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Effects of climate activism on firm productivity and uncertainty: Evidence from global oil extraction

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ABSTRACT

We present global microeconometric evidence on the impact of climate advocacy on hydrocarbon production. We construct two panel data sets by first linking climate activist campaigns to several thousand oil fields, which together account for 72% of global production. Second, we use textual analysis of over 140 million words from 1832 annual reports to compute a measure of activism-induced uncertainty for the corporations that control these oil fields. We find robust evidence that climate activism directly reduced not only oil field productivity but also increased company-level uncertainty. By utilising the ownership links between corporations and their oil fields, we also uncover an indirect mechanism in which the initial activism-induced company uncertainty leads to further productivity losses at the field level. Our findings demonstrate the presence of two pathways through which climate advocacy impacts hydrocarbon extraction.

1. Introduction

The growing perception that policymakers and fossil fuel producers are not addressing global warming urgently has motivated many climate action groups[1] to attack petroleum corporations by damaging their infrastructure and disrupting their production activities. For example, in March 2024, a network of European climate activist groups organized an unprecedented operation that erected blockades across the North Sea, effectively halting oil production in Denmark, Germany, the Netherlands, Norway, Sweden, and the United Kingdom (Guardian, 2024). Such a campaign is reminiscent of the numerous attacks by armed militia and activist groups on oil infrastructure in Nigeria's Niger Delta during the early 2000s.[2]

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[1] Some high-profile examples of environmental interest groups are "Extinction Rebellion (XR)", "Just stop oil" and the Climate Action Network (CAN).

[2] The Economist, "Pouring trouble on oily waters", January 19, 2006. https://www.economist.com/middle-east-and-africa/2006/01/19/pouring-trouble-on-oily-waters

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According to anecdotal evidence, the intensity and prevalence of climate activism has affected the petroleum industry's future outlook. An example is Shell Petroleum's observation that "*climate activists are challenging the grant of new and existing regulatory permits, and protesting at some of our facilities and projects. We expect that these challenges and protests are likely to continue and could delay or prohibit operations in certain cases*" (Royal Dutch Shell, 2023, *p*.15). We also read in British Petroleum's annual report that "… *activism and similar activities directed against our operations and facilities, pipelines, transportation or digital infrastructure could cause harm to people and severely disrupt operations*" (British Petroleum, 2023, *p*. 79).

Other than this anecdotal evidence, there is little empirical evidence on the extent to which climate action impacts plant-level[3] productivity in hydrocarbon extraction, as well as how these actions drive uncertainty at the corporate level. We fill this gap by taking a systematic look at measures of petroleum industry performance across a large and diverse sample of oil fields[4] scattered across 78 countries, and by employing an original time-varying company-level measure of activism-induced uncertainty.

Our paper contributes to the broad literature on climate activism where a stream of theoretical studies demonstrates that the pursuit of social goals (Baron, 2001; 2003) and the perception that government policies are insufficient to address pollution externalities (Daubanes and Rochet, 2019) are two key sources of inspiration for environmental activists. These pursuits are further stimulated by recent shifts in societal perceptions of global warming (Passarelli and Tabellini, 2017; Abito et al., 2019). These elements have encouraged "private politics," in which activists attempt to penalize polluters using methods other than the established legal systems (Besley and Persson, 2023). Hence, we test the validity of this idea by assessing how climate activism affects petroleum extraction using an identification strategy that exploits the microgeography of global hydrocarbon endowment.

Further, our study is most closely related to contributions on how climate activism affects firm-level outcomes. If any, our study has very few relatives in the existing literature, which has two essential features that motivate the current investigation. First, this literature has mostly focused on how climate activism affects financial and stock market indices (e.g., Lewis et al., 2017; Bessec and Fouquau, 2024; Ramelli et al., 2021). We depart from the aforementioned approach in this study by providing much-needed empirical evidence on how climate action affects plant-level performance (i.e., the underlying economic activity which triggered agitation in the first place)

A second feature is that studies on hydrocarbon extraction usually focus on climate activists' efforts to limit production-related pollution by putting pressure on policymakers rather than directly on firms (Piggot, 2018). Our focus on TFP stems from the reality of significant variation in productivity (and implicitly, cost) in tightly defined/homogeneous product marketplaces (Syverson, 2011; Foster et al., 2008). The petroleum extraction sector is a prime example of an industry where productivity-cost variations are crucial due to differences in resource endowment and geology, which impose physical constraints on extraction rates (Asker et al., 2019).

Although climate activists have recently turned their attention towards the supply side of the hydrocarbon economy (Lazarus and van Asselt, 2018; Harrison, 2020), we know little about the material implications of this attention for hydrocarbon extraction. Existing research already indicates that environmental activists may tailor their actions to complement or substitute regulatory stringency according to the required effort and campaign cost (Baik and Shogren, 1994; Adetutu et al., 2023). Therefore, we turn attention from the climate activists' perspective to that of the petroleum companies by addressing two largely unexplored questions: do climate activist actions affect plant-level petroleum productivity and corporate uncertainty? What are the direct and indirect mechanisms through which activists impact petroleum sector performance?

By addressing the latter uncertainty question, our work adds to the underexplored intersection of climate activism, uncertainty, and petroleum sector performance. Theoretically, climate activism will plausibly exacerbate the economic uncertainties[5] of pollution-generating entities by increasing their perceived operating risks (Lenox and Eesley, 2009; Brav et al., 2015; Lewis et al., 2017). There is, however, a dearth of empirical evidence regarding how climate advocacy drives petroleum sector uncertainty, particularly with regard to how corporations perceive the risks posed by climate activists. Therefore, we contribute to the literature on economic uncertainty by investigating the petroleum sector as a new setting within it. To do this, we compute an original time-varying company-level measure of climate activism concern (henceforth CAC); by applying textual analysis to over 140 million words found in 1832 annual reports of 166 petroleum companies from 2010 to 2022.

More specifically, we generate the CAC measure by using a dictionary-based approach[6] to quantify company level sentiment on climate activism risk. This method examines the text of annual reports using previously identified negative keywords based on a specialist industry dictionary (Loughran et al., 2019), derived from the broad dictionary by Loughran and McDonald (2011). Apart from providing a transparent and straightforward approach to textual analysis, the lexicon compiled by these dictionaries has been proven to be well suited to analysing financial and petroleum sector sentiments (Lucey and Ren, 2021; Ardia et al., 2023; Bessec and Fouquau, 2024).

Our motivation for developing the CAC measure stems from the fact that several aspects of the petroleum industry are linked to uncertainty, and these aspects have the potential to amplify the effects of heightened climate activism and may further distort firms' economic outlook. For example, petroleum extraction is a capital-intensive activity with huge sunk costs across several oil fields that hold substantial hydrocarbon reserves; the development of these assets often spans long time horizons. According to real options theory, uncertainty can influence production and investment choices when sunk costs are substantial (Arrow, 1968; Bernanke, 1983;

[3] In the petroleum industry, oil fields represent plant level production facilities.

[4] Throughout this paper, "oil fields" refers to both crude oil and natural gas fields.

[5] A broad literature highlights the adverse effect of uncertainty on a range of firm performance measures (e.g., Davis et al., 2019, Hassan et al., 2019; Caldara et al., 2020, and Benguria et al., 2022).

[6] For a more complete description of this approach, please see the online appendix.

Dixit and Pindyck, 1994). Given that petroleum firms' investments are *options*, they must decide whether to invest now or wait and see how potential returns evolve (Saniere et al., 2004; Kellogg, 2014). Moreover, the irreversibility of these investments could further fuel uncertainty regarding investment choices (Elder and Serletis, 2010; Kellogg, 2014; Dossani and Elder, 2020). Thus, it is conceivable that increased climate activism will exacerbate all the aforementioned aspects.

To mitigate any possible endogeneity problems associated with climate activism, we use local youth population and heatwave incidence as instrumental variables (IVs). To summarize our key empirical findings, we find that climate advocacy affects hydrocarbon extraction via two paths. First, activist campaigns directly hinder extraction activities, lowering oil field productivity. Second, an indirect effect implies that activist campaign efforts exacerbate company-level managerial uncertainty, resulting in reduced investment or extraction at the field level.

