	(2)	(3)	(4)	(5)	(6)
*75-100th N°.Physicians*Post*	0.1191**	0.1053*	0.1075*	0.1066*	0.1104**	0.1067**
	(0.0511)	(0.0542)	(0.0558)	(0.0563)	(0.0511)	(0.0490)
NUTS-2 FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
Demographic controls * Post		yes	yes	yes	yes	yes
Mortality rate (TV)			yes	yes	yes	yes
Geographic controls * Post				yes	yes	yes
Internet-related controls * Post					yes	yes
Socio-economic controls * Post						yes
Observations	142	142	142	142	142	142
R-squared	0.7434	0.7522	0.7525	0.7747	0.7763	0.7900

Notes: The variable Top 75th–100th N°.Physicians*Post is the difference-in-differences interaction term between the post-pandemic dummy and a dichotomous variable, equal to 1 if the number of physicians is above the 75th percentile and 0 otherwise. TV stands for time-varying. Demographic controls include population, percentage of graduates, percentage over age 75, the number of women per 100 men and population density. Geographic controls include latitude, ruggedness, area surface, distance from the coast and distance from Codogno. Internet-related controls are the number of households with internet access and the amount of time spent on social networks. Socio-economic controls include GDP per capita, EQI index, the share of high-tech firms and the unemployment rate. Standard errors are clustered at the NUTS-2 region level. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table A.11 shows a supplementary robustness check using the alternative measure of health system endowment. Following the previous table, we create four different dummy variables equal to 1 if the number of physicians (NUTS-2 level) is within the 0–25th, 25th–50th, 50th–75th and 75th–100th percentiles, respectively. We then interacted these variables with the post-pandemic variables. For the sake of brevity, we reported only the coefficient of the most complete specification for each dependent variable. The results reveal that regions in the first quartile (those with the lowest number of physicians per capita) reduce the number of positive tweets towards taxation in the post-pandemic period, while those within the fourth quartile (with the highest number of physicians) increase positive tweets. The second and third quartiles around the median have no significant relationship.

Table A.11: Robustness to alternative measure of health system endowment II

Dep. Var: Positive tweets (%)	(1)	(2)	(3)	(4)
*0-25th N°.Physicians*Post*	-0.1751**			
	(0.0753)			
*25-50th N°.Physicians*Post*		0.0612		
		(0.0497)		
*50-75th N°.Physicians*Post*			-0.0545	
			(0.0528)	
*75-100th N°.Physicians*Post*				0.1067**
				(0.0490)
NUTS-2 FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
Demographic controls * Post	yes	yes	yes	yes
Mortality rate (TV)	yes	yes	yes	yes
Geographic controls * Post	yes	yes	yes	yes
Internet-related controls * Post	yes	yes	yes	yes
Socio-economic controls * Post	yes	yes	yes	yes
Observations	142	142	142	142
R-squared	0.7959	0.7841	0.7837	0.7900

Notes: The variable N°.Physicians*Post is the difference-in-differences interaction term between the post-pandemic dummy and a dichotomous variable, equal to 1 if the number of physicians is above the 75th percentile and 0 otherwise. TV stands for time-varying. Demographic controls include population, percentage of graduates, percentage over age 75, the number of women per 100 men and population density. Geographic controls include latitude, ruggedness, area surface, distance from the coast and distance from Codogno. Internet-related controls are the number of households with internet connection and the amount of time spent on social networks. Socio-economic controls include GDP per capita, EQI index, the share of high-tech firms and the unemployment rate. Standard errors are clustered at the NUTS-2 region level. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table A.12 replicates the main results (Table 4), showing the coefficients of all controls.

Table A.13 below shows that there are no significant differences in the number of physicians per 100,000 inhabitants between regions with high and low quality of institutions (EQI), at least until the third quartile of the distribution.

Table A.12: Impact of the Covid-19 pandemic on attitudes towards taxation across regions with different health system endowments

Dep. Var: Positive tweets (%)	(1)	(2)	(3)	(4)	(5)	(6)
*N°.Physicians*Post*	0.1021**	0.0974**	0.0979**	0.0969**	0.0972**	0.0866**
	(0.0417)	(0.0420)	(0.0424)	(0.0428)	(0.0428)	(0.0402)
*Population*Post*		0.0000	0.0000	0.0000	0.0000	0.0000
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
*TertiaryEdu*Post*		-0.0056	-0.0051	-0.0352	-0.0460	-0.0691
		(0.0399)	(0.0403)	(0.0482)	(0.0487)	(0.0572)
*Over75*Post*		0.0560	0.0581	0.0832	0.0848	0.1180*
		(0.0399)	(0.0411)	(0.0506)	(0.0513)	(0.0605)
*Women100Men*Post*		-0.0112	-0.0113	-0.0108	-0.0123	-0.0177*
		(0.0077)	(0.0078)	(0.0074)	(0.0090)	(0.0101)
*PopDensity*Post*		-0.0000	-0.0000	0.0000	-0.0000	-0.0000
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
MortalityRate			-9.2670	-31.2842	-27.5621	-26.3938
			(21.0050)	(30.2424)	(30.1896)	(30.3759)
*DistanceCoast*Post*				0.0002	0.0002	0.0000
				(0.0003)	(0.0003)	(0.0003)
*Latitude*Post*				-0.0167**	-0.0184**	-0.0233*
				(0.0077)	(0.0087)	(0.0125)
*Ruggedness*Post*				-0.0302	-0.0288	-0.0395
				(0.0213)	(0.0214)	(0.0241)
*Area*Post*				-0.0000	-0.0000	-0.0000
				(0.0000)	(0.0000)	(0.0000)
*DistanceCodogno*Post*				-0.0001**	-0.0001**	-0.0002*
				(0.0001)	(0.0001)	(0.0001)
*Social*Post*					-0.0022	-0.0026
					(0.0044)	(0.0043)
*Broadband*Post*					0.0022	-0.0026
					(0.0043)	(0.0070)
*Unemp*Post*						0.0071
						(0.0111)
*EQI*Post*						0.0513
						(0.0531)
*GDP*Post*						0
						(0)
*HightechEmp*Post*						0.0757
						(0.0670)
NUTS-2 FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
Demographic controls * Post		yes	yes	yes	yes	yes
Mortality rate (TV)			yes	yes	yes	yes
Geographic controls * Post				yes	yes	yes
Internet-related controls * Post					yes	yes
Socio-economic controls * Post						yes
Observations	142	142	142	142	142	142
R-square	0.7651	0.7754	0.7758	0.7961	0.7972	0.8075

Notes: The variable *N^o Physicians*Post*is the difference-in-differences interaction term between the number of physicians at the NUTS-2 region level (2018) and the pandemic dummy. TV stands for time-varying. Demographic controls include population, percentage of graduates, percentage over age 75, the number of women per 100 men and population density. Geographic controls include latitude, ruggedness, area surface, distance from the coast and distance from Codogno. Internet-related controls are the number of households with internet access and the amount of time spent on social networks. Socio-economic controls include GDP per capita, EQI index, unemployment rate and the share of high-tech firms. Standard errors are clustered at the NUTS-2 region level. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table A.13: Distribution of the number of physicians per 100,000 inhabitants in low EQI and high EQI sample.

	N.° Physicians x 100,000 inhabitants	
Percentiles	*lowEQI*	*high EQI*
1%	259.75	260.93
5%	285.53	263.35
10%	304.99	286.52
25%	358.25	309.94
50%	401.74	376
75%	442.275	428.58
90%	457.67	528.66
95%	471.35	542.38
99%	476.86	629.07

Notes: The variable N.°Physicians per 100,000 inhabitants is defined at NUTS-2 region level (2018).

How Environmental Performance and Innovation Affect the Lobbying Expenditures of Firms in the EU

Giulio Mazzone*

Abstract

Lobbying can help policy makers access relevant sector-specific information and make informed decisions. However, lobbying can also harm economic welfare if it successfully persuades policy makers to impose unnecessary regulations or maintain excessive market barriers. This study examines the relationship between lobbying expenditures, the environmental policy stringency regulation, firm-level green innovation and environmental reputation. Using a sample of 590 firms from 43 countries across 98 industries, we analyze firm-level financial and environmental data from the period of 2012 to 2020. Our results show that highly green innovative firms tend to spend more on lobbying, and that lobbying expenditures are negatively associated with environmental performance. We also find that environmental policy stringency has a positive impact on corporate environmental performance, while innovation and other factors have mixed effects. Our study contributes to the growing literature on the intersection of political economy, innovation, and climate transition.

Keywords: Lobbying, Climate transition, Reputation Risk, Transition Risk, Green innovation.

JEL: D72, Q55, Q58.

1 Introduction and research questions

Understanding the role of lobbying activity in climate transition is a subject of deep concern among researchers. This study aims to provide insights into the circumstances under which lobbying firms might be incentivized to adjust their lobbying expenditure based on the level of environmental legislation and protection and their own level of green innovation and environmental reputation. This rationale is broken down into several parts throughout this introduction.

One significant hurdle for environmental regulations is the lack of political support, often resulting in delays or weak implementation. Financial markets can be a potent source of such support. Environmental policymakers often assert that this support is almost a prerequisite for practical environmental regulation, as economic interests often overshadow environmental concerns. Although firms invest heavily in lobbying, it is generally perceived that polluting firms use their lobbying power to obstruct measures aimed at environmental protection (Cai et al., 2020). However, significant exceptions to this pattern, which have prompted much of this research, have been observed.

The importance of a company's reputation and its perceived commitment to environmental sustainability and social responsibility has been widely acknowledged, as these factors can influence a firm's financial market performance (Semieniuk et al. 2021). Risks arising from climate change can be categorized into physical risks and transition risks. Physical risks are directly linked to climate change effects, such as extreme weather events. Conversely, transition risks are associated with the gradual shift towards a low-carbon economy and the resulting structural changes. If the transition is not adequately anticipated or carried out too late, transition risks can cause economic shocks with substantial financial implications (Bolton and M. Kacperczyk 2021).

Climate transition risk, as defined by the Bank of England (2015), refers to risks that could arise from transitioning towards a more carbon-efficient economy. If businesses cannot handle the changes promptly, these adjustments could reevaluate asset values and jeopardize the economy's financial stability. Changes

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influence climate transition risk in policy, legislation, renewable energy targets, sustainable land use, and the timing and speed of the transition (Newell 2020).

In light of this, it is crucial to emphasize how environmental regulations can increase the *climate transition risk* for firms with high environmental impacts and those struggling to modify their business models. Conversely, such regulations can benefit firms and sectors with low environmental impacts or high levels of innovation. Lobbying expenditures, among other strategies, may serve to delay the application of green policies. Lobbying activities can shape climate policy by influencing domestic political processes (Vesa, Gronow, and Ylä-Anttila 2020). Both green and brown sectors invest resources in lobbying over the environment. Empirical evidence shows an increase in the number of green firms switching to direct lobbying (Yu 2005). However, brown groups still predominate in number and total expenditures (see Figure 1).

Finally, environmental protection has emerged as a critical political issue in recent years, and there is a growing recognition of the need for more environmentally friendly policies and regulations. While there has been a significant increase in scientific studies evaluating the severity of environmental problems caused by GHG emissions and climate change, a considerable gap exists between political commitments and actual progress on environmental regulation. Despite the growing public and political support for environmental protection, in many cases, regulatory measures are being relaxed rather than strengthened (Vesa, Gronow, and Ylä-Anttila 2020). Therefore, understanding the factors that influence environmental policy-making and implementation is essential to ensure an ordered climate transition.

Based on the above, we set our research questions and the relative hypothesis. The first objective of this study is to analyze the lobbying expenditure firms in the EU in response to different levels of green innovation, represented here by the stock of green patents, of environmental reputation at the company level, represented by the E score, and of the environmental performance index of the domicile country of a lobbying firm. So, our analysis aims to investigate the possible magnitude of the correlation between these variables. The first research question to which we try to find an answer is the following:

1. *Is there a correlation between lobbying expenditure, ability to implement environmental policies of a country and the company's environmental performance? and if so, what is the nature of this relationship?*

On this research question, we build the first hypothesis of this paper:

H_1 Lobbying expenditures are higher in countries with a lower environmental performance index and higher in firms with a lower level of green innovation, and they are negatively correlated with these indicators.