The remainder of this paper is organized as follows. Section 2 provides a comprehensive discussion of the data, which covers, among other things, the method for the textual analysis to construct the company-level CAC measure. Section 3 presents the conceptual framework that captures the causal relationship and mechanisms through which climate activism shapes performance. Section 4 contains the empirical methodology, which includes our strategy for dealing with the endogeneity of climate activism. Section 5 presents and discusses the estimation results as well as some mechanisms that influence the activism-performance relationship. Section 6 concludes.

2. Data

Our empirical analysis is divided into two parts. In the first part, we assess how climate activism has affected petroleum extraction productivity at the micro-geographical level (i.e., field level) between 2010 and 2022. In the second part, we construct a time-varying company-level CAC measure, which we then use as a dependent variable at the company level over the same period.

2.1. Data sources and sampling

We use information from three main sources to build our databases at the field and company levels. First, the data to estimate field-level TFP are accessed via a subscription to the Rystad Energy U-Cube database,[7] the leading source of micro-level data on upstream petroleum operations. Throughout this paper, TFP refers to the natural log of productivity, i.e., ln(TFP). Specifically, we gather data on labour and administrative costs, capital expenditure (CAPEX), field-level fossil fuel production, and other field-level attributes including field size and age.

Second, we construct company-level CAC by using Natural Language Processing (NLP) techniques to analyse the content in the annual reports of the 166 petroleum companies in our data sample. Third, we gather company-level information, like age and business size, from the Thomson Reuters Refinitiv (Eikon API) database. In addition to these three data sources, our empirical estimates also include information on (a) income at the district level, (b) institutional quality and economic development at the national level, and (c) global oil prices. For a complete list of data sources, see the online appendix.

To arrive at our final data sample, we detail our sampling procedure as follows. First, we start with a large universe of over 20,000 oil and gas fields undertaking petroleum production using the directory in the Rystad Energy U-Cube database. To estimate the impact of climate activism on field level productivity, we need production data on output, capital input, and labour input (and other field-level characteristics). Second, we eliminate fields with missing data observations, given that we require non-missing[8] production function observations for each field-year to estimate field-level TFP and subsequent panel data analysis of firm performance. As a result, we have rich but unbalanced field-level panel data for our study period that includes 14,483 oil and gas fields that are owned or controlled by 166 corporations.

Our data sample is comparable to those used by Asker et al. (2019), which included 13,248 oil and gas fields. Our final dataset provides a good representation of global oil and gas production. For instance, 72% of the world's petroleum production in 2022 came from these sampled fields which are scattered across 240 provinces in 78 countries (Fig. 1 shows the global spread of our dataset).

2.2. Measures of climate activism

We compute our activism variable using campaign events at the field level. In order to do this, we exploit the geolocation

[7] A few other recent research, like Asker et al. (2019), Bartik et al. (2019), and Bornstein, et al. (2023) have also used the rich Rystad data, although in different study contexts.

[8] In our raw data sample, about 80% of oil fields with missing production and investment data have no proven reserves, implying that data availability is primarily determined by the existence of positive hydrocarbon reserves (see Table B1 in Online Appendix B). This means that the missing data points are an artefact of the underlying petroleum production process, which involves the extraction of oil and gas reserves. The remaining possible bias is presumably mitigated by the inclusion of field-level reserves and fixed effects in our model. As a result, we do not expect the fields in our data sample to differ systematically from omitted fields or have a meaningful impact on the estimated activism–productivity relationship.

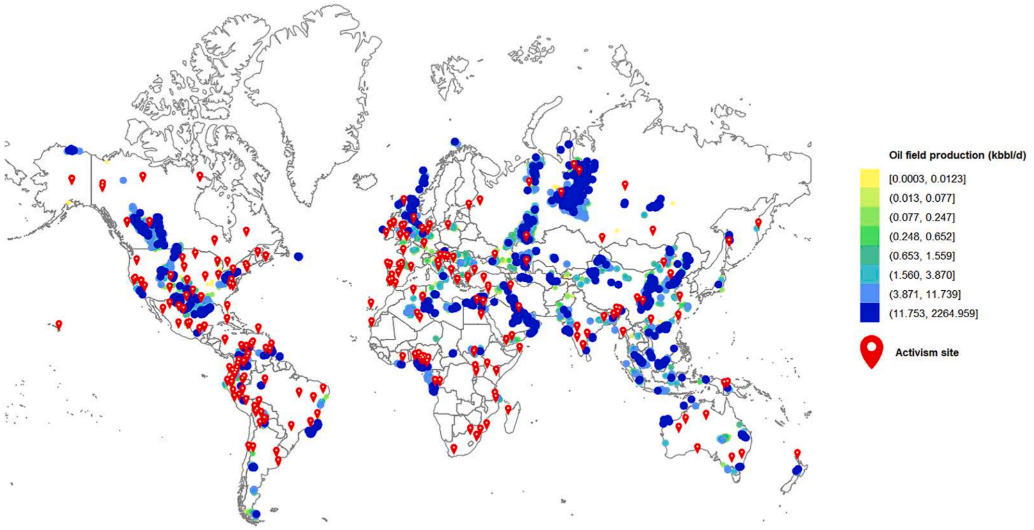

Fig. 1. Locations of oil fields and climate actions.
Notes: Shaded points represent the locations of the 14,605 oil and gas fields in the data sample as well as their hydrocarbon production in 2022. The red points indicate the geo-coded locations of all the climate action campaigns captured in the EJAtlas. In some cases, multiple climate actions were observed for certain locations. *Source*: Rystad Energy U-Cube database and Environmental Justice Atlas (EJ-Atlas).

information of climate activist campaigns (such as those run by NGOs, community organizations, etc.) that are found in the Environmental Justice Atlas (EJAtlas) database's event-based maps.[9] We overlay and match the EJAtlas location information with Rystad data since the oil field data also includes geolocation coordinates (longitude and latitude). The number of activist campaigns[10] within 5 km of each oil and gas field is therefore our primary independent variable.

Our map matching exercise is depicted in Fig. 1 which displays the geographical distribution and output across oil fields, as well as the climate actions. Besides verifying the geographic dispersion of oil fields, the diagram also indicates that climate activism directed at oil companies is a global phenomenon, as demonstrated by their dispersion throughout the different continents. Fig. 2 shows the petroleum corporations that own the most targeted oil fields. We observe that the most targeted companies are well-known petroleum companies such as ExxonMobil, Chevron, Shell, and BP.

Studies in the social conflict literature (e.g., Maystadt et al., 2014; Berman et al., 2017; Henderson et al., 2017) generally employ well-known datasets such as the Armed Conflict Location and Event Data (ACLED), the Uppsala Conflict Data Program Georeferenced Event Dataset (UCDP-GED), the Mass Mobilisation in Autocracies Database (MMAD), and the Social Conflict Analysis Database (SCAD). However, we prefer the approach used in a recently emerging literature (e.g., Reeder et al., 2022; Adetutu et al., 2023), which utilizes the event-based data from the Environmental Justice Atlas (EJAtlas). Our motivation is twofold.

First, the well-known data sources are unsuitable for the analysis of climate activism conducted in this study. For example, the ACLED dataset focuses mostly on political violence (e.g., repression, targeting of people, foreign military involvement, etc.) while largely excluding environmental campaigns, particularly nonviolent ones. Thus, it understates the incidence of climate activism. Second, the MMAD dataset is similarly limited for our research because it only includes protest information from autocratic countries. Like ACLED, MMAD also focuses on politically motivated mass mobilizations. Furthermore, the MMAD data has little overlap with our study because it covers 2003–2012, whereas our study spans 2010–2022.