In other words, we expect that highly green innovative firms tend to spend less on lobbying activities. The rationale behind this could be that these entities might be attempting to influence policies in ways that would minimize the regulatory impact on their operations. For example, a sector that relies heavily on fossil fuels and thus has a low environmental performance might spend a lot on lobbying to resist stricter emissions regulations.

The term green innovation refers to the stock of green patents at the firm level. These could include innovations linked to renewable energy technologies, energy-efficient appliances, or sustainable agriculture practices. Environmental performance generally refers to how well a company, sector, or country manages its impact on the environment. This could be measured in various ways, such as the amount of greenhouse gas emissions or generally with environmental scores (e.g. ESG scores or Environmental Performance Indicator (EPI)) from third-party providers.

To test our first hypothesis, we will empirically analyse whether in our three sub-panels of data, based on the stock of green patents, respectively, in terms of low, medium and high numbers of the stock of green patents, we find different correlations in terms of sign and magnitude.

Then the second hypothesis of our study is the following:

H_2 Environmental policy outcomes and regulations in the EU can have a positive effect on Lobbying expenditures, especially for medium green innovative firms that trying to remain competitive with highly innovative firms.

This hypothesis is suggesting a possible correlation between environmental policy outcomes and regulations in the European Union (EU) and the amount of money firms spend on lobbying activities.

In essence, it proposes that stricter environmental regulations or policy changes that are more beneficial for the environment could lead to increased lobbying expenditures by companies. The rationale here is that companies, particularly those with moderate (or "medium") levels of green innovation, might increase their lobbying efforts in response to these policy changes. These firms, which may be trying to remain competitive with highly green innovative firms, could be especially responsive to changes in environmental policy. In other words, these medium-green innovative firms might feel threatened by policy changes that could benefit their highly innovative competitors or that could require costly adaptations on their part. As a result, these firms might invest more heavily in lobbying efforts in an attempt to influence policy outcomes in their favour or to mitigate the impact of these policy changes on their competitiveness.

Finally, the third and last hypothesis of our study is the following:

H_3 The higher the green innovation of a firm, the lower the lobbying expenditures will be.

This last hypothesis is based on the assumption that lobbying is often used to influence policy-making in favour of the interests of the lobbyists, which may not align with the environmental goals of the European Union[1]. However, this hypothesis may not be valid for all sectors or countries, as some may lobby for more ambitious climate action or green innovation.

The act of lobbying can serve as an important tool in providing policymakers with in-depth knowledge about various sectors and technical questions, aiding in the development of informed policy decisions. However, excessive lobbying can result in negative consequences such as unwarranted restrictions on regulation for incumbent firms, hindering the opening of over-regulated markets, and ultimately leading to a decrease in welfare (Grossman et al.,1994; Yu 2005; Coen 2007). While theoretical contributions to the literature have demonstrated the incentives for firms to engage in such behaviour, empirical evidence is difficult to find due to the lack of transparency in lobbying practices (Bunea 2018).

Given all of the above, the aim of this paper is to draw a picture of who has been lobbying in Europe between 2012 and 2020 and if this lobby is related, in any way, to the performance of firms in what regards their ESG scores, in particular the environmental ones. In order to do so, an empirical approach is followed, and a panel is built using the following data. We retrieved lobby expenditures from LobbyFacts and EU Transparency Register[2] as a source of data on lobbying expenditure. The financial and environmental indicators, like E score and GHG emissions, were retrieved from the Bloomberg database. Moreover, we retrieved, at the firm level, environmental performance data, such as GHG Emissions Scope 1& 2 and the E Score as an environmental reputation variable, and control variables for each firm, such as market cap, revenues, sector, and industry. In addition, we use the country head of the office of the lobbying firms, which has crucial information for our assessment based on the Environmental Performance Index (EPI). Finally, performing a fixed-effect Poisson model, we estimate the correlations among our key variables.

First, the main results suggest that there is a positive correlation between firms engaging in lobbying activities and scoring higher in their environmental indicators. Moreover, the evidence indicates that medium innovative groups had, on average, a higher probability of lobbying, which suggests that the incentive to lobby is higher for firms that suffer a competitive disadvantage.

Finally, the fact that environmental pillar scores are not necessarily related to verifiable actions to reduce pollution and given the positive relation these indicators show with lobbying activity, may increase the probability of green-washing activities since firms could hide brown activities (e.g. lobby against the environment) behind the green image provided by a high score.

To conclude, the paper seeks to contribute to the understanding of lobbying activities in Europe, particularly in the context of environmental regulation and protection, as well as the relationship between lobbying expenditure, innovation, and environmental reputation. Additionally, we present evidence that firms with a higher environmental reputation level are less likely to spend on lobbying activity. Although our analysis is subject to limitations, our results support the existing literature, suggesting that policymakers must strike a delicate balance between gaining valuable information and preventing lobbying activities from undermining

[1] www.euractiv.com/section/energy-environment/news/the-green-brief-eu-parliament-hit-by-tsunami-of-lobbying
[2] https://www.lobbyfacts.eu/

an ordered and regulated climate transition.

The rest of the paper is structured as follows: Section 2 provides a background and context of the study. Section 3 provides a literature review on the previous studies about lobbying activity, its link with environmental performances and innovation and where and how our work adds elements to the results of this strand of research. Section 4 presents data and the descriptive statistics. Section 5 outlines the research design and methodology, including a description of the methodology and the rationale behind our empirical approach. Section 6 presents the study's results and analyses the effects of the environmental policy stringency and our reputation environmental score on the lobbying activity of the selected sample, broken down by level of innovation. Finally, Section 7 concludes the study, outlines the limitations of the works and provides insights into the findings' implications for future research.

2 Background and context of the study

As stated in the introduction, firms may lobby to preserve protective regulations. Our research aims to determine whether lobbying firms are more or less innovative and exhibit particular environmental performances. The literature presents divergent views on this matter. On the one hand, innovative firms may be more inclined to lobby for the protection of their innovations, and a positive correlation may exist between lobbying and innovative capacity, as EU firms are significant beneficiaries of research and development funds under the EU framework funds (Hix and Høyland 2013). Therefore, we could hypothesise that firms lobby in Brussels to secure these funds. On the other hand, it may be argued that firms in protected markets face less competition and are, therefore, under less pressure to innovate than firms in highly competitive industries. For example, as reported by Dellis et al. (Dellis and Sondermann 2017) this tend to be true for American manufacturing firms.

Given the divergences in the previous results, it is crucial to contextualise our data as much as possible in our empirical analysis, which will be presented in the following sections. In this section, we offer additional insights into the firms' lobbying activity, innovation, and environmental performances under examination.

2.1 Lobbying Activity in EU and Climate Change

Lobbying activity in EU is the practice of trying to influence the decisions and policies of the EU institutions by various interest groups or lobbies (Coen 2007). Lobbying is officially recognized as a legitimate and necessary part of the democratic process by the EU[3], but it is also subject to rules and regulations to ensure transparency and accountability[4]. According to the EU transparency register (2021), there are more than 12,000 registered lobbyists representing different sectors, such as business, civil society, trade unions, think tanks among others. As previously said, lobbying can have positive or negative impacts on the EU decision-making, depending also on the quality, quantity and balance of the information and arguments provided by the lobbyists.

According to the OECD (OECD 2021b), the total spending on lobbying in the EU by the top 100 lobbying organisations was estimated at €271 million in 2019, with the highest spending coming from the pharmaceutical, chemical, and technology sectors. The spending on lobbying in the EU is lower than in the US, where the total spending by the top 100 lobbying organisations was estimated at $3.5 billion in 2019. Looking at the economic actors involved in lobbying activity, according to the *EU Transparency Register*, the most active sectors in lobbying the EU are business, civil society, trade unions, think tanks, and public authorities. While, the most targeted EU institutions by the lobbyists are the European Commission, the European Parliament, and the Council of the EU, some of the issues that are often targeted by lobbying in the EU are digital, environment, trade, and finance[5].

The literature on lobbying in Europe is relatively limited, particularly compared to other regions, and primarily consisted of textual analysis at the beginning (Klüver 2013; Supran and Oreskes 2017). This limitation may be attributed to a lack of available data in recent decades. However, the Transparency Register,

[3] See also https://www.europarl.europa.eu/at-your-service/en/transparency/lobby-groups

[4] See also: https://www.europarl.europa.eu/news/en/headlines/eu-affairs

[5] https://corporateeurope.org/en/lobbying-the-eu

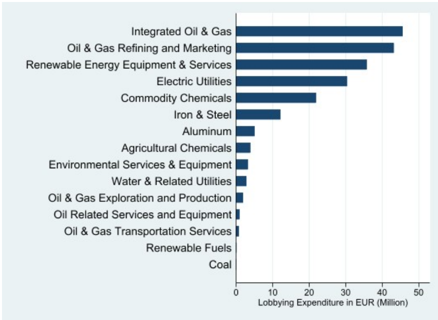
established in response to the European Transparency Initiative in 2005, has become the primary database for tracking lobbying activities in the EU since 2008. The Register is managed by the Joint Transparency Register Secretariat (JTRS), composed of the Commission and the European Parliament. Before the Register, information on lobbying in the EU was scattered across multiple databases with significant differences in methodology and content, such as the CONECCS database and the Phillip and Landmarks directories. Registration in the Register is voluntary but necessary for firms and organizations seeking access to EU institutions, data, public consultations, and meetings with officials, including Members of the European Parliament, Commissioners, Cabinet Members, and Commission Services representatives. The Transparency Register Implementing Guidelines (JTRS 2015) provide clear instructions on the data that firms must submit during registration. These guidelines are based on the Interinstitutional Agreement between the European Commission and European Parliament (EU, 2011).

After having just outlined the EU dynamics of recording direct lobbying expenses, it is appropriate now to shed some light on the development of climate change lobbying in recent years. The failure to implement effective policies to combat climate change, despite growing evidence of its devastating impacts, can also be attributed to significant corporate lobbying by industries with interests in the fossil fuel economy (OECD 2022). Often such lobbying has impeded the implementation of critical climate regulations around the world. The limited success of carbon pricing systems, with fewer than 15% of emissions covered by binding systems, is a clear example of this in action (Influence Map 2020). Second, the fossil fuel industry has hindered key regulations, such as the US Clean Power Plan and the EU's Emissions Trading Scheme, through lawsuits and lobbying. Furthermore, auto industry lobbying has compromised climate rules on vehicles in both the US and the EU, while vested interests have directed Japan to pursue a coal future. Fourth, UN bodies for shipping and aviation have also been captured by industry, undermining the development of critical climate policy for these sectors. In light of these issues, persistent negative lobbying must be addressed if global progress on climate change is to be achieved.

As a result of all these events, corporate lobbying has played a significant role in hindering the progress of climate policies since the possibility of regulation emerged in the late 1980s (Principles for Responsible Investment 2018). Corporate lobbyists have employed two main strategies to obstruct binding regulatory measures: capturing the public narrative on climate change and directly lobbying against regulations (Yu 2005; OECD 2022; Influence Map 2020). In the past, companies such as Exxon Mobile have sought to weaken the scientific consensus on climate change through advertising, strategic messaging by CEOs, and funding of think tanks (Supran and Oreskes 2017; Influence Map 2020). However, as the global climate consensus has strengthened, companies have shifted to questioning the extent of the impact of climate change or its consequences for business while acknowledging its human-made origin. Simultaneously, fossil fuel companies have challenged regulations by emphasizing their potential adverse effects on jobs and growth. In recent years, companies have outsourced lobbying activities to powerful trade associations, such as the Alliance of Automobile Manufacturers, which helped the automotive industry roll back US vehicle emissions standards in 2018, keeping the worst of these activities increasingly behind the scenes since the Paris Agreement in 2015.

In the wake of the Paris Agreement's establishment in 2015, a corporate battle over climate policy has emerged (Influence Map 2020; Yu 2005). While the proportion of the world's largest industrial companies opposing climate policy has decreased from 45% to 30%, there is still significant opposition to binding climate policy from influential trade groups (OECD 2021b). Additionally, the automotive and coal sectors have increased their opposition to climate policy over the last three years. Most industrial companies in sectors such as retail and healthcare remain disengaged from climate policy. However, many tech, utility, and consumer goods companies, including Apple and Unilever, advocate for strong policies to support their climate goals. Many utility firms are now pushing for strong renewable policies to facilitate their transition. Some, such as RWE and Japanese utilities, continue to advocate for coal-based energy policies along with coal value chain players like Glencore. As a result (see Figure 1), not only fossil fuel companies or utility companies but also green companies or firms involved in low emissions sectors started to use direct lobbying to try to influence legislators in order to to make the implementation of climate mitigation policies more

Figure 1: Lobbying Expenditures in green and brows industries



Note: Figure 1 shows the amount for the high polluting sectors vs green sectors in terms of "direct" Lobbying amount in EUR for the entire period of the analysis (2012-2020). Data Source: LobbyFacts. The author elaborated the data.

effective[6].

In addition to these challenges, there is also evidence to suggest that the relationship between lobbying, market power, and competitiveness is an important factor to consider in the context of climate change. In some industries, companies with market power may use lobbying to protect their market share and reduce expenditures on research and development (R&D). This can lead to a reduction in innovation and competition and can result in policies that are less effective in promoting the transition to a low-carbon economy (Coen 2007; Bernhagen and Mitchell 2009; Yu 2005).

Given the above, the purpose of this paper is to examine the relationship between direct lobbying and climate change policies, with a focus on the economic incentives and motivations behind lobbying on this issue. The paper seeks to provide a deeper understanding of the role of lobbying in shaping climate change policies and to highlight the potential benefits and challenges of lobbying in this context.

2.1.1 Environmental Agreements: IPPCC and the increase of environmental regulations

Our work has developed after a decade in which there have been numerous international and non-international agreements on climate change, environmental law and mitigation policies.

It is important to note that the concepts of environmental agreements and environmental law are distinct, albeit related. Environmental agreements refer to voluntary or contractual arrangements between parties, such as businesses, trade associations, governments, or non-governmental organizations, that aim to achieve environmental goals or improve environmental performance. In contrast, environmental law refers to the body of rules and principles that regulate human activities that affect the environment, such as pollution, conservation, biodiversity, or climate change. Environmental law can be based on international treaties, national legislation, or customary practices (Lawrence and Wong 2017).

Environmental agreements are diverse and cover various issues, including biodiversity, climate change, ozone depletion, pollution, and conservation. Some examples of international environmental agreements are the Convention on Biological Diversity, the Kyoto Protocol, the Montreal Protocol on Substances that Deplete the Ozone Layer, the Paris Agreement[7], and the World Heritage Convention. These treaties regulate or manage human impact on the environment, trying to protect it. They are intergovernmental and legally binding, creating obligations and rights for the parties that sign and ratify them. Environmental agreements can have political and economic implications beyond their environmental goals, and they can be global or regional in scope.

Enforcement of environmental agreements is a complex and challenging issue involving different levels of actors, laws, and institutions (Harstad, 2016; Clémençon 2016). Generally, enforcement refers to the

[6]Climate mitigation policies refer to a set of measures and actions aimed at reducing GHG emissions and limiting their concentration in the atmosphere.

[7]http://unfccc.int/files/essential_background/convention/application/pdf/english_paris_agreement.pdf.

actions that deter and respond to violations of environmental laws and regulations that implement the obligations of environmental agreements. Enforcement can be carried out by national authorities, such as courts, police, or environmental agencies, or by international bodies, such as compliance committees, dispute settlement mechanisms, or sanctions regimes. It can also involve cooperation and coordination among different actors, such as states, international organizations, civil society, or the private sector, to share information, expertise, and resources. However, enforcement faces many difficulties, such as a lack of political will, capacity, and resources, conflicts of interest, or divergent interpretations of the agreements. The challenges of enforcing environmental agreements include insufficient enforcement mechanisms at the international level, ineffective implementation of environmental agreements at the national level, lack of coordination and cooperation among different actors and levels of governance, lack of public awareness, participation, or access to information, justice, or remedies, and lack of scientific certainty, data, or evidence. These challenges can hinder or undermine environmental protection, and addressing them requires concerted efforts from various stakeholders.

In this context, lobbying activity, as explained in the previous sub-section, plays its role as a possible additional issue or as a facilitator in the implementation of the efficient application from an environmental materiality[8] perspective of the design of these agreements. In order to find a way to measure the enforcement and efficacy of the environmental agreements at the country level, so the level of advancement of a given country in terms of environmental policies, we use the Environmental Performance Index (EPI). EPI is a method of quantifying and numerically marking the environmental performance of a state's policies (Kruse et al. 2022; OECD 2021a). It is a global rating system that ranks nations based on their environmental health and sustainability. This index is able to provide a data-driven evaluation of the global sustainability level of the domicile country of our lobbying firms, and it helps identify trends, understand outcomes and identify the level of effective policy methods for environmental performance. The EPI uses 40 performance indicators across 11 issue categories, such as climate change, air quality, water resources, biodiversity, and waste management, and we're going to provide more insights about this indicator in Section 4.

2.1.2 Environmental Scores and GHG Emissions

To conclude our section about the context, we provide an overview of the environmental firm-level indicators and their meaning for this study and financial markets.

In recent years, there has been a growing interest in Environmental, Social, and Governance (ESG) indicators among investors as they seek to incorporate sustainability considerations into their investment decision-making processes. However, using ESG scores such as the E-Score, which aims to capture a company's environmental performance, has been subject to much debate in the academic and financial communities. While high E-Scores can increase a company's reputation for sustainability, studies have found a low correlation between E-Scores and actual environmental metrics, such as CO2 emissions. (Boffo, Marshall, and Patalano 2020; OECD 2022).

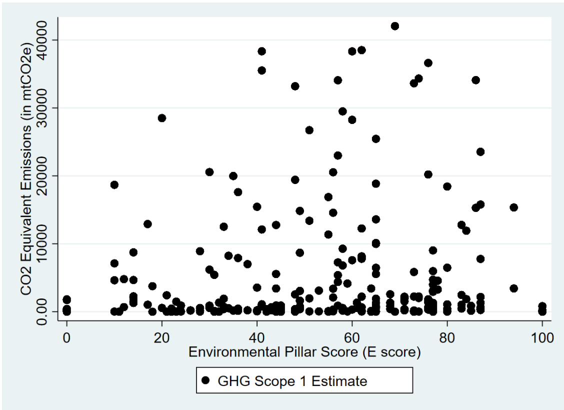
The OECD papers (Boffo and Patalano 2020; OECD 2022) on ESG ratings and climate transition provide valuable insights into the alignment of E pillar scores and environmental metrics. First, these works assess the correlation between E scores, which investors use to measure a company's environmental sustainability, and various environmental metrics, including carbon emissions. Second, these studies find that while E scores may be a valuable indicator of a company's reputation and perceived commitment to environmental sustainability, they are only sometimes well-aligned with actual environmental performance. E scores consider a wide range of factors, including economic and financial performance, which can result in a high score for a company even if its environmental performance is poor. In particular, the OECD report of 2022 (OECD 2022) notes that the correlation between E scores and metrics such as carbon emissions remains low, indicating that E scores are not capturing the complete picture of a company's environmental impact, raising concerns about the reliability of E scores as a measure of environmental sustainability and highlights the need for additional metrics in the assessment of a company's environmental performance. From a technical perspective, as an investment tool, previous studies have demonstrated a limited ability to predict returns based on overall ESG ratings (Boffo and Patalano 2020; Pedersen et al., 2021), and there exists mixed evidence when considering different ESG proxies (Hong and M. Kacperczyk 2009; Bolton and

[8] Here intended as the effectiveness and environmental significance of a specific measure.

P. Kacperczyk 2021). Our contribution is to show the argument that ESG uncertainty and low reliability may influence not only the relationship between ESG performance and returns but also the perception and the financial choice of investors.

Overall, economic literature provides essential insights into the limitations of using E scores to measure environmental sustainability. First, E scores align with economic and financial performance rather than environmental performance (Venturini 2021; OECD 2022; Edmans 2023). Second, this lack of alignment is particularly concerning as it raises questions about the reliability of ESG scores in assessing a company's environmental impact, also from a forward-looking perspective (Cornell and Damodaran 2020).

Figure 2: Correlation CO2 Equivalent Emissions vs Environmental Pillar Score



Notes: Figure shows the linear correlation between the GHG Scope 1 CO2 Equivalent Emissions in mtCO2e and the Environmental pillar score. Paerson's correlation index = -0.00213.
Data Source: Bloomberg. The author elaborated the data on STATA.

So, we use the Environmental pillar score as an index of environmental reputation score for two main reasons. First, the E pillar score evaluates a wide range of information on the environmental performance of a company, such as waste and emission, climate change, and risk management. These aspects are important for the stakeholders and investors who care about the environmental impact and sustainability of the company but also for the legislators that receive active lobbying activity. Second, the E pillar score should also reflect the company's ability to adapt to the changing environmental regulations and policies that are influenced by lobbying activities. A higher E pillar score may indicate that the company is more proactive and responsive to the environmental issues and challenges that are relevant to its industry and market. It will use in our empirical analysis to check the correlation between the implementation of environmental policies, the level of innovation and the lobbying activity of the firms in our selected sample.

3 Related Literature

The theory of private interest in regulations, first introduced by Stigler (1971) and later developed by Peltzman (1976), forms the basis for the expectation that firms are financially motivated to engage in lobbying activities for protection. According to Stigler (1971), the state possesses the authority to levy taxes, provide subsidies, and regulate economic agents, mainly firms, thereby selectively benefiting or disadvantaging specific firms or industries. If successful, lobbying can yield positive returns for firms by securing direct subsidies, reducing taxes, obtaining government contracts, or limiting competition. In the latter case, private firms engaged in rent-seeking activities attempt to maximize their profits by manipulating, distorting, or maintaining regulations (Coen 2007). Given that, our literature review will focus on three main strands concerning the activities of political influence and lobbying, in line with the scope of our work.

It is worth noting that a large strand of literature, especially in the last two decades, has devoted itself to analysing, both theoretically and empirically, the link between innovation, pollution and political influence. This link represents the main rationale for our analysis. The relationship between lobbying and innovation in firms has been a subject of debate in the literature. Some argue that innovative firms are more likely to lobby to safeguard their innovation. Moreover, it is expected that firms that receive significant research and development funds under the EU framework funds, such as those in the EU, would lobby in Brussels for those funds. As a result, a positive correlation between lobbying and innovative capacity can be hypothesized (Ozer et al., 2013; Hix and Høyland 2013). On the other hand, it could be argued that firms in protected markets are less likely to innovate due to the lack of pressure, in contrast to firms in highly competitive industries who tend to make more significant efforts to innovate (Coen, Katsaitis, and Vannoni 2021).

Of the strands we want to explore, the three main ones are as follows.

First, this paper aims to contribute to the extensive literature on the political economy of environmental regulation. Stigler (1971) posited that the profit-seeking motives of firms are a significant driver of regulation. Buchanan and Tullock (1975) observed that different environmental regulations have varying distributional consequences and proposed that firms would select regulations that maximize their profits. Contemporary political economy scholarship has built upon these insights, with lobbying emerging as a mechanism through which firms influence policy. Grossman and Helpman (1994) pioneered the common agency model of Bernheim and Whinston (1986) for lobbying, which has since become customary. The application of this model to environmental policymaking was first demonstrated by Fredriksson (1997), who illustrated how environmental lobby groups could counter the influence of polluters' lobby groups, resulting in the enactment of environmental protection laws. Although this remains an active and productive area of research, the prevailing finding is that polluting firms consistently lobby against environmental protection, necessitating an environmental lobby group with preferences for environmental preservation.

So, the literature on environmental policy-making has identified various factors that may impact the implementation of environmental regulations and, in particular, link to the innovation level of a sector or a market. These factors include the economic and political context, the degree of public awareness and engagement, the influence of interest groups and stakeholders, and the role of international cooperation and agreements (Harstad et al., 2011;Yu 2005; Coen 2007; Stern 2015; Bombardini and Trebbi 2020). Previous studies have also examined the effects of environmental policies on various outcomes, including environmental performance, innovation, and competitiveness. However, despite the significant body of research in this area, much debate and discussion still need to be made on the most effective approaches to address environmental challenges and which are the main dynamics that can affect the efficacy of environmental policies (Grey 2018). Thus in this context, our paper tries to add insights and proof about the relationships between the environmental performances of a country to apply efficient regulations, using the EPI and the direct lobbying activity of firms.

Second, linked to the main scope of our work, a conflicting point arises when brown firms lobby the government trying to delay the climate transition while at the same time sending messages of sustainability to the public or, more in particular, to potential investors (Stern 2015; Influence Map 2020).