To confirm the limitations of these data sources for our investigation, we downloaded the datasets listed above. During our investigation, we discovered <40 environmentally related events in the ACLED or MMAD datasets. This pales in comparison to EJAtlas, which covers a considerably greater number of environmental activist events. Similar limitations were observed in the SCAD, which exclusively includes social conflicts in Africa and Latin America. As a significant proportion of world petroleum production takes place in the Middle East, North America, and the Commonwealth of Independent States (CIS), SCAD also underreports environmental activist campaigns. We thus found only 15 environmental events in SCAD.

[9] EJAtlas data is available at https://ejatlas.org/. The EJAtlas data has become a key source of information on conflicts between environmental interest groups and businesses. For empirical economic analysis using EJAtlas data, see Aydin *et al.* (2017), Pérez-Rincón *et al.* (2019) and Adetutu *et al.* (2023)

[10] For robustness testing, we use alternative activism variables: the intensity and share of oil fields affected. For each campaign, the EJAtlas provides details on its severity, allowing us to compute an alternative climate activism index (i.e., 1 = low, 2 = medium, and 3 = high). Lastly, we use the field ownership information to construct an alternative climate activism measure at the company level.

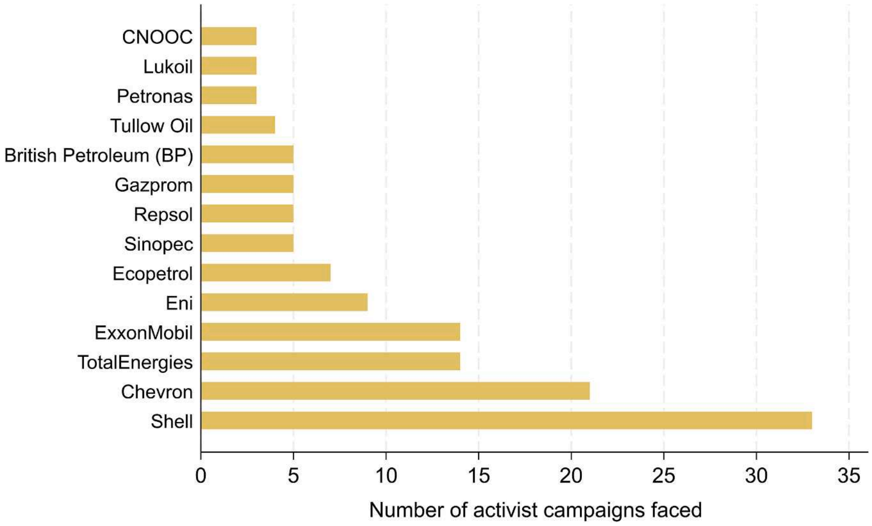

Fig. 2. Most targeted petroleum companies.
Source: Environmental Justice Atlas (EJ-Atlas).

2.3. Field level production performance

We estimate ln(TFP) using a Cobb-Douglas production function following the Ackerberg et al. (2015) (ACF) approach:

$$y_{it} = \alpha + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \delta_{it} + \varepsilon_{it}, \tag{1}$$

where all the variables are logged, the companies are indexed $i \in 1,\ldots,N$, and the time periods, which are years, are indexed $t \in 1,\ldots,T$. For the *ith* company in year t, y_{it} is the observation of petroleum extraction (1000 barrels per day, Kbbl/d). k_{it} is an observation of the capital input, where this input is the state variable for the fields. l_{it} is an observation of the labour input, which in direct contrast to capital is the fields' freely adjustable input. m_{it} is a measure of material/intermediate inputs.[11] The common intercept α and the coefficients β_k, β_l and β_m are to be estimated, and ε_{it} is the usual noise term representing an idiosyncratic output shock. The random component δ_{it} in Eq. (1) represents unobserved TFP which is assumed to follow a first order Markov process:

$$\delta_{it} = E(\delta_{it}|\delta_{it-1}) + \xi_{it} = f(\delta_{it-1}) + \xi_{it} \tag{2}$$

This represents δ_{it} as a function of its value in the previous period, $f(\delta_{it-1})$, and the TFP[12] shock ξ_{it}. Because we lack field-level information on value added, the production function specified in Eq. (1) is based on physical output. Using output quantities instead of value added/revenue addresses the disparity between physical and revenue productivity, as well as bias in productivity estimates due the confounding effects of prices and quantity, as well as unobserved product quality (Foster et al. 2008; De Loecker 2011; Bond et al. 2021; Forlani et al., 2023). Although the physical output model may face aggregation issues when a firm produces several outputs, the homogeneity of crude extracted from a specific location however limits these challenges in our analysis.

2.4. Climate activism concern (CAC) at the company level

We employ the textual analysis technique used in recent economics research (e.g., Caldara et al., 2020, and Benguria et al., 2022) to generate the original time-varying company-level CAC measure. For a sample of 166 petroleum corporations, this approach entails compiling all of their annual reports from 2010 to 2022. These reports contain companies' operational and financial performance indicators, as well as commentaries on strategic issues, new concerns, and information about future plans.

2.4.1. Construction method

Every report that the petroleum companies have filed between 2010 and 2022 is available for download in PDF format from their individual websites. Using the Rystad Energy U-Cube database's oil field dataset, we identified the companies that own/control the oil fields in our data sample, yielding a company-level sample of 166 companies[13] with available annual reports. After collecting the annual reports, we compute the firm-level CAC measure by implementing the following four steps.

[11] We compute the material input variable as the sum of purchased services which include facility service expenses, transportation costs, etc.
[12] See Appendix C for details on our ln(TFP) estimation.
[13] According to the Rystad database, these 166 companies produced 72% of the world's petroleum in 2022, offering a global representation of the industry.

First, after scraping the annual reports in PDF format from the companies' websites, we convert them into text format and store each sentence of a report as an observation. Second, we search each sentence for word stems related to climate activism (e.g., *climate activist(s), environmental group(s)*, etc.). Our keyword search employs a dictionary-based approach to identify annual corporate sentiment or sensitivity towards climate advocacy. This lexicon-based technique compares previously defined keywords to a text of interest. See Appendix C for more information.

This initial search is regardless of the context in which the keyword is used. Third, since we are interested in the context of the activism keywords, we need to incorporate further keywords that capture the pessimism associated with each company's activism-induced concern. We thus search each line for *concern*-related keywords such as *reduced production, delay operations, threat*, etc. Fourth, we search for and obtain annual counts of instances when climate activism keywords and concern-related keywords appear in close proximity,[14] i.e., the same line or one line above or below (see Table A2 for a few examples of keywords used).

Fig. 3 uses an example from Royal Dutch Shell's 2023 annual report to demonstrate the fourth step of our keyword counting scheme. An activism-related keyword that appears near a concern-related keyword is highlighted in yellow. We note that steps 2–4 above are implemented using the Natural Language Processing (NLP) technique which is a machine learning protocol that exploits computing and statistical power in processing and breaking down (or making sense) text or language in a systematic fashion with minimal human involvement beyond the coding. The *R* statistical software is used for this textual analysis/NLP. Finally, we normalize the count variable by the length of each annual report, the total word count of each report.

Formally, we can define the CAC measure for each firm *i* in each year *t* as:

$$CAC_{it} = \frac{1}{W_{it}} \sum_{w=1}^{W_{it}} \left\{ 1\left[w \in \mathbf{Keywords}^{Climate\ \ activism} \right] \times 1\left[|w - p| \le Oneline \right] \right\} \tag{3}$$

where $w_{it} = 1, \ldots, W_{it}$ are members of the set of keywords: $\mathbf{Keywords}^{Climate\ \ activism}$ and p is the position of the nearest concern or negative tone-related words (i.e., $p \in \mathbf{Keywords}^{Concern}$). Intuitively, the underlying CAC measure is a count of instances in which climate activism-related words are found in the same line or one line below or above concern-related words.