Corporate lobbying has been identified as a significant contributor to the failure to implement effective policies to combat climate change (OECD 2022). Climate transition risk has been especially problematic as mounting evidence suggests the devastating impacts of climate change (Carattini et al., 2021). However, in many instances, lobbying by industries interested in the fossil fuel economy has impeded the implementation of critical climate regulations worldwide. The limited success of carbon pricing systems covering fewer than 15% of emissions is a clear example of this action (Influence Map 2020). Using lawsuits and lobbying tactics, the fossil fuel industry has also hindered key regulations such as the US Clean Power Plan and the EU's Emissions Trading Scheme. The auto industry's lobbying efforts have similarly compromised climate rules on vehicles in both the US and the EU. Moreover, vested interests have directed Japan towards pursuing a coal future. Even UN bodies for shipping and aviation have been captured by industry, undermining the development of critical climate policy for these sectors. These events demonstrate how persistent negative lobbying has significantly hindered climate policy progress since the possibility of regulation emerged in the late 1980s (Principles for Responsible Investment, 2018). Corporate lobbyists have employed two main strategies to obstruct binding regulatory measures: capturing the public narrative on climate change and directly lobbying against regulations (Yu 2005). These elements gave us the rationale for trying to find which kind of link exists between lobbying activity and the direct environmental impacts of the lobbying firms. In order to do that, we created a unique dataset including firm-level GHG emissions.

Finally, behind this behaviour, there exists a high probability of greenwashing practices (Freitas Netto et al. 2020). Empirical evidence seems to show sceptical results regarding the impact of investments based on Environmental, Social and Governance (ESG) indicators. ESG scores serve as signals that firms send to investors regarding these three dimensions but might not constitute a good proxy –at least not- for the actual environmental performance of the firm (Boffo, Marshall, and Patalano 2020; Boffo and Patalano 2020). Actually, firms may score high on the ESG while delivering a poor impact over different environmental indicators, such as recently stressed in some papers such as those of Cohen, Gurun and Nguyen (2020), Green and Roth (2021) and Oehemke and Opp (2022), among others.

So, in our study, we utilize the Environmental pillar score as an index of environmental reputation score for two main reasons. Firstly, the E pillar score evaluates a wide range of information on a company's environmental performance, including waste and emission, climate change, and risk management. These aspects are significant for stakeholders, investors, and legislators who prioritize the environmental impact and sustainability of the company. Moreover, a key issue when analyzing the role of brown and green groups is identifying which firms are brown or green. In these last years, the emergence of ESG indicators has served as a guide for investors who want to impact the environment positively. According to Kolbel et al. (2021), there exist growing expectations that sustainable investing (SI) will allow for achieving environmental goals, and this is the reason why, for example, banks cater these expectations by offering investment options that fit them, or policymakers discuss the potential impact of SI, as in the International Panel on Climate Change in 2018. However, the evidence regarding the actual impact of SI is more limited. Busch et al. (2021) affirm that impact does not equal ESG and that it is time to put impact at the centre of the debate. Indeed, since impact investment is often used interchangeably for any investment that incorporates ESG dimensions, and since transformational change is not the main purpose of these investments, then there exists a high risk of greenwashing. Cohen et al. (2021), for example, show that ESG indicators in some sectors are not a good proxy for green patenting. Boffo et al. (2020), for instance, point out that environmental pillar scores for some providers are positively correlated with carbon emissions, which suggests that firm's plans reduce emissions in the future play an important role in determining the scores, rather than the level of emissions at the point of calculations.

Secondly, and most importantly, the E pillar score is an indicator of a company's ability to adapt to changing environmental regulations and policies that lobbying activities may influence. A higher E pillar score suggests that a company is more proactive and responsive to the relevant environmental issues and challenges in its industry and market. This score is used in our empirical analysis to examine the correlation between the implementation of environmental policies, the level of innovation, and the lobbying activity of the firms in our selected sample.

In the next section, a descriptive analysis of who has been lobbying in Europe since 2012 is provided to see whether green or brown firms were more active. Later, the relationship between the lobby and environmental pillar scores is addressed with a formal econometric approach.

4 Data and Descriptive Statistics

After presenting our study context, the objectives of our work and the link with previous findings in related literature, the following section presents an overview of the selected data and the relative descriptive statistics used in this study.

Lobbying Expenditures The Lobbying dataset utilized in this study is based on LobbyFacts.com[9], which sources data from the EU Transparency Register. However, it is essential to note that the lobbying data has several limitations that require consideration (Gutiérrez, Philippon, et al. 2018). Firstly, the EU Transparency Register is voluntary; therefore, the dataset may underestimate the extent of lobbying activities. Nonetheless, it is noteworthy that the data still capture a substantial proportion of lobbying expenditures, given that prominent players are well represented in the dataset. For instance, according to Greenwood and Dreger (Greenwood and Dreger 2013), 75% of businesses and 60% of NGOs actively engaging EU political institutions were registered. Moreover, registrants have increased by more than 50% since 2013.

[9]See also: `https://www.lobbyfacts.eu/?sort=lob&order=desc`.

Another issue is that the data may suffer from double-counting, as the dataset includes corporations engaging in lobbying activities and their lobbying intermediaries. Additionally, the dataset may present measurement issues for small firms. Therefore, we adopt LobbyFacts.com's approach of applying restrictions based on the number of European Parliament passes and European Commission meetings to address these issues. Specifically, we eliminate observations in the top 5% of lobbying expenditures for firms with no European Parliament passes or European Commission meetings. We also address outliers in the data. For instance, we replaced lobbying expenditures for the University College Dublin National University of Ireland, Dublin, in 2015 with the prior year's quantity, as it is an extreme outlier. The same approach is taken for the European First Institute and Sagorday Abogados. It is essential to acknowledge that most firms report ranges of lobbying expenditures instead of specific amounts. Therefore, we utilize the midpoint of all ranges in our estimates. Finally, we base our annual totals for the EU on the complete register available through LobbyFacts as of semester-end for 2012 to 2020.

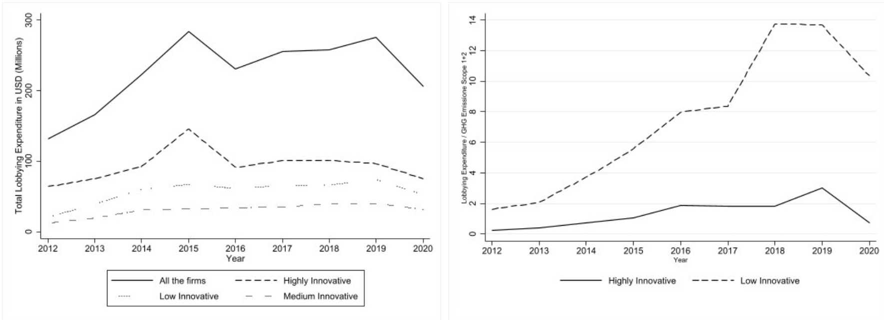
So, concerning lobbying activity, our dataset includes the following variables: *Lobby Expenditures*: This variable measures the lobbying costs for each lobby in units of 10,000 euros. *European Passes (EP)*: The EP passes figure is derived directly from the European Parliament's records and provides information on the number of accredited European Parliament pass-holders. Concerning this point, while the EP passes figure accurately reflects all lobbyists with EP passes, it may not capture all of an organisation's lobbyists. *Meetings with EC*: This variable captures the number of meetings between lobbyists and the European Commission. *Country's Head of Office*[10]: This variable is based on the information provided to the register about the location of the head office of registrants and provides the geographical localization of the organizations. We selected this dataset as it may be relevant to understanding the relationship between lobbying expenditure and innovation, specifically in the context of green patents. Furthermore, as outlined in the previous section, these variables have been subjected to a rigorous data-cleaning process.

Environmental Policy *Environmental Policy Stringency*: This variable measures the degree to which a country's environmental policies and regulations are stringent. The OECD's "Environmental Policy Stringency Index" provides a composite score based on the comprehensiveness and strictness of a country's environmental policies across various sectors, such as air and water quality, biodiversity, and climate change (Kruse et al. 2022). The index ranges from 0 to 6, with higher values indicating greater policy stringency. This variable is relevant to our study as it enables us to examine the impact of policy stringency on the relationship between lobbying expenditure and green patents, and this index has been widely used as a tool for policy analysis (Albrizio et al., 2017; Lee and Olasehinde-Williams 2022).
Carbon Tax: This variable measures the tax levied on the carbon content of fossil fuels, such as coal, oil, and gas. It is also sourced from the OECD and expresses the *Effective Carbon Rates* dataset, which provides information on carbon taxes, emissions trading systems, and other carbon pricing mechanisms across various countries (Kruse et al. 2022). The variable is measured in euros per tonne of CO2 emissions and varies across countries based on their respective carbon pricing policies. This variable is essential to our study as it allows us to investigate the impact of carbon pricing policies on the relationship between lobbying expenditure and green patents, specifically in the transition to a low-carbon economy.

Green patents data The *stock of Green Patents*: This variable measures the number and economic value of patents related to environmentally friendly technologies and processes, also known as "green patents". The stock of green patents can provide insight into a country's innovation and competitiveness in sustainable development. In our study, we measure the stock of green patents in two ways: (1) by the number of green patents granted by the European Patent Office[11] (EPO) and (2) by the economic value of green patents, as estimated by the renewal fees paid by patent holders. The *stock of Total Patents*: This variable measures the number and economic value of all patents granted by the EPO, regardless of their environmental relevance. The stock of total patents is a widely used indicator of a country's innovation activity and can provide insight into its overall competitiveness and economic performance. In our study, we measure the stock of total patents in two ways: (1) by the number of total patents granted by the EPO and (2) by the economic value of total patents, as estimated by the renewal fees paid by patent holders.

[10]see Table A.2 in the Appendix for the complete number of lobbying firms by Country Head of Office in Europe.
[11]See also: https://www.epo.org/searching-for-patents/legal/register.html

Figure 3: Lobbying Expenditure by level of innovation



Patent renewal fees are a good proxy for the economic value of patents, as they reflect the willingness of patent holders to maintain their patent rights over time. However, this measure may only partially capture the actual economic impact of patents, as some patents may generate significant economic value despite not being renewed. Furthermore, the number of patents granted is only a partial measure of innovation activity, as it does not capture the quality or originality of the patented inventions.

The stock of patents in mitigation technologies issued by a firm is often used to measure its green innovation level, and this information is obtained from PATSTAT [12], a comprehensive database of all patents filed by firms worldwide that are maintained and updated by the European Patent Office (Calel and Dechezleprêtre 2016; Dechezleprêtre et al. 2022). This paper focuses explicitly on patent applications related to climate change mitigation technologies, which are identified through the *Y02* tagging system developed by the European Patent Office and available on all patent applications recorded in the global PATSTAT database. These inventions include technologies for buildings (such as efficient home appliances), clean energy generation, innovative grid technologies, transportation, and mitigation technologies for the production or processing of goods (such as metals, chemicals, and minerals) (European Patent Office 2016). In contrast to measuring patent flows, this analysis uses the accumulated stock of low-carbon patents not as the explanatory variable but as a way to define a sub-sample of innovative firms and a sub-sample of low-innovation firms. This is because it takes time for firms to benefit from innovation, which must first be developed into marketable products. In addition, the uptake of new technologies by the market may take time. As a result, a firm's patent stock in low-carbon technologies is a more appropriate measure for assessing the impact of low-carbon innovation on the propensity to lobbying activity.

Environmental score and GHG emissions The Environmental pillar score measures a company's environmental sustainability that has gained significant interest among investors seeking to incorporate sustainability considerations into their investment decision-making processes. However, the reliability of using ESG scores, including the E-Score, to capture a company's environmental performance has been subject to much debate in both the academic and financial communities. As said in the previous section, previous studies have found a low correlation between E-Scores and actual environmental metrics such as CO2 emissions. As a result, high E scores may be awarded to companies with poor environmental performance.

Given these limitations, we will use the company's environmental score, a continuous variable between 0 and 100, retrieved from the Bloomberg platform, as a reputation environmental score, given that investors use it to differentiate portfolio composition based on the possible environmental impacts of their investments.

Firm-level emissions data is obtained from Bloomberg and measured in CO2 equivalents (tons). These emissions include direct emissions from company-owned resources (Scope 1) and indirect emissions from purchased energy (Scope 2). Emissions are reported voluntarily or in compliance with existing regulations, such as the European Union Emission Trading System, and predominantly follow the GHG Protocol. The analysis calculates firms' emission intensity by dividing emissions by total assets. However, in the robustness check, emissions are alternatively divided by the firm's value-added, despite this variable being less frequently reported.

[12]See also: https://data.epo.org/expert-services/index.html

Firm-level financial data We retrieved firm-level financial data from the Bloomberg database and, precisely, total revenues, market capitalization, country of domicile, and sector. Total revenue is a measure of the total amount of income generated by a company through its sales activities. Market capitalization, on the other hand, represents the total market value of a company's outstanding shares of stock. The country of domicile refers to the country where the company is incorporated and legally registered. Finally, the sector of the company refers to the industry in which it operates. The country of domicile and sector in particular related to lobbying activity can provide insights into the regulatory environment and competition faced by the firm.

The descriptive statistics of our dataset is reported in Table 1.

Table 1: Descriptive Statistics

	Mean	SD	Min	Max	N
Lobbying Expenditure in EUR	384,182.97	1.1e+06	0.00	55,000,000	5,283
Lobbying by type of firms					
Highly Innovative firms	649,239.68	732107	0.00	55,000,000	144
Low Innovative firms	318,087.30	612230.4	0.00	11,750,000	176
Medium Innovative firms	267,944.68	448512.9	0.00	2,439,500	114
Market Capitalisation in USD (Billion)	57.67	165.67	0.30	2154.75	3,914
Total Revenue in USD (Million)	23,143.87	41762.75	0.19	467,153.00	5,283
GHG Emission Scope 1+2 in mtCO2	6,049,701.51	1.86e+07	0.00	194,000,000	3,914
Environmental Policy Stringency	3.17	0.68	0.25	4.89	5,022
Carbon Tax	1.26	2.09	0.00	6.00	5,121
E Score	55.67	30.93	0.00	99.12	4,620
Stock of Green Patents	314.77	1,372.57	0.00	22,271	3,914
Value of the Stock of Green Patents in EUR	517.12	2108.87	0.00	33176.50	3,914
Total Stock of Patents	2997.74	9680.97	0.00	117,220	3,914
Value of the Total Stock of Patents in EUR	4609.29	2108.87	0.00	185199.57	3,914
% of green patents value of the Total Stock value	11.26	16.83	0.00	100	
% of green patents of the Total Stock	9.76	14.77	0.00	100	
Number of firms					590
Country					43
Sector					98

Notes: Table 1 reports Descriptive statistics. *Sources*: Bloomberg, OECD, Lobbyfacts.eu; European Patent Office (EPO); the authors processed the data.

Table 1 presents the descriptive statistics for all the variables in our dataset, reporting mean, standard deviation, minimum, maximum, and the number of observations (N) for each variable. The numbers indicate that the average lobbying expenditure for all firms in EUR is 384,182.97, with a maximum expenditure of 55,000,000 for a single firm. Furthermore, highly innovative firms have a higher mean lobbying expenditure of 649,239.68 than low innovative and medium-innovative firms, with mean expenditures of 318,087.30 and 267,944.68, respectively (see Figure 3 for the trend of the entire period of the analysis). The market capitalization in USD billion ranges from 0.30 to 21,54.75, with a mean of 57.67. The average total revenue in USD million is 23,143.87, with a minimum of 0.19 and a maximum of 467,153.00. The GHG Emission Scope 1+2 variable indicates the sum of GHG Emissions Scope 1 and Scope 2 (in mtCO2), with a mean of 6,049,701.51, with a maximum emission of 194,000,000 for a single firm. The average environmental policy stringency for the countries where our firms are based is 3.17, ranging from 0.25 to 4.89. Moreover, the average carbon tax rate is 1.26, with a standard deviation of 2.09, ranging from 0 to 6.00. The E Score, representing the environmental performance of firms, has a mean of 55.67, ranging from 0 to 99.12. The stock of green patents has an average of 314.77, with a standard deviation of 1,372.57 and a maximum of 22,271. The average value of the stock of green patents in EUR is 517.12, ranging from 0 to 33,176.50. Additionally, the total stock of patents has a mean of 2997.74, ranging from 0 to 117,220, with an average value in EUR of 4609.29. The % of green patents value of the total stock value and % of green patents in the total stock has a mean of 11.26 and 9.76, respectively, indicating that green patents represent a small percentage of the total patents held by the firms. Finally, the data includes observations for 590 firms from 43 countries and 98 sectors for a period that comes from 2012 to 2020.

5 Methodology

This section proposes the methodology used to explain our empirical method better, just outlined in the previous subsection. Our dependent variable, Lobbying Expenditure, is recorded by the lobbying firm in the European Commission register, as explained in Section 4. Given this, the result of our research allowed us to derive the lobbying expenditure for each year and for each firm. In addition, the resulting dataset from this research presents the lobbying variable as a count variable, as it is not a continuous variable between one period and the next. In fact, between one year and the next, a firm may spend 0 or a certain amount, always greater than zero. Since our variable is necessarily discrete, it cannot have values less than zero (by definition), and its distribution is highly skewed and not bounded above. Therefore, we adopted the Poisson fixed effects model for count data, as often suggested in the literature in cases like these (e.g. the number of children or arrests in the past five years) (Greene 2001; Baltagi and Song 2006; Wooldridge 2010; Fankhauser, Gennaioli, and Collins 2015;).

It is worth mentioning that our methodology is based on the one used in two seminal papers that used this methodology. The first is the paper written by Hausman, Hall, and Griliches (1984), who were interested in showing the link between patent applications by firms in terms of spending on research and development (Hall, Griliches, and Hausman 1984). The second is the paper written by Ferguson and Horwood (2000) (Fergusson and Horwood 2000), in which authors analyzed linkages between patterns of alcohol abuse and crime in New Zealand, taking into account confounding factors through the use of fixed-effects regression methods.

Linear panel data models adopt the linear additivity of the fixed effects to eliminate them and avoid the incidental parameter problem. Although Poisson models are inherently nonlinear, the use of the linear index and the exponential link function results in multiplicative separability as shown in the equation:

$$E[y_{it} \vee x_{i1} \ldots x_{iT}, c_i] = m(x_{it}, c_i, b_0) = exp(c_i + x_{it}b_0) = a_i exp(x_{it}b_0) = \mu_{ti} \quad (1)$$

Here, μ_{ti} represents the Poisson parameter, a_i represents the individual-specific fixed effect, and x_{it} denotes the observable variables. Since the conditioning set includes the observables over all periods, we are in the static panel data world and are imposing strict exogeneity. Andersen's conditional Maximum Likelihood methodology is used by Hausman, Hall, and Griliches to estimate b_0 by using $n_i = \sum y_{it}$. This allows us to obtain the distributional result of y_i shown in equation (2):

$$y_i \vee n_i, x_i, c_i \sim Multinomial(n_i, p_1(x_i, b_0), ..., p_T(x_i, b_0)) \quad (2)$$

where $p_t(x_i, b_0)$ is the multinomial probability function. The fixed-effect Poisson model is estimated by maximum-likelihood estimation techniques for multinomial log-likelihoods, which is not computationally restrictive. However, the distributional assumptions up to this point are fairly stringent. Wooldridge (Wooldridge 2010) has provided evidence of the robustness properties of these models as long as the conditional mean assumption (equation 1) holds.

To conclude this brief paragraph that explains the model used in our analysis, we decided to apply a fixed-effects Poisson model for the following reasons. First, our main variable has no negative value. Second, It is not bounded above. Third, it is discrete. Fourth, the distribution of our dependent variable is highly skewed. Fifth, we can absorb fixed-effects levels at the firm level without incurring biased estimators of our coefficients. Finally, the Poisson fixed effects estimator is a quasi-maximum likelihood estimator (Wooldridge, 2010). As a result, it provides consistent parameter estimates even if the underlying distribution is not Poisson, provided as long as the conditional mean assumption is well specified.

Given all of the above, to test our hypotheses defined in our introduction, we use the following equation defined in the next part of this paper. Firstly, we present our first specification model, defining our dependent variable as the absolute value of expenditures in lobbying activity at the firm level for the entire period of the analysis. In Appendix A.1, we set as a dependent variable the same amount for lobbying but relative to the total revenue of the firm, variable was also used to identify the possible propensity to lobby in relation to the size of the individual firm. Moreover, in order to check our hypothesis that wants to investigate the correlation between lobbying expenditure and the level of green innovation of each firm, we split our sample into three based on the level of the green patents count, high innovation firms, medium innovation firms and low innovation firms.

From this, as discussed in the previous parts of this paper, our empirical analysis will focus on which kind of relationship intercourse between direct lobbying activity and some measure of environmental policy and behaviour. Equation 3 represents our baseline regression model for our analysis, where the dependent variable is the lobbying expenditure incurred by firms during the analysis period, and the independent variables are the Environmental Performance Index (EPI) and E Score.

$$Lobbying\ Expenditure_{it} = \beta_0 + \beta_1 EPI_{it} + \beta_2 E\ Score_{it} + \eta_i + \pi_t + \epsilon_{it} \tag{3}$$

The coefficients β_1 and β_2 represent the effect of EPI and E Score on lobbying expenditures, respectively. The EPI is a composite index that reflects a country's environmental performance, while the E Score measures a company's environmental performance on a scale of 0 to 100. The last three terms of the equations explain the following. On one hand, η_i accounts for firms fixed effects, while π_t accounts for time fixed effects and its variations over time. The error term ϵ_{it} captures the variability in the dependent variable that is not explained by the independent variables. By estimating this model, the paper aims to investigate the relationship between firms' environmental performance and lobbying activities and shed light on the potential motives behind firms' lobbying expenditures.

$$Lobbying\ Expenditure_{it} = \beta_0 + \beta_1 EPI_{it} + \beta_2 E\ Score_{it} + \beta_3 GHG_{it} + \eta_i + \pi_t + \epsilon_{it} \tag{4}$$

The second equation of our model, Equation 4, explain still the relationship between lobbying expenditure (dependent variable) and environmental performance index, E Score, but including also the possible effect of the level GHG emissions. The rational for this specification is given by the insights provided in section 2. During the period under analysis, most firms engaged in lobbying activities in either high-polluting or green sectors, as the implementation of environmental regulations was on the rise. This trend aligns with previous studies, which have shown that firms in industries that are particularly affected by government regulations often undertake to lobby. However, the extent to which lobbying activity in these sectors has influenced environmental policy outcomes remains debatable. Some argue that lobbying by polluting firms has weakened environmental regulations, while others contend that lobbying by firms with green credentials has led to more stringent regulations. Given the above, we include in our regression model also the GHG emissions to control also for the net impact on the environment. That said, the coefficient β_1 represents the effect of the environmental performance index on lobbying expenditure, while β_2 and β_3 represent the effects of E Score and GHG emissions, respectively, ϵ_{it} is the error term that captures unexplained variation in lobbying expenditure. Again, η_i accounts for firms' fixed effects, while π_t accounts for time-fixed effects and their variations over time. Based on our initial assumptions, this equation should suggest that firms in countries with higher environmental performance, lower GHG emissions, and higher E Scores that are more innovative are likely to have lower lobbying expenditures.

Moreover, we expand the previous equation by including a new independent variable, total revenue. The addition of this variable justified the previous conclusions of the relative strand of the literature. The assumption is that firms with higher revenues are more likely to defend their profitability and protect their market position. Therefore, it is reasonable to expect that firms with higher revenues will engage in more lobbying activities to influence environmental policies in their favour. In this expansion, the β coefficient would represent the regression coefficient which shows the effect of Total Revenue on the dependent variable, lobbying expenditure, aiming to provide a more comprehensive model to explore the relationship between lobbying activity and various factors, including a firm's environmental performance, GHG emissions, and total revenue. It highlights the potential influence of revenues as a critical determinant of lobbying activity, and It can offer valuable insights for policymakers and stakeholders in understanding the motivations and behaviour of firms in the context of environmental regulation.

Section 6 will provide and show the empirical results of our analysis.

6 Results

The Results section presents our findings of the analysis conducted to test the research hypotheses provided in Section 1 about the possible correlations among lobbying, green innovation and environmental indicators.