Fig. 4 plots the total count of instances where both sets of keywords appear within a line of each other (± 1 line), normalized by the word count of each annual report. We observe increased variability in the combined count measure, especially after 2019, the period following the establishment of the world-leading environmental movement, *Extinction Rebellion*, in October 2018. The sharp decline between 2021 and 2022 reflects the restrictions on mass mobilization[15] imposed during the COVID-19 pandemic. Given that the CAC plotted in Fig. 4 captures firm-level sentiment regarding climate activism, we intuitively expect its dynamics to be shaped by changes in the underlying climate action within the industry. Meanwhile, research indicates that annual reports embody months-long production lags such that the perception about developments in year *t* will feature in the discussions in report for $t + 1$ (Abernathy et al., 2017). Such lags are particularly moderate firm sentiment on climate and environmental related issues (Nagar and Schoenfeld, 2024). Given the steady increase in CAC over the decade, we conclude that the fall in CAC sentiment in 2022 reflects the lagged effect of reduced climate demonstrations in 2020–21.

2.5. Control variables

The field-level productivity and company level uncertainty models contain control variables such as field size and age, company size and age, as well as country-level (i.e., per capita income, resource dependence,[16] and institutional quality) that are key determinants of productivity and uncertainty. Table A1 in the appendix provides detailed information on all variables employed, along with their formal definitions and sources.

2.6. Summary statistics and trends

The summary statistics for the field and company data are shown in Tables 1 and 2, respectively. Real U.S. dollars (2017=100) are used to express the monetary variables in these tables and throughout the empirical models. Table 1 shows that the field level production variable has a mean of 6.01 Kbbl/d and a much larger standard deviation (30.96 Kbbl/d). This suggests that there is significant output variability across the oil fields studied, which is consistent with our expectation. With the oldest being >180 years old, these fields have also been in production for an average of about 38 years.

Additionally, Table 1 shows that the average number of climate actions is 0.003. Whilst this figure is not particularly big, the standard deviation of the variable is considerably larger, so there is evidently non-negligible dispersion across the observations of the activism variable. The company-level data is shown in Table 2, which indicates that the average normalized annual count of the

[14] The procedure for combining these two sets of keywords should ensure that the CAC variable appropriately reflects firm-level concern about the impact of climate action on production activities. Nonetheless, we go a step further to determine if the CAC variable is mostly or partially picking up corporate signals to the public, rather than being a measure of actual activism concern (see Section 5.4.1 for some robustness testing).

[15] In many countries, it was a crime to converge for mass actions. For example, see: https://committees.parliament.uk/publications/5153/documents/50935/default/

[16] The resource dependence variable is an implicit measure of global oil prices, which would be otherwise difficult to incorporate into our model in the presence of time dummies.

Risk description

Societal demand for urgent action on climate change has increased, especially since the Intergovernmental Panel on Climate Change (IPCC) Special Report on Global Warming of 1.5 °C effectively made the more ambitious goal of the Paris Agreement to limit the rise in global average temperature this century to 1.5 °C the default target. This increasing focus on climate change and drive for an energy transition have created a risk environment that is changing rapidly, resulting in a wide range of stakeholder actions at global, local and company levels. The potential impact and likelihood of the associated exposure for Shell could vary across different time horizons, depending on the specific components of the risk.

We expect that a growing share of our greenhouse gas (GHG) emissions will be subject to regulation, resulting in increased compliance costs and operational restrictions. Regulators may seek to limit certain oil and gas projects or make it more difficult to obtain required permits. Additionally, climate activists are challenging the grant of new and existing regulatory permits, and protesting at some of our facilities and projects. We expect that these challenges and protests are likely to continue and could delay or prohibit operations in certain cases. Our journey to achieving our target of becoming a net-zero emissions energy business has resulted in and could continue to require additional costs. We also expect that actions by customers to reduce their emissions will lower demand and potentially affect prices for fossil fuels, as will increasing levels of GHG emissions regulation through taxes, fees and/or other incentives. This could be a factor contributing to additional provisions for our assets and result in lower earnings, cancelled projects and potential impairment of certain assets.

Fig. 3. Climate activism and concern keywords in an annual report.
Source: 2022 Annual Report: "Powering progress", Royal Dutch Shell, *p*.15.

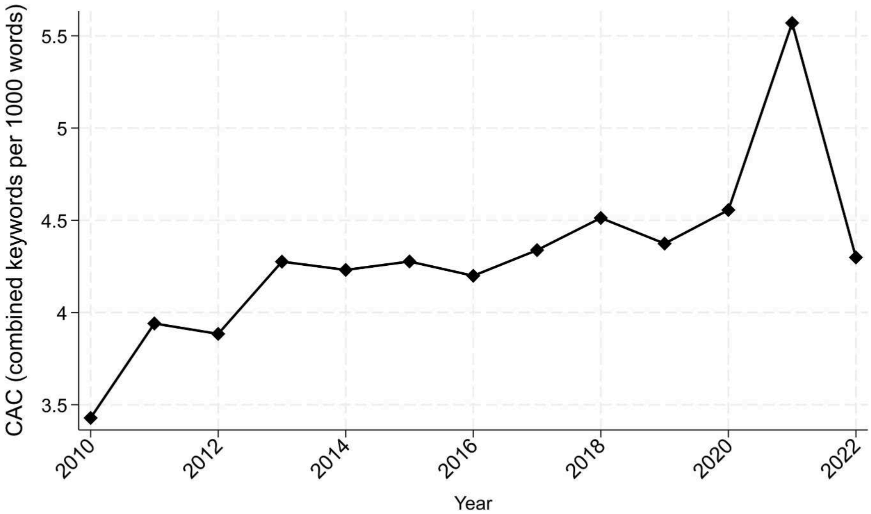

Fig. 4. Combined keywords normalised by report wordcount.
Source: Authors' calculations based on the Natural Language Processing (NLP) of annual reports.

climate activism-related and concern-related keywords appear in proximity is 4.3 instances per 1000 words. When compared to the mean value, CAC's standard deviation of 5.4 indicates a good level of variability in the data observations across the sampled companies.

3. Conceptual framework

In this section, we set out the underlying hypotheses underpinning the causal relationship between climate activism and performance. More specifically, we identify two pathways through which climate activism may possibly impact hydrocarbon extraction. The

Table 1
Summary statistics for the field level variables.

Variable	Obs.	Mean	Std. Dev.	Min	Max
ln(TFP)	140,652	0.160	0.595	−8.492	5.913
Production (thousand barrels extracted, Kbbl/d)	143,128	6.008	30.955	0	1966.11
Climate activism campaigns (count)	143,128	0.003	0.031	0	12
Climate activism campaigns (intensity, index)	143,128	0.002	0.023	0	3
Climate activism campaigns (duration, years)	143,128	0.043	0.439	0	6
CAPEX (mil., 2015 U.S. dollars)	141,038	13.059	60.213	0	3617.9
Admin and labour expenses (mil., 2015 U.S. dollars)	142,190	2.858	14.15	0	1185.53
Material expenses (mil., 2015 U.S. dollars)	143,128	9.916	52.732	0	2499.99
Field age (years since discovered)	143,128	37.963	21.368	0	184
Field size (Big proved reserve dummy=1)	140,977	0.494	0.499	0	1
Gas flared (billion cubic meters, bcm)	143,128	0.007	0.034	0	0.658
Province level income (index)	4843	0.807	0.128	0.304	1
Average annual temperature (°C)	4843	15.004	9.554	−10.34	29.95
Neighbour's heatwave deviation (ratio of deviation)	4843	0.028	0.283	0	10.68
Youth population in 2008 (% of total population)	4843	21.520	3.794	5.5	36.4
Television access (% of total population)	4843	21.09	20.05	0	80

Table 2
Summary statistics for the company and country variables.

Variable	Mean	Std. Dev.	Min	Max
Activism + Uncertainty instances (per 1000 words)	4.299	5.371	0	20.09
Share of field attacked (%)	3.440	16.220	0	89.77
Risk premium (%)	2.773	1.380	−0.278	13.64
Other uncertainty instances (per 1000 words)	5.206	6.215	0	24.504
Company age (years)	37.66	33.54	0	181
Company size (total assets, 2015 U.S. dollars)	2.863e+10	6.811e+10	.452	6.004e+11
GDP per capita (constant 2021 international $)	48,535.605	21,450.346	4332.81	129,083.48
Institutional quality (corruption index)	0.925	0.958	−1.284	2.287
Oil and gas rent (% of GDP)	4.937	8.108	0	58.36
Environmental policy (tax, % of GDP)	0.949	0.978	0	4.458
Religion (index)	4.747	1.338	1	6

first is a direct local disruption channel in which activists disrupt production processes at the field level to pressure businesses to reduce their environmental impact. The second is an indirect uncertainty channel in which climate activism raises managerial or investor uncertainty, which can influence subsequent company-level production and investment decisions.