The following paragraphs describe the statistical results and their implications for the research questions. All the models presented include time-year and firm-level fixed effects. The tables also report the number of observations, the number of groups, and the ln(alpha) estimate of the over-dispersion parameter. Robust standard errors are used, and the clustering is at the firm level. The table also reports the likelihood ratio test results for the hypothesis that all coefficients except for the intercept are equal to zero.

Table 2: Fixed Effects Poisson Model - High Innovative Lobbying Firms

Firm Cluster: High Innovative Dependent Variable: Lobbying Expenditure	(1)	(2)	(3)	(4)
Environmental Policy Stringency	-0.045	-0.043	0.054	0.063
	(0.245)	(0.247)	(0.254)	(0.253)
E Score	0.007**	0.007**	0.006**	0.006**
	(0.003)	(0.003)	(0.003)	(0.003)
Total Revenues in USD		-0.000	-0.000	-0.000
		(0.000)	(0.000)	(0.000)
Carbon Tax			-0.090*	-0.000
			(0.041)	(0.054)
GHG Emission Scope 1+2				-0.000*
				(0.000)
Constant	11.392***	11.433***	11.298***	11.153***
	(0.724)	(0.682)	(0.681)	(0.691)
Time year FE	Yes	Yes	Yes	Yes
Firm-level FE	Yes	Yes	Yes	Yes
Number of obs.	1271	1271	1271	1271
Number of groups	168	168	168	168
ln(alpha)	1.276	1.294	1.298	1.305
	(0.887)	(0.880)	(0.881)	(0.878)
vce(cluster firm)	Yes	Yes	Yes	Yes
Prob > chi2	0.000	0.000	0.000	0.000

Notes: Table 2 reports the outcome table from our regression model. From model (1) to model (4) we provide all the different specifications designed in the methodological section of our paper. Time year and firm-level fixed effects are included. Robust Standards error are included in our regression analysis. *Sources*: Bloomberg, OECD, Lobbyfacts.eu; European Patent Office (EPO); the authors processed the data.

Table 2 shows our results for High innovative lobbying firms in our sample, based on the stock of green patents. As assumed in Section 1, the coefficient for the Environmental Policy Stringency variable is negative in all four models, which suggests that firms in high innovative clusters may reduce their lobbying expenditure when environmental policy stringency increases, given the accommodate environmental policies already put in place by policymakers. However, the coefficients are not statistically significant at the conventional confident level, indicating that we cannot confidently conclude that there is a strong correlation between these two variables. The E Score variable has a positive coefficient in all four models, indicating that firms in high innovative clusters potentially increase their lobbying expenditure as their E Score (a measure of environmental reputation) increases. This is in line with our general conclusion about the meaning of the E score. It is not a direct indicator of the environmental impact, but it is more an indicator of environmental engagement and reputation. The coefficients are statistically significant at the 1% level ($p < 0.01$) in all models, suggesting that this correlation is robust. However, the magnitude of this impact is low: the probability of having an increase in lobbying expenditure is below 0.10%. The Total Revenues in USD variable has a very low negative coefficient in the second, third and fourth models. However, these coefficients are not statistically significant at conventional levels ($p > 0.05$) in either model, indicating that if companies grow in size, they do not tend to spend more on lobbying. The Carbon Tax variable has a negative coefficient in the third and fourth models, indicating that firms in high innovative clusters may reduce, given this correlation, their lobbying expenditure because of the carbon tax rate increases. However, this coefficient is statistically significant at conventional levels ($p > 0.10$) only in model (3), also indicating here that we cannot confidently conclude that there is a correlation between these variables. Finally, the GHG Emission Scope 1+2 variable has a positive coefficient in the fourth model, indicating that firms in highly green innovative clusters increase their lobbying expenditure as their GHG emissions increase. The coefficients are statistically significant at the 1% and 5% levels ($p < 0.01$ and $p < 0.05$, respectively), suggesting that there could be a relationship that is statistically significant. However, it's not surprising to see that for innovative firms, the magnitude of this correlation is very low, indicating that if companies pollute more (in terms of GHG emissions), they do not tend to spend more on lobbying.

In summary, Table 2 suggests that for highly green innovative lobbying firms, there is no statistically significant relationship between environmental policy stringency and lobbying expenditure. A positive and significant correlation exists between lobbying expenditure and the E Score in all models, while the correlation with Total Revenues is not significant. The correlation between lobbying expenditure and GHG Emission Scope 1+2 is negative and significant, while the correlation with Carbon Tax is statistically significant only in model 3.

Table 3: Fixed Effects Poisson Model - Medium Innovative Lobbying Firms

Firm Cluster: Medium Innovative Dependent Variable: Lobbying Expenditure	(1)	(2)	(3)	(4)
Environmental Policy Stringency	0.385***	0.336**	0.322**	0.323**
	(0.143)	(0.135)	(0.139)	(0.131)
E Score	0.011*	0.007*	0.008*	0.008
	(0.006)	(0.005)	(0.006)	(0.005)
Total Revenues in USD		0.000**	0.000***	0.000***
		(0.000)	(0.000)	(0.000)
Carbon Tax			0.011	0.011
			(0.041)	(0.041)
GHG Emission Scope 1+2				-0.000
				(0.000)
Constant	9.895***	9.742***	9.742***	9.774***
	(0.560)	(0.539)	(0.539)	(0.497)
Time year FE	Yes	Yes	Yes	Yes
Firm-level FE	Yes	Yes	Yes	Yes
Number of obs.	827	827	827	827
Number of groups	104	104	104	104
ln(alpha)	1.179	1.132	1.131	1.134
	(1.043)	(1.100)	(1.100)	(1.098)
vce(cluster firm)	Yes	Yes	Yes	Yes
Prob > chi2	0.000	0.000	0.000	0.000

Notes: Table 3 reports the outcome table from our regression model. From model (1) to model (4) we provide all the different specifications designed in the methodological section of our paper. Time year and firm-level fixed effects are included. Robust Standards error are included in our regression analysis. *Sources*: Bloomberg, OECD, Lobbyfacts.eu; European Patent Office (EPO); the authors processed the data.

Table A.9 reports the results of our fixed effects Poisson regression model estimating the correlation of environmental policy stringency and the E score on lobbying expenditure for medium innovative lobbying firms. Also, for this group of firms, the table presents four different models with varying specifications.

Differently from what has been shown for highly innovated firms, here, the correlation among our key variables is different but in line with our hypothesis. In all four models, environmental policy stringency positively and significantly affects lobbying expenditure. The coefficient estimates range from 0.322 to 0.385, depending on the model specification. This confirms our second hypothesis, which posits that environmental policy outcomes and regulations in the EU can positively be correlated with lobbying expenditures, particularly for moderately green innovative firms striving to maintain competitiveness with highly green innovative firms. This is validated across all four model specifications.

Moreover, for medium innovative firms, the E score is not significant only in the model (4). In the baseline model, it has a significant and positive correlation with lobbying expenditure, but this effect becomes smaller and not significant in model 4.

Again, total revenues are included as an independent variable in models (2), (3) (4) and have a positive and significant correlation with lobbying expenditure, but a very low magnitude (less than 0.001% of the probability to increase lobbying expenditure comes from total revenues). GHG emission scope 1+2 is included in model (4), and like the Carbon tax, they do not have a significant correlation with the probability of an increase in lobbying expenditure.

To conclude, results from Table 3 suggest that for medium innovative lobbying firms, there is a positive and statistically significant correlation between environmental policy stringency and lobbying expenditure. A positive and significant correlation exists between lobbying expenditure and the E Score in model (1), (2) and (3) and Total Revenues in models (2) to (4). The correlation between lobbying expenditure, GHG Emission Scope 1+2, and Carbon Tax are not statistically significant.

Table 4: Fixed Effects Poisson Model - Low Innovative Lobbying Firms

Firm Cluster: Low Innovative Dependent Variable: Lobbying Expenditure	(1)	(2)	(3)	(4)
Environmental Policy Stringency	-0.350	-0.371	-0.364	-0.364
	(0.280)	(0.283)	(0.286)	(0.315)
E Score	0.011*	0.009*	0.010*	0.008
	(0.006)	(0.005)	(0.005)	(0.005)
Total Revenues in USD		0.000*	0.000*	0.000*
		(0.000)	(0.000)	(0.000)
Carbon Tax			-0.011	-0.000
			(0.000)	(0.045)
GHG Emission Scope 1+2				0.000
				(0.000)
Constant	13.250***	13.191***	13.186***	13.187***
	(0.726)	(0.670)	(0.674)	(0.728)
Time year FE	Yes	Yes	Yes	Yes
Firm-level FE	Yes	Yes	Yes	Yes
Number of obs.	1243	1243	1243	1243
Number of groups	144	144	144	144
ln(alpha)	1.125	1.076	1.076	1.068
	(1.412)	(1.473)	(1.473)	(1.485)
vce(cluster firm)	Yes	Yes	Yes	Yes
Prob > chi2	0.000	0.000	0.000	0.000

Notes: Table 4 reports the outcome table from our regression model. From model (1) to model (4) we provide all the different specifications designed in the methodological section of our paper. Time year and firm-level fixed effects are included. Robust Standards errors are included in our regression analysis. *Sources*: Bloomberg, OECD, Lobbyfacts.eu; European Patent Office (EPO); the authors processed the data.

Finally, to conclude our empirical analysis, Table 4 displays the results of a fixed effects Poisson model for low-innovative lobbying firms. Again, the dependent variable is lobbying expenditure, and our key independent variables are environmental policy stringency and the E Score. The model still includes firm-level and time-year fixed effects. The statistical significance of the model is tested using a chi-squared test, report below in the table. Also here, in line with our hypothesis, the results suggest that environmental policy stringency has a negative impact on lobbying expenditure for low-innovative lobbying firms, with coefficient estimates of -0.350, -0.371, -0.364, and -0.364 in models (1), (2), (3), and (4), respectively. The negative coefficient indicates that the correlation with lobbying expenditure decreases for low-innovative lobbying firms as environmental policy stringency increases. The coefficients are not statistically significant at the 5% level in all models, even if at the boundaries of the statistical significance. Also, for low-innovative firms, E Score, our measure of a firm's environmental reputation, has a positive effect on lobbying expenditure in all the models, with coefficient estimates of 0.011, 0.009, 0.010 and 0.008, respectively. However, in model

(4), the coefficient is not statistically significant. This suggests that a higher E Score is correlated with increased lobbying expenditure for low-innovative lobbying firms, but the effect is inconsistent across all model specifications. The economic and size effect, apparently, is more correlated with lobbying expenditure for this kind of firm. Total revenues have a positive correlation on lobbying expenditure for low-innovative lobbying firms, with a statistically significant coefficient estimate between 0.00012, 0.00011 and 0.00035 in models (2), (3), and (4). This indicates that as a firm's total revenues increase, lobbying expenditure also increases, indicating a positive correlation, in line with the past literature that analyzed the direct lobbying behaviour of polluting firms (Yu 2005). Conversely, GHG Emission Scope 1+2 and carbon tax are not statistically significant predictors of lobbying expenditure for low innovative lobbying firms in models (3) and (4), respectively. The constant term is statistically significant in all models, with coefficient estimates of 13.250, 13.191, 13.186, and 13.187, respectively. In addition, including firm-level and time-year fixed effects helps to control for unobserved heterogeneity and increases the precision of the estimated coefficients. And this has been considered for all the models just presented. The model fit is good, as indicated by all models' significant chi-squared test results. Overall, the results suggest that environmental policy stringency, E Score, and total revenues in USD are important determinants of lobbying expenditure for low-innovative lobbying firms.

In summary, the table suggests that there is a negative correlation between environmental policy stringency and lobbying expenditure for low-innovative lobbying firms, although it is not statistically significant. A positive and significant correlation exists between lobbying expenditure and both the E Score (in models (1), (2) and (3)) and Total Revenues. The correlation between lobbying expenditure, GHG Emission Scope 1+2, and Carbon Tax are not statistically significant.

Finally, the main insights from our analysis can be outlined as follows. First, high-innovative firms might be better equipped to adapt to environmental policies and respond to changes in EPI levels. In addition, as their E score increases, the probability of investing more in lobbying, suggesting that they might be proactive in shaping regulations that align with their environmental performance and business interests. Second, for medium-innovative firms, EPI levels play a critical role in influencing their lobbying expenditures. As the EPI level rises, these firms might be more likely to increase lobbying efforts. This could indicate that they could be more sensitive to regulatory changes and may need to invest more resources in influencing policies to maintain their competitiveness. Third, for what concerns low-innovative firms, one could infer that they face more challenges in adapting to stringent environmental policies. These firms may need to invest in innovation to improve their environmental performance and reduce the potential negative impacts of EPI changes on their operations. This could explain why a rise in EPI or E score does not necessarily lead to a higher probability of lobbying expenditures for such firms. It is worth mentioning that companies with limited innovative capacity may employ alternative means of political influence, such as indirect lobbying.