3.1. Direct effects

The direct effects of activism on field productivity and company uncertainty are

$$TFP = f(activism; \mathbf{x}, \mathbf{z}),\ f_1 < 0 \tag{4}$$

$$CAC = g(activism; \mathbf{c}, \mathbf{z}),\ g_1 > 0 \tag{5}$$

where TFP and CAC are field total factor productivity (i.e., ln(TFP)) and company level climate activism concern, respectively. $\mathbf{x}$, $\mathbf{c}, \mathbf{z}$ contain field, company, and location-based characteristics. The consequences in (4) and (5) occur through a local disruption mechanism in which organized climate movements directly impede local extraction activities and productivity. This assumption accords well with evidence suggesting that climate activists are becoming increasingly disruptive (Temper et al., 2015; Daubanes and Rochet, 2019; Guardian, 2022; Adetutu et al., 2023), leading to a negative local productivity effect, $f_1 < 0$. Given that oil field operating activities are managed by oil companies, the local disruptions will also likely lead to elevated economic uncertainty facing petroleum companies. Thus, $g_1 > 0$.

3.2. Indirect effects

Aside from the direct local disruption effect of climate activism on hydrocarbon extraction or operational activity at the field level, we note the possibility of an indirect feedback effect in which activism-induced managerial or investor uncertainty limits field level investment and extraction, both at affected sites and elsewhere. Research has shown that parent company uncertainty can have an impact on subsidiary plant productivity performance (Arnold and Javorcik, 2009; Kellogg, 2014; Dossani and Elder, 2020). This is especially true when the uncertainty stems from worries about operating conditions across host communities (Lin et al., 2025).

Thus, we link field level TFP and company level CAC, showing that activism influences TFP by influencing business decision making in reaction to increased CAC. We can rewrite field performance as

$$TFP = f(\mathbf{x}, \mathbf{c}, \ \mathbf{z}, \ \lambda[activism; inv(CAC)]) \tag{6}$$

We assume that TFP depends on the previously defined characteristics and a local output parameter, $\lambda > 0$ which is influenced by investments and climate activism. This parameter is a decreasing function of *activism* directed toward the field, when activists directly oppose extraction activities, lowering local output: $\lambda'(activism) < 0$. Although $\lambda'(inv) > 0$, the size of investment, *inv*, allocated to the field is likewise a decreasing function of climate activism, as it responds negatively to the CAC-induced managerial or investor uncertainty and concern among companies affected by activist campaigns: $\frac{\partial inv}{\partial CAC} < 0$. Thus, $\lambda'(CAC) < 0$. The arguments in (6) effectively reflect the causal pathways included within the activism-performance relationship: activism's direct effect on field production, as well as its indirect effect via the firm-level uncertainty embodied in CAC.

4. Empirical strategy

4.1. The direct impact of climate activism on field level TFP

We estimate the following equation for outcome variable $\ln(TFP)_{ft}$[17] where the subscripts refer to field (*f*) and year (*t*):

$$\ln(TFP)_{ft} = \alpha_f + \alpha_t + \beta Activism_{ft} + \gamma_1' \boldsymbol{x}_{ft} + \gamma_2' \boldsymbol{c}_t + \gamma_3' \boldsymbol{z}_t + \varepsilon_{ft}, \tag{7}$$

The model specification includes field, α_f, and year fixed effects, α_t. $Activism_{ft}$ is the climate activism variable given by the number of activist actions targeted at each field *f*. The parameter of interest, β, captures the difference-in-differences effect of field-specific actions on $\ln(TFP)_{ft}$. It estimates the change in the difference in productivity between oil fields with high and low incidence of activist actions, after targeted campaigns were initiated, relative to the period preceding its initiation

To ensure the estimate of β captures the effect of climate activism on field level TFP rather than other contemporaneous factors, we include a vector of other field-year explanatory variables, $\boldsymbol{x}_{ft}$. More specially, we control for field age and size, as existing research indicates that variation in oil field productivity and costs is influenced by size and age differences (Managi et al., 2006; Asker et al., 2019; Hamang, 2024). Moreover, the characteristics and governance structure of operating companies may influence oil field productivity (Coulomb et al., 2025). Hence, $\boldsymbol{c}_t$ is a vector containing the size and age of the ownership or operating companies for each oil field.

Finally, $\boldsymbol{z}_t$ includes location-based factors at the province and nation levels to ensure that the activism coefficient is not merely reflecting economic and regulatory conditions in the local areas or countries where each oil field is located. Prior studies indicate that hydrocarbon discoveries and production are linked to local economic development and the stringency of national environmental policies (Managi et al., 2006; Munasib and Rickman, 2015; Hamang, 2024). Furthermore, macroeconomic factors such as aggregate demand might also affect the decision to produce hydrocarbons (see Arezki et al., 2017; Bjørnland et al., 2021). Consequently, $\boldsymbol{z}_t$ incorporates province-level income and country-level per capita income, institutional quality, environmental regulation, and oil and gas rents (% of GDP) as a proxy for global oil prices.

ε_{it} is the idiosyncratic error. We cluster the standard errors at the level of aggregation of the variable of interest,[18] which is at the oil field level, so that the parameter estimates are robust to possible arbitrary serial correlation in the data.

4.2. The direct relationship between climate activism and company level concern

In the second part of our empirical analysis, we seek to estimate the effect of climate activism on company level climate concern, CAC_{it} where the subscripts refer to company (*i*) and year (*t*):

$$CAC_{it} = \alpha_i + \alpha_t + \beta Activism_{it} + \delta_1 \boldsymbol{c}_{it} + \delta_2 \boldsymbol{z}_t + \varepsilon_{it}, \tag{8}$$

where CAC_{it} is the observation of the constructed climate activism concern measure we defined in subSection 2.4. α_i and α_t are firm and time fixed effects. $Activism_{it}$ is the climate activism variable, $\boldsymbol{c}_{it}$ and $\boldsymbol{z}_t$ are the vectors of company and country level control variables. We note that, because the underlying climate activism measure is computed at the field level, we collapse the field level data to company-year level, i.e., only one observation per company per year. Collapsing field-level activism data to create the company-level variable may not adequately capture the intensity of firm-targeted activism. As a result, our robustness analysis employs an alternative firm-level activism variable: the share of a company's oil fields that are targeted.

4.3. Identification strategy

Any identification strategy based on the assumption that oil field exposure to climate action is exogenous will be threatened by the possibility that many targeted oil fields were not chosen randomly but, rather, chosen based on their (pollution-generating) activity. In

[17] We also experiment with field-level cash flows as an alternative measure of performance across each field.

[18] See Abadie et al. (2023)

other words, the productivity of oil fields is plausibly increasing in environmental damages, and local resistance is increasing in such damages since higher damages will likely draw the attention of activist groups (Pardini and Espinola-Arredondo, 2021; Besley and Persson, 2023). Consequently, a naive OLS analysis may be vulnerable to the problem of reverse causation running from TFP_{ft} to $Activism_{ft}$. In this sense, comparisons between oil fields hit by climate action and those ignored by activists is rendered invalid.

Our IV strategy is based on the idea that the operating conditions of oil fields vary geographically, impacting the frequency and severity of observed climate activism. For example, Tanimoune and Haslam (2024) found that localized factors influence the occurrence of social conflict at mining sites throughout Latin American countries. Other studies (e.g., Berman and Couttenier, 2015; Reeder et al., 2022) support this claim, demonstrating that the onset and intensity of conflicts in communities near resource extraction sites are correlated with local conditions (e.g., geographic, economic and social outcomes). Hence, we employ IVs that reflect such local conditions.