That said, the distinct behaviour of high, medium, and low innovative firms regarding E score and EPI highlights the importance of understanding the underlying drivers of innovation and environmental performance within each firm category. Policymakers and regulators should consider these differences when designing and implementing environmental policies to ensure that they promote innovation and do not disproportionately affect firms with varying innovation capabilities. The correlation between E score, EPI, and lobbying expenditures also underscores the need for increased transparency in the lobbying process. In addition, ensuring that lobbying activities align with broader societal goals and sustainable development can create a level playing field for firms across the innovation spectrum. In conclusion, the results try to analyse the complex interplay between innovation, environmental performance, and policy engagement. Understanding these dynamics can help policymakers design more effective, inclusive regulations that foster innovation and promote sustainable development.

7 Conclusions

This paper presents a study on the direct lobbying activity in the European Union, with a focus on examining the correlation between the following key variables: environmental regulation at the country level, green innovation, and the environmental performances and reputation of firms involved in lobbying activities.

To achieve this, we provided a study context to establish a foundation for the reader regarding lobbying activities in the EU, the state of the art on environmental regulations, and the meaning and technicalities of environmental pillar scores, which investors and financial markets now use. Additionally, we conducted an extensive literature review, with a particular focus on studies examining lobbying activities, environmental performance, and their link with green innovation levels.

Our primary objective was to find a correlation and the type of relationship involving three key variables: lobbying expenditure (firm-level), the level of environmental policy performance of each European country, and the environmental reputation level of each company that lobbied between 2012 and 2020. This was done while considering the varying levels of green innovation in our analyzed sample. Our initial hypothesis, confirmed by our results, was to find a strong negative relationship between lobbying activities for firms in countries with high environmental policy performance but with a high level of green innovation. Conversely, we expected to find a strong correlation towards direct lobbying activities for those companies that demonstrate innovative activities in the environmental field but show a competitive disadvantage compared to more innovative companies. Finally, concerning the least environmentally innovative companies, coinciding with the most polluting ones, we expected to find, in line with part of the literature, a weak correlation between their lobbying activities and environmental policy performance.

To demonstrate this, we created a unique database based on lobbying information (company-level expenditure) obtained from the European Transparency Register, the level of green innovation (represented by the number of green patents obtained from the European patent register), and environmental and financial performance for each of the companies involved in lobbying activities in Europe during the selected analysis period. The empirical procedure involved applying a fixed-effects Poisson model, justified by the nature of our available data.

Despite being in line with our hypotheses and expectations, our work presents some problems and limitations. First, the paper does not aim to establish cause-and-effect relationships. The sample is limited to only those companies that have engaged in lobbying at least once during the chosen period. This precludes the application of counterfactual studies involving companies that did not spend on lobbying during the eight-year period. Second, the study is limited to finding correlations between key variables and does not include other information that may have statistical and economic value (e.g., sector concentration index and level of competition). Third, the country differentiation is based on a single indicator, the Environmental Performance Index, in terms of environmental legislation. Although considered a scientifically valid and sound indicator by existing literature, it can be complemented with other ideal tools to deepen the analysis (e.g., application of environmental directives at the national level).

Despite these limitations, there are opportunities for further scientific inquiry and development of research on environmental lobbying and dynamics related to climate change risk.

In particular, potential areas of further research may include, first, investigating the impact of different policy instruments on lobbying behaviour, such as carbon trading systems, renewable energy incentives, or subsidies for clean technology development. Second, examining the role of non-governmental organizations and civil society in shaping environmental lobbying strategies and their influence on policy outcomes. Third, analyzing the role of multinational corporations in influencing environmental policy across multiple jurisdictions and the potential spillover effects on domestic firms.

These potential research directions can contribute to a deeper understanding of the complex interplay between environmental lobbying, corporate innovation, and climate change risk, ultimately helping to inform more effective policy interventions and business strategies.

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Appendix

8 Descriptive Statistics - II

Table A.1: Top25 Lobbying Firms by Lobbying Expenditures - 2012 to 2020

	Lobby Expenditure	Firm Type
General Electric Co	78,100,000	Brown
Alphabet Inc	43,050,000	Brown
Royal Dutch Shell PLC	40,647,000	Brown
Exxon Mobil Corp	39,624,500	Brown
Bayer AG	38,700,000	Brown
Facebook Inc	38,700,000	Green
Microsoft Corp	38,700,000	Brown
FTI Consulting Inc	33,260,500	Grey
Siemens AG	29,545,440	Grey
Siemens Gamesa Renewable Energy SA	29,545,440	Green
Deutsche Bank AG	24,800,000	Green
Basf SE	24,325,000	Brown
Volkswagen AG	22,697,498	Brown
Dow Inc	22,250,000	Brown
Daimler AG	22,201,398	Brown
BP PLC	22,149,996	Brown
Engie SA	21,525,000	Brown
TotalEnergies SE	19,999,996	Brown
Telefonica SA	17,653,500	Green
EnBW Energie Baden Wuerttemberg AG	17,203,000	Grey
Enel SpA	16,650,000	Brown
Morgan Stanley	16,500,000	Green
Novo Nordisk A/S	15,525,000	Green
Evonik Industries AG	15,124,996	Grey
Intel Corp	14,624,996	Brown

Notes: Table A.1 reports the top lobbyst firms in EU. *Sources*: Lobbyfacts.eu; the authors processed the data.

Table A.2: Number of Lobbies by domicile in a European Country.

Country Head Office	2012	2013	2014	2015	2016	2017	2018
Aland Islands	0	1	1	0	0	1	0
Albania	2	1	2	4	4	2	2
Austria	104	118	163	189	237	236	240
Belarus	0	0	0	0	1	0	0
Belgium	1,340	1,449	1,673	1,894	2,063	2,116	2,164
Bosnia-Herzegovina	2	4	3	3	5	6	5
Bulgaria	28	34	34	55	55	59	77
Croatia	10	19	29	46	59	58	57
Cyprus	12	11	13	18	24	26	30
Czech Republic	42	38	55	71	89	107	112
Denmark	88	86	117	147	185	193	203
Estonia	1	5	8	16	43	51	50
Finland	70	81	128	169	208	213	244
France	559	600	729	896	1,035	1,063	1,099
Germany	651	713	865	1,064	1,339	1,444	1,491
Gibralter	0	0	0	1	1	0	0
Greece	44	41	66	85	111	137	138
Guadeloupe	0	0	0	0	0	1	1
Hungary	63	60	60	69	96	96	95
Iceland	2	2	4	4	3	7	8
Ireland	67	64	84	117	152	180	185
Isle of Man	0	0	0	1	1	1	1
Italy	433	475	636	638	798	858	834
Jersey	0	0	0	0	1	1	1
Kosovo	0	0	0	0	0	1	1
Latvia	10	10	15	26	31	35	39
Liechtenstein	0	1	1	2	3	4	5
Lithuania	11	12	15	14	33	42	56
Luxembourg	25	29	39	51	65	74	73
Macedonia	5	3	4	8	5	9	6
Malta	11	10	18	22	30	26	27
Moldova	3	4	5	3	7	5	5
Monaco	2	2	2	1	2	2	2
Montenegro	1	0	1	0	1	2	3
Netherlands	253	281	343	453	580	629	657
Norway	40	50	46	53	77	81	85
Poland	62	74	101	130	202	219	217
Portugal	60	62	94	124	166	176	183
Reunion	0	0	0	0	0	0	1
Romania	57	59	88	84	103	111	109
Russia	5	3	6	8	12	13	13
San Marino	1	2	1	2	2	2	2
Serbia	10	8	6	13	13	13	16
Slovakia	15	11	18	30	44	66	62
Slovenia	12	11	22	25	45	60	69
Spain	309	336	418	524	625	700	713
Sweden	102	104	131	171	224	252	261
Switzerland	83	92	132	171	208	240	255
Turkey	16	13	19	21	21	25	26
Ukraine	9	8	9	15	19	21	18
United Kingdom	525	579	708	975	1,144	1,175	1,150
Total	5,145	5,566	6,912	8,413	10,172	10,839	11,091

Table A.2 shows the number of Lobbies by European country. Numbers are yearly reported. French Guinea is merged with France, Netherlands with Netherlands Antilles since they have the same jurisdiction. Source: Lobbyfacts.com

Table A.3: Top 10 Lobbying Expenditures - 2012 to 2015

2012			
Company	Country	Sector	Lobbying exp.
EnBW Energie Baden Wuerttemberg Aktiengesellschaft	Germany	Electric Utilities	10,000,000
Exxon Mobil Corporation	UnitedStates	Oil & Gas Refining and Marketing	4,875,000
Siemens Gamesa Renewable Energy, SA	Spain	Renewable Energy Equipment & Services	4,729,533
Siemens Aktiengesellschaft	Germany	Renewable Energy Equipment & Services	4,729,533
Microsoft Corporation	UnitedStates	Software	4,650,000
Facebook Inc.	UnitedStates	Online Services	4,650,000
Bayer Aktiengesellschaft	Germany	Pharmaceuticals	4,650,000
Airbus SE	Netherlands	Aerospace & Defense	4,625,000
Electrolux Aktiebolag	Sweden	Appliances, Tools & Housewares	4,250,000
SHELL PLC	Netherlands	Integrated Oil & Gas	4,150,000
2013			
Company	Country	Sector	Lobbying exp.
Philip Morris CR as	CzechRepublic	Tobacco	5,125,000
Exxon Mobil Corporation	UnitedStates	Oil & Gas Refining and Marketing	4,875,000
Siemens Gamesa Renewable Energy, SA	Spain	Renewable Energy Equipment & Services	4,729,533
Siemens Aktiengesellschaft	Germany	Renewable Energy Equipment & Services	4,729,533
Microsoft Corporation	UnitedStates	Software	4,650,000
Bayer Aktiengesellschaft	Germany	Pharmaceuticals	4,650,000
Facebook Inc.	UnitedStates	Online Services	4,650,000
SHELL PLC	Netherlands	Integrated Oil & Gas	4,375,000
Roche Holding AG	Switzerland	Pharmaceuticals	4,300,000
Societe Generale SA	France	Banks	4,000,000
2014			
Company	Country	Sector	Lobbying exp.
FTI Consulting Inc.	UnitedStates	Business Support Services	6,125,000
Exxon Mobil Corporation	UnitedStates	Oil & Gas Refining and Marketing	4,875,000
SHELL PLC	Netherlands	Integrated Oil & Gas	4,624,500
Microsoft Corporation	UnitedStates	Software	4,500,000
Bayer Aktiengesellschaft	Germany	Pharmaceuticals	4,500,000
Facebook Inc.	UnitedStates	Online Services	4,500,000
Siemens Aktiengesellschaft	Germany	Renewable Energy Equipment & Services	4,355,792
Siemens Gamesa Renewable Energy, SA	Spain	Renewable Energy Equipment & Services	4,355,792
Deutsche Bank Aktiengesellschaft	Germany	Banks	4,000,000
Dow Inc.	UnitedStates	Commodity Chemicals	3,850,000
2015			
Company	Country	Sector	Lobbying exp.
General Electric Company	UnitedStates	Consumer Goods Conglomerates	55,000,000
Morgan Stanley	UnitedStates	Investment Banking & Brokerage Services	11,750,000
Exxon Mobil Corporation	UnitedStates	Oil & Gas Refining and Marketing	4,875,000
SHELL PLC	Netherlands	Integrated Oil & Gas	4,624,500
Facebook Inc.	UnitedStates	Online Services	4,500,000
Microsoft Corporation	UnitedStates	Software	4,500,000
Bayer Aktiengesellschaft	Germany	Pharmaceuticals	4,500,000
Alphabet Inc.	UnitedStates	Online Services	4,250,000
Deutsche Bank Aktiengesellschaft	Germany	Banks	3,950,000
Dow Inc.	UnitedStates	Commodity Chemicals	3,850,000

Notes: Table A.3 reports Descriptive statistics. *Sources*: Bloomberg, OECD, Lobbyfacts.eu; European Patent Office (EPO); the authors processed the data.