To preserve the exogeneity of the IVs and to strengthen the case for our exclusion restrictions, for each province in which sampled oilfields are located, we employ IV values for neighbouring provinces. Our assumption is that each oil field is located within a province in which operating conditions trigger some push back against environmental externalities by activist groups. These operating conditions are shaped by the shocks from the IVs, which are measured at the neighbouring province level.

4.3.1. Heatwaves

We use the shocks caused by extreme weather occurrences (i.e., heat waves) across time and place, to instrument for climate activism. Heat waves are often employed as exogenous determinants of a wide range of social and economic outcomes, as they represent physical or meteorological processes triggered by the unpredictable or exogenous nature of weather (Barreca, 2012; Miao and Popp, 2014; Groppo and Kraehnert, 2017; Jiang et al., 2025; Chen et al., 2025).

Aside from the fact that heat stress episodes provide firsthand experience with climate change, empirical research has demonstrated that heat stress is a significant predictor of social conflict, crime, and violence (Anderson et al., 1997; Burke et al., 2015; Eberle et al., 2025). Furthermore, previous studies in this field have found that such local heat stress might cause climate-related agitation and unrest (Harari and Ferrara, 2018; Grechyna, 2025; Lei and Xu, 2025). Extreme weather events often result in human suffering and exacerbate vulnerabilities such as poverty, which is a key mechanism for these outcomes (Lei, 2026). Given the foregoing, we anticipate that random weather shocks caused by heat waves will be linked to observed climate activist movements in communities near oil fields.

In addition to the above arguments for instrument relevance, our identification strategy assumes that heat waves are orthogonal to the error term in a second-stage regression. This is because weather shocks are as good as randomly assigned, and the lack of oil field managers' option or self-selection into heat wave sites strengthens the case for exogeneity. Furthermore, our fixed-effects structure should allow comparability between treated and control oil fields, ensuring that, after accounting for potential confounders (e.g., field-specific seasonality, province-level factors), exposure to heat waves is essentially randomly assigned. This assumption seems reasonable considering that the bulk of the 439 heatwaves detected throughout our study period lasted only a few days on average (about 6 days), with longer-duration occurrences lasting approximately 18 days. These relatively short timescales should correspond well to the emotional activity and outbursts exemplified in climate activism, without having any direct impact on observed oil field performance (which is measured annually).

We construct the heat wave IV based on the observed incidence and magnitude of province-level heat waves for each oil field. To begin, we collect heat waves data for our study period from the international disaster database EM-DAT, deriving the heat wave instrument using the conceptual idea that each heat wave shock is defined by the extent to which it exceeds annual average temperature, i.e., the heat shock IV measures the deviations between the observed heatwave magnitude (°C) and average temperature (°C) in neighbouring province n during period t,

$$Heat_{pt} = \begin{cases} \dfrac{(Heat\ wave_{nt} - Ave.\ temp_{nt})}{Ave.\ temp_{nt}}, during\ time\ t \\ 0,\ otherwise \end{cases} \tag{9}$$

4.3.2. Youth population

A substantial body of research[19] shows that young[20] people are actively involved in climate advocacy. This phenomenon gained considerable intensity in the 2000s, a period marked by the United Nations (UN) Climate Summits and youth-inspired 'Fridays for Future' (FFF) campaign. Young people will bear the long-term repercussions of global warming, giving them stronger incentives to take climate action now because it will have a greater impact on their future adult life than older people today (IPCC, 2022). Furthermore, because some of them may be too young to hold office or vote in elections, they have limited options for turning their concerns into substantial influence on public policy, thereby making climate activism appealing (Neas et al., 2022; Besley and Persson, 2023).

Given that younger people are more likely to favour climate action, we use the youth share of the provincial population (of host municipalities where oil fields are located) as an instrument for climate activism. However, a strong association with climate activism does not prove that the youth proportion of the population is exogenous to oil field performance. Some conceptual and methodological issues are worth highlighting. Acemoglu et al. (2020) suggest that the youth population could be endogenous to population growth.

[19] See Neas et al. (2022) for a review of this literature.

[20] The United Nations (UN) defines "youth" as those aged 15 to 24. See https://www.un.org/en/global-issues/youth

Furthermore, social movements driven by young people could decrease the youth cohort's size through mortality and displacement (Flückiger and Ludwig, 2018).

A methodological problem also stems from the well-known fact that age composition is a slow-moving demographic trend (Francis and Ramey, 2009; Ferraro and Fiori, 2020; Jones, 2023). Thus, with modest variations in province-level young population share, we have little temporal variation to exploit as an instrument. To address these concerns, we built our youth instrument using the pre-sample youth share of the population (i.e., 2008 data), with temporal variation applied using media access:

$$Young_{pt} = Young\_2008_p \times TV_{nt} \tag{10}$$

where p, n, and t denote province, neighbouring province, and time periods. TV_{nt} denotes the proportion of neighbouring province households with access to television, a proxy for media access. By employing pre-sample values of youth population (from two years prior), we strengthen the case for exclusion restrictions.

Regarding the theoretical basis for our media access variable, research studies demonstrate that citizens rely on the media to help them understand the intricacies of climate science and policy (Boykoff, 2009). As a result, increased media coverage shapes youth environmental attitudes and activism (Franzen and Vogl, 2013; Hansen, 2018; Fabel et al., 2025). This is because climate activist groups frequently use the media to educate citizens about climate concerns and encourage collective action (Dablander et al., 2025). Visual portrayals of environmental and climate risks shape citizen attitudes toward climate change (O'Neill, 2020), with other studies indicating that citizens exposed to environmental-related television content were more likely to be concerned about climate change impacts and demand policy actions (Romero-Canyas et al., 2019).

The above IV formulation in Eq. (10) ensures that the pre-sample youth population share eliminates the potential that any climate movement during our sample period influenced the size of the youth cohort through activism-induced displacement. Using television access in neighbouring provinces further allows us to overcome the methodological challenge of limited variation in the youth variable, while also limiting the possibility that the resulting instrument is correlated with unobservable factors in each of the reference provinces, i.e., the instrument has no direct relationship with the operating performance of each oil field. The indirect mechanism of influence is that environmental awareness spreads across space, sensitizing youth populations in neighbouring provinces and encouraging them to take climate action.

5. Results

5.1. The impact of climate activism on oil field productivity

Our initial empirical objective is to study the impact of climate activism on oil field productivity,[21] as specified in Eq. (7). Table 3 reports the estimates from five alternative model specifications, each building upon the previous specification. We start in column (1) with a basic OLS specification estimated without field fixed effects, but includes country dummies and year dummies, with standard errors clustered at the country level. The negative and statistically significant coefficient on $Activism_{it}$ suggests lower levels of productivity in oil fields targeted by climate action compared to other fields in the same year.

Column (2) displays the results of a model specification that accounts for field fixed effects, with the country dummies removed and standard errors clustered by field. Accounting for field-level fixed effects is critical for determining the magnitude of the impact of climate action. The magnitude of the activism coefficient decreases by an order of magnitude while remaining statistically significant at the 5% level. Columns (3) and (4) retains the same specification as column (2) but add company-specific or country-specific time effects, respectively. The coefficient remains qualitatively and statistically stable.

To move closer to causal inference, we run two-stage least squares (2SLS) estimation of Eq. (7). The IV coefficient in column (4) can be interpreted as the local average treatment effect (LATE), which identifies the average treatment effect on the subpopulation of treated units (i.e., "compliers") whose covariate of interest, $Activism_{ft}$, is induced by our instruments.

The first-stage regression in panel B indicates that both instruments have a positive and statistically significant effect on $Activism_{it}$. Thus, they are both relevant IVs for $Activism_{it}$. Furthermore, we reject the hypothesis that the instruments are weak as the F-statistic in Panel B (55.1) is greater than the critical value of 10 suggested by Staiger and Stock (1997). We further test the validity of the IVs using the under-identification LM test (Kleibergen and Paap, 2006) and the overidentification test (Hansen, 1982). The test statistics on the former (=139.59) strongly rejects the null hypothesis that the estimated model is underidentified. Using the p-value of the latter (J-p = 0.86), we cannot reject the null of the validity of the overidentifying model restrictions, conditional on having enough valid instruments to identify the model. The J test result implies the validity of these overidentifying conditions.

The importance of addressing endogeneity bias is evident from the sizable quantitative difference between the OLS and 2SLS coefficients on $Activism_{it}$ in Table 3. When Eq. (7) is estimated using OLS, we find a weak correlation between climate activism and oil field productivity, given the point estimate of −0.003, which is smaller (in absolute terms) than the IV coefficient of −0.281. The difference between OLS and 2SLS coefficients of activism signals the significance of time-varying endogeneity, which underscores the importance of the IV strategy advocated in this study.

There are several possible reasons for the large difference between the IV and OLS estimates. First is the possibility of weak identification. Here, a larger coefficient in the presence of large standard errors would indicate that our instruments are weak.

[21] Table F1 in the Appendix contains the fitted Cobb-Douglas production functions that underpin our TFP estimations.

Table 3
Baseline results.

Dep var: ln(TFP)	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	2SLS
Panel A: Second-stage regressions					
Climate activism	−0.013***	−0.003**	−0.002**	−0.003***	−0.281***
	[0.004]	[0.001]	[0.001]	[0.001]	[0.050]
Field size	0.163***	0.107***	0.095***	0.071***	0.013
	[0.017]	[0.008]	[0.008]	[0.008]	[0.010]
Field age	0.046***	0.308***	0.312***	0.316***	0.395***
	[0.010]	[0.016]	[0.016]	[0.016]	[0.023]
Province income	−0.000***	0.000***	0.000***	0.000***	−0.636**
	[0.000]	[0.000]	[0.000]	[0.000]	[0.283]
Company size	−0.184	−0.278*	−0.232	−0.299*	0.002***
	[0.242]	[0.150]	[0.147]	[0.155]	[0.000]
Country per capita income	0.011	0.041	0.031	0.049*	0.222***
	[0.041]	[0.026]	[0.026]	[0.027]	[0.061]
Country institutions	0.022	0.023**	0.021*	0.018	0.143***
	[0.015]	[0.011]	[0.011]	[0.011]	[0.021]
Country env. policy	0.052***	0.033***	0.034***	0.032***	0.069***
	[0.013]	[0.009]	[0.009]	[0.009]	[0.012]
Oil dependency	0.007**	0.011***	0.011***	0.012***	0.013***
	[0.003]	[0.002]	[0.002]	[0.002]	[0.003]
Dep var: Climate activism ***Panel B: First-stage regression***					
Neighbour_Heat waves					0.021***
					[0.003]
Youth2008 × Neighbour_TV					0.010***
					[0.001]
Under id test: Kleibergen-Paap rk LM statistic					139.59
					[0.000]
Weak id test: Kleibergen-Paap F-test					55.10
					[0.000]
Hansen *J*-test (p-value)					0.858
Dep var: ln(TFP) ***Panel C: Reduced form regression***					
Heat waves					−0.005**
					[0.002]
Youth2008 × Neighbor TV					−0.003***
					[0.000]
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	No	No	No	No
Field fixed effects	No	Yes	Yes	Yes	Yes
Company-specific time effect	No	No	Yes	No	No
Country-specific time effect	No	No	No	Yes	Yes
R-squared	0.112	0.811	0.821	0.838	
Observations	138,598	138,414	136,427	130,325	138,012
No. of oil fields	14,483	14,299	14,294	14,257	13,896

Notes. This table presents the OLS and 2SLS regression results of the effect of climate activism on field-level productivity. The dependent variable is total factor productivity (TFP) computed following the Ackerberg et al. (2015) (ACF) method, and the activism variable is the number of climate actions targeted at oil fields in each given year. The model specifications control for field and year fixed effects, and a range of field, company, province, and country (of field location)-specific variables. Columns (1)-(4) report standard OLS estimates with different fixed effects specifications. Column (5) is estimated using the IV estimator with field fixed effects, country-specific time effects. Standard errors are in parentheses and are clustered either at the country (column 1) or field level (column 2–5). * $p< 0.1$, ** $p< 0.05$ and *** $p< 0.01$.

However, this is not likely the case here, given the above F-static which is greater than the rule of thumb that $F > 10$. Because weak identification problems may persist despite $F > 10$, we go further by implementing falsification tests in Section 5.2 which suggest that our identification strategy is appropriate.[22]

Second, the exclusion restriction stipulates that our instruments have no effect on ln(TFP) other than through its effect on climate activism. Although it is usually (almost) impossible to ascertain that an exclusion restriction holds, we believe it is highly likely due to our intuitive approach to use neighbouring province instruments for all sampled oilfield locations.

A third, more compelling reason is that the IV coefficient reflects the local average treatment effect (LATE) of climate activism,[23] which is likely greater than the population average treatment effect. If our instruments shift the subset of oil fields whose activism

[22] Our Durbin-Wu-Hausman test result of 47.82 [*p*-value=0.000] further indicates that our IV model fits our data better than an alternative OLS model, suggesting the consistency of our IV strategy compared to the less efficient but consistent OLS approach.

[23] See Mkrtchyan et al. (2024) for similar effects.

exposure are higher-than-average, the IV estimator yields a larger coefficient. In essence, the raw correlation between activism and field productivity is likely to be upwardly biased (towards zero) because areas with higher levels of climate advocacy (in the cross section) will tend to contain highly productive oilfields for both observable (e.g., larger hydrocarbon deposits) and unobservable reasons. Thus, endowment likely promotes productivity and increases environmental damage from fossil fuel extraction, thereby heightening citizens' concerns about the potential adverse consequences in their communities, motivating climate action. The bias is also consistent with the view that activists will likely target highly productive oil fields with higher operational and financial loss probability (Lenox and Eesley, 2009).

We now turn to interpreting the IV coefficient. Because the TFP variable is in natural logs, the IV point estimate of −0.281 in column (4) indicates that a one-standard deviation increase in climate actions (i.e., 0.031 in our data sample, as shown in Table 1) results in a 0.87% (i.e., 0.031 x 0.281 x 100%) decrease in productivity. Because our estimates are the first to be obtained for activism-induced productivity shock in the petroleum extraction sector, there are no directly comparable results in the literature for this type of temporary shock. Nonetheless, our estimated productivity effect appears to be bounded by results from other studies of temporary productivity shocks.

For example, ignoring the sign of the productivity shock and focusing simply on magnitudes, Bornstein et al. (2023) estimated a short-run shock parameter of roughly 0.21 when evaluating the effect of oil price volatility on extraction productivity across oil fields globally. In terms of similar (i.e., conflict or disturbance-induced) productivity shocks in other sectoral contexts, Allcott et al. (2016) find that power outage distort reduced TFP by 0.27% in the Indian manufacturing sector. Bloom (2009) estimated the productivity effects of major shock events (e.g., the Cuban missile crisis, presidential assassinations, the OPEC I oil-price shock, the 9/11 terrorist attacks, etc.) on U.S. industrial production to be 1%, which is more consistent with the magnitude of our estimated productivity loss.

The relatively large magnitude of the activism-induced productivity loss seems consistent with the well-established notion that restarting hydrocarbon production after temporarily shutting down an oil well can be expensive, with significant risk of reduced reservoir productivity without any guarantee of attaining previous flow rates (SPE, 2020; Gars et al., 2025). To give further insight into the economic implications of our estimated productivity effects, it is more instructive to translate the productivity effects into profitability impacts at the field level. Using the basic OLS relationship[24] between ln(TFP) and financial performance[25] at the field level, we find that a 1% increase in productivity enhances field cashflows by \$0.14 m. Given our data sample's mean cashflow value of \$22.93 million, we can infer that, ceteris paribus, our estimated activism-induced productivity loss of 0.89% will likely cut field cashflows by \$0.12 million,[26] indicating a 0.5% cashflow decline at the sample mean.