Table A.4: Top 10 Lobbying Expenditures - 2016 to 2020

2016			
Company	Country	Sector	Lobbying exp.
Alphabet Inc.	UnitedStates	Online Services	5,750,000
General Electric Company	UnitedStates	Consumer Goods Conglomerates	5,300,000
Exxon Mobil Corporation	UnitedStates	Oil & Gas Refining and Marketing	4,875,000
Microsoft Corporation	UnitedStates	Software	4,650,000
Facebook Inc.	UnitedStates	Online Services	4,650,000
Bayer Aktiengesellschaft	Germany	Pharmaceuticals	4,650,000
SHELL PLC	Netherlands	Integrated Oil & Gas	4,624,500
Deutsche Bank Aktiengesellschaft	Germany	Banks	3,250,000
BP P.L.C.	UnitedKingdom	Oil & Gas Refining and Marketing	2,875,000
Siemens Gamesa Renewable Energy, SA	Spain	Renewable Energy Equipment & Services	2,764,773
2017			
Company	Country	Sector	Lobbying exp.
Alphabet Inc.	UnitedStates	Online Services	6,125,000
FTI Consulting Inc.	UnitedStates	Business Support Services	6,125,000
Bayer Aktiengesellschaft	Germany	Pharmaceuticals	5,125,000
Microsoft Corporation	UnitedStates	Software	5,125,000
Facebook Inc.	UnitedStates	Online Services	5,125,000
SHELL PLC	Netherlands	Integrated Oil & Gas	4,624,500
Exxon Mobil Corporation	UnitedStates	Oil & Gas Refining and Marketing	4,624,500
BASF SE	Germany	Diversified Chemicals	3,300,000
Dow Inc.	UnitedStates	Commodity Chemicals	3,125,000
Equinor ASA	Norway	Integrated Oil & Gas	3,125,000
2018			
Company	Country	Sector	Lobbying exp.
Alphabet Inc.	UnitedStates	Online Services	8,125,000
Facebook Inc.	UnitedStates	Online Services	5,125,000
Microsoft Corporation	UnitedStates	Software	5,125,000
Bayer Aktiengesellschaft	Germany	Pharmaceuticals	5,125,000
SHELL PLC	Netherlands	Integrated Oil & Gas	4,624,500
Exxon Mobil Corporation	UnitedStates	Oil & Gas Refining and Marketing	3,875,000
BASF SE	Germany	Diversified Chemicals	3,300,000
Deutsche Bank Aktiengesellschaft	Germany	Banks	3,250,000
Volkswagen Aktiengesellschaft	Germany	Auto & Truck Manufacturers	2,875,000
Dow Inc.	UnitedStates	Commodity Chemicals	2,800,000
2019			
Company	Country	Sector	Lobbying exp.
FTI Consulting Inc.	UnitedStates	Business Support Services	6,875,000
Alphabet Inc.	UnitedStates	Online Services	5,900,000
Bayer Aktiengesellschaft	Germany	Pharmaceuticals	5,500,000
Microsoft Corporation	UnitedStates	Software	5,500,000
Facebook Inc.	UnitedStates	Online Services	5,500,000
SHELL PLC	Netherlands	Integrated Oil & Gas	4,624,500
Apple Inc.	UnitedStates	Phones & Handheld Devices	3,625,000
Siemens Gamesa Renewable Energy, SA	Spain	Renewable Energy Equipment & Services	3,522,448
Siemens Aktiengesellschaft	Germany	Renewable Energy Equipment & Services	3,522,448
Exxon Mobil Corporation	UnitedStates	Oil & Gas Refining and Marketing	3,375,000
2020			
Company	Country	Sector	Lobbying exp.
FTI Consulting Inc.	UnitedStates	Business Support Services	6,875,000
Alphabet Inc.	UnitedStates	Online Services	5,900,000
SHELL PLC	Netherlands	Integrated Oil & Gas	4,375,000
BP P.L.C.	UnitedKingdom	Oil & Gas Refining and Marketing	3,625,000
Exxon Mobil Corporation	UnitedStates	Oil & Gas Refining and Marketing	3,375,000
BASF SE	Germany	Diversified Chemicals	3,125,000
Siemens Gamesa Renewable Energy, SA	Spain	Renewable Energy Equipment & Services	3,125,000
Volkswagen Aktiengesellschaft	Germany	Auto & Truck Manufacturers	3,125,000
Siemens Aktiengesellschaft	Germany	Renewable Energy Equipment & Services	3,125,000
AMAZON.COM, INC.	UnitedStates	Department Stores	2,800,000

Notes: Table A.4 reports Descriptive statistics. *Sources*: Bloomberg, OECD, Lobbyfacts.eu; European Patent Office (EPO); the authors processed the data.

A.1 Fixed-Effect Poisson Regression: Lobbying Expenditure (% of Revenue)

In this sub-section of the Appendix, as robustness check for our main results in the paper, we estimated the following equations, that present as dependent variable Lobbying expenditure as percentage of the Total Revenue of our lobbying firms.

$$\frac{LobbyingExpenditure_{it}}{TotalRevenue} = \beta_0 + \beta_1 EPI_{it} + \beta_2 E\ Score_{it} + \eta_{CT} + \pi_{ST} + \epsilon_{it} \tag{5}$$

$$\frac{LobbyingExpenditure_{it}}{TotalRevenue} = \beta_0 + \beta_1 EPI_{it} + \beta_2 E\ Score_{it} + \beta_3 GHG_{it} + \eta_{CT} + \pi_{ST} + \epsilon_{it} \tag{6}$$

The results are shown in the table below.

Table A.5: Fixed-Effect Poisson Regression: Lobbying Expenditure (% of Revenue)

Firm Group: Dependent Variable: Lobbying Expenditure/Total Revenue (%)	Low Innovative	Higly innovative	Medium Innovative
Environmental Policy Stringency	-2.394*	-0.198	-0.994***
	(1.257)	(0.163)	(0.321)
E Score	-0.054***	-0.028***	0.004
	(0.006)	(0.009)	(0.004)
Constant	1.745	-4.273***	-4.768***
	(3.396)	(0.934)	(0.848)
Time year FE	Yes	Yes	Yes
Firm-level FE	Yes	Yes	Yes
Number of obs.	1,243	1,271	827
Number of groups	144	168	104
lnalpha	-0.178	-15.152***	-14.563***
	(3.820)	(2.058)	(2.535)
vce(cluster firm)	Yes	Yes	Yes
Prob > chi2	0.000	0.000	0.000

Notes: Table A.5 reports Descriptive statistics. *Sources*: Bloomberg, OECD, Lobbyfacts.eu; European Patent Office (EPO); the authors processed the data.

Table A.6: Fixed-Effect Poisson Regression: Lobbying Expenditure (% of Revenue)

Firm Cluster: High Innovative Dependent Variable: Lobbying Expenditure (% of Revenue)	(1)	(2)	(3)	(4)
Environmental Policy Stringency	-0.198	-0.198	-0.164	0.008
	(0.163)	(0.163)	(0.158)	(0.185)
E Score	-0.028***	-0.028***	-0.027***	-0.026***
	(0.009)	(0.009)	(0.009)	(0.009)
GHG Emission Scope 1+2			-0.000**	-0.000**
			(0.000)	(0.000)
Carbon Tax				-0.114**
				(0.052)
Constant	-4.273***	-4.273***	-4.290***	-4.766***
	(0.934)	(0.934)	(0.851)	(0.852)
Time year FE	Yes	Yes	Yes	Yes
Firm-level FE	Yes	Yes	Yes	Yes
Number of obs.	1,271	1,271	1,271	1,271
Number of groups	168	168	168	168
ln(alpha)	1.125	1.076	1.068	1.068
	(1.412)	(1.473)	(1.485)	(1.485)
vce(cluster firm)	Yes	Yes	Yes	Yes
Prob > chi2	0.000	0.000	0.000	0.000

Notes: *Sources*: Bloomberg, OECD, Lobbyfacts.eu; European Patent Office (EPO); the authors processed the data.

Table A.7: Fixed-Effect Poisson Regression: Lobbying Expenditure (% of Revenue)

Firm Cluster: Medium Innovative Dependent Variable: Lobbying Expenditure (% of Revenue)	(1)	(2)	(3)	(4)
Environmental Policy Stringency	-0.994***	-0.994***	-0.271*	-0.375***
	(0.321)	(0.321)	(0.147)	(0.143)
E Score	0.004	0.004	-0.007**	-0.007**
	(0.004)	(0.004)	(0.003)	(0.003)
GHG Emission Scope 1+2			0.000***	0.000***
			(0.000)	(0.000)
Carbon Tax				0.070
				(0.043)
Constant	-4.768***	-4.768***	-6.557***	-6.297***
	(0.848)	(0.848)	(0.524)	(0.501)
Time year FE	Yes	Yes	Yes	Yes
Firm-level FE	Yes	Yes	Yes	Yes
Number of obs.	827	827	827	827
Number of groups	104	104	104	104
ln(alpha)	1.125	1.076	1.068	1.068
	(1.412)	(1.473)	(1.485)	(1.485)
vce(cluster firm)	Yes	Yes	Yes	Yes
Prob > chi2	0.000	0.000	0.000	0.000

Notes: *Sources*: Bloomberg, OECD, Lobbyfacts.eu; European Patent Office (EPO); the authors processed the data.

Table A.8: Fixed-Effect Poisson Regression: Lobbying Expenditure (% of Revenue)

Firm Cluster: Low Innovative Dependent Variable: Lobbying Expenditure (% of Revenue)	(1)	(2)	(3)	(4)
Environmental Policy Stringency	-2.394*	-2.394*	-2.282*	-2.762*
	(1.257)	(1.257)	(1.167)	(1.510)
E Score	-0.054***	-0.054***	-0.056***	-0.055***
	(0.006)	(0.006)	(0.007)	(0.007)
GHG Emission Scope 1+2			0.000	0.000
			(0.000)	(0.000)
Carbon Tax				0.238
				(0.306)
Constant	1.745	1.745	1.306	2.272
	(3.396)	(3.396)	(3.183)	(3.825)
Time year FE	Yes	Yes	Yes	Yes
Firm-level FE	Yes	Yes	Yes	Yes
Number of obs.	1243	1243	1243	1243
Number of groups	144	144	144	144
ln(alpha)	1.125	1.076	1.068	1.068
	(1.412)	(1.473)	(1.485)	(1.485)
vce(cluster firm)	Yes	Yes	Yes	Yes
Prob > chi2	0.000	0.000	0.000	0.000

Notes: *Sources*: Bloomberg, OECD, Lobbyfacts.eu; European Patent Office (EPO); the authors processed the data.

Table A.9: Fixed Effects Poisson Model - All Lobbying Firms

Dependent Variable: Lobbying Expenditure	(1)	(2)	(3)	(4)
Environmental Policy Stringency	-0.062	-0.076	-0.048	-0.164
	(0.173)	(0.173)	(0.188)	(0.217)
E Score	0.01***	0.001***	0.008***	0.008***
	(0.002)	(0.005)	(0.006)	(0.0033)
Total Revenues in USD		0.000**	0.000**	0.000***
		(0.000)	(0.000)	(0.000)
Carbon Tax			-0.025	-0.019
			(0.023)	(0.031)
GHG Emission Scope 1+2				0.000**
				(0.000)
Constant	12.095***	11.742***	11.742***	12.774***
	(0.560)	(0.539)	(0.539)	(0.497)
Time year FE	Yes	Yes	Yes	Yes
Firm-level FE	Yes	Yes	Yes	Yes
Number of obs.	4400	4398	4398	3341
Number of groups	560	560	560	416
ln(alpha)	1.223	1.200	1.131	1.134
	(0.547)	(0.548)	(0.478)	(0.538)
vce(cluster firm)	Yes	Yes	Yes	Yes
Prob > chi2	0.000	0.000	0.000	0.000

Notes: Table A.9 reports the outcome table from our regression model for all the firms of the dataset. From model (1) to model (4) we provide all the different specifications designed in the methodological section of our paper. Time year and firm-level fixed effects are included. Robust Standards error are included in our regression analysis. *Sources*: Bloomberg, OECD, Lobbyfacts.eu; European Patent Office (EPO); the authors processed the data.