5.2. *Falsification*

Despite our instrumental variables (IV) strategy, there might be concern that our causal analysis simply captures spurious changes in production dynamics or unobserved productivity shocks unrelated to climate action. However, because the timings of activist campaigns vary between fields-firms, we are unable to test for parallel trends in the traditional manner when a treatment period for a uniformly[27] implemented universal policy intervention can be identified. As a result, we conducted a negative control outcome (NCO) test using an alternative dependent variable (i.e., petroleum fiscal regimes) to assess the robustness of our identification strategy.

We substitute ln(TFP) with a field-level measure of the petroleum fiscal regime across sampled of oil fields. We use petroleum royalty as a proxy for petroleum fiscal regime across. Petroleum royalties represent a guaranteed share of the actual hydrocarbon resources produced, or a percentage of the revenue generated from such production. It is often paid by petroleum companies to the owner of the resource rights without requiring them to cover the exploratory, drilling, and operational costs. Mineral right owners (i.e., petroleum-rich countries) often determine petroleum royalty rates using long and winding legislative processes. Hence, because the resulting petroleum royalty rates or bands[28]are generally historically stable,[29] we treat them as pre-determined. Since we have annual royalty payment information for each oil field, we compute field-level royalty rates as the ratio of royalty amount to the economic value of output. These royalty rates should not be causally affected by climate activism although it plausibly shares similar sources of bias or potential confounders with TFP.[30] Our assumption that climate activism should not causally affect royalties is based on the premise that petroleum fiscal regimes are exogenously determined by national laws and legislations (IMF, 2010; Riak, 2024), and the

[24] Because we only utilise this estimate for a simple quantitative exercise without accounting for endogeneity, we interpret it as a lower bound to the productivity effect on profitability. See Table F4 of the Online Appendix.

[25] Since there is no direct measure of profitability at the field level, we utilise free cashflows (FCF) as an alternative measure of field financial performance.

[26] If a 1% rise in productivity is associated with \$0.14m rise in cashflows, we assume that a 0.89% decline in productivity will likely cause roughly [89% x \$0.14m = \$0.12m] fall in field cashflows.

[27] There are several instances of 'treatment' switching where a campaign is recorded in one period and none in the following periods, and another thereafter.

[28] For example, see: https://www.parliament.qld.gov.au/Work-of-the-Assembly/Tabled-Papers/docs/5619t1028/5619t1028.pdf and https://tile.loc.gov/storage-services/service/ll/llglrd/2014504238/2014504238.pdf

[29] See Diaz-Rioseco (2016), Brunnschweiler and Poelhekke (2021).

[30] For example, both resource owners and oil companies may face significant uncertainty about the future value of resource endowments (a price effect), oil field owners (i.e., oil companies) may also have significant technological capabilities (quality effect), resulting in variations in extraction rates (quantity effect) across oil fields. These effects, which are either unmeasured or unobservable, will most likely have an impact on both field-level levies and productivity. See Brown et al. (2016).

legislative process underlying such legislations can be complex and long-winded (Ashworth et al., 2006; Gouglas et al., 2018).

In a second test, we use a sub-population analysis, i.e., the data sample for 2020–2021, a period coinciding with the exogenous global shocks arising from the COVID-19 lockdown. During this period, lockdown and social distancing rules would have limited the mass mobilisation and protests that often characterize climate advocacy. Consequently, the activism-productivity nexus should be weaker during this period.

The falsification test findings for the above tests are presented in Table F2 of the online appendix. We found no statistically significant relationship between climate activism and royalty rates. Likewise, the activism coefficient is not statistically significant in the TFP model, when we restricted our data sample to the COVID-19 period. These results indicates that there are no hidden confounding effects in our climate activism-TFP relationship, validating our conclusion that the observed productivity effects are unique to fields facing activist campaigns.

5.3. *Robustness*

So far, we have concentrated on the average effects of climate activism on oil field productivity. However, the overall effect of climate action on productivity may obscure significant variety in productivity responses based on individual field, business, or even country variables. To shed light on this, we undertake a series of robustness tests to see how sensitive our findings are to different measures of the dependent and independent variables, company characteristics, and location features.

5.3.1. *Alternative measures of field performance and climate activism*

First, we use an alternative ln(TFP) measure derived from the Levinsohn and Petrin (2003) approach, as well as other measures of field-level operations and performance. The latter approach is important for addressing the concerns that our results might be dependent on the assumptions about the production function underlying the TFP estimates (e.g., that oil production follows a Cobb-Douglas functional form). Moreover, it is also useful to assess the impact of climate activism on production or emissions. We thus directly use field-level production and investments as alternative dependent variables.[31] To further confirm the reliability of our results, we use satellite imaging data on upstream gas flaring available from the Earth Observation Group.[32]

Second, we substitute the (count) activism variable with the intensity and longevity of activist campaigns. The former is represented by an average index that assesses the intensity of climate actions (i.e., 1=low, 2=medium, and 3=high) directed at each oil field over the course of a year, whilst the latter relates to the average duration of these campaigns. The point estimates from the IV-2SLS regressions are shown in Table 4. The findings show that, with the exception of the duration measure, climate advocacy generally retains its detrimental and statistically significant impact on field-level performance.

5.3.2. *Heterogeneity based on field and firm characteristics*

Table 5 shows regression findings for five subsamples: (i) fields in advanced (OECD), emerging (BRIC), and other developing (ROW) nations; (ii) fields owned by state-owned enterprises (SOEs) versus those owned by publicly quoted companies; (iii) environmental sensitivity of local area; (iv) field location based on proximity to population centers (i.e., levels of urbanization); and (v) whether an oilfield operates onshore or offshore. Consistent with the baseline results, the impacts of climate activism on the field are unchanged, with the coefficients remaining statistically significant at conventional levels, apart from the offshore sample coefficient. These results indicate that our baseline findings are robust to field location and firm ownership differences.

Beyond the statistical significance of these split sample regressions, it might be more instructive to consider the relative magnitudes of the different coefficients. For example, the larger point estimate for the BRIC sample indicates that the average effects reported in the baseline model in Table 3 are due to the larger productivity losses across fields located in key emerging economies. This finding seems consistent with a strand of research showing that emerging market economies suffer much more from exogenous shocks (Carrière-Swallow and Céspedes, 2013; Miescu, 2023). Furthermore, the absolute magnitude of the productivity loss in the SOE sample is significantly larger than the estimate for the publicly owned data sample, consistent with the notion that SOEs are less efficient than publicly owned enterprises (Dewenter and Malatesta, 2001; Li et al., 2020), and the adverse effects of exogenous shocks on them tend to be larger and longer-lasting (Wei and Guo, 2016).

In Column (12), we test whether within-group spatial spillover effects exist by augmenting the baseline model in Table 3 with a variable capturing the intensity of activism faced by co-owned neighbouring fields. We compute this variable as the sum of all activist campaigns encountered by other oilfields (i.e., located within 5 km) owned by same company. We obtain a negative and statistically significant coefficient indicating that oilfields record lower productivity when other neighbouring co-owned fields face more intense climate actions. This finding supports the notion of the indirect effect of activism on productivity which operates spatially through the ownership network.

[31] Our Rystad Energy subscription (U-Cube) exclusively includes field-level economic, output, and reserves data for the upstream petroleum industry. We do not, however, have access to the Rystad Emissions Solution, the module containing field-level emissions data. Therefore, emissions are not included in our analysis here. Nonetheless, we think that emissions patterns are implicitly captured by the operational information contained in the production and investment data.

[32] https://eogdata.mines.edu/products/vnf/global_gas_flare.html#data_download

Table 4
Alternative measures.

	Alternative dependent variables				Alternative activism variables	
	ln(TFP-LP)	Investment	Production	Gas flare	Severity	Duration
	[1]	[2]	[3]	[4]	[5]	[6]
	Second-stage regression					
Climate activism	−0.216***	−8.200***	−0.715***	−0.008**	−3.323*	0.018
	[0.053]	[3.141]	[0.100]	[0.003]	[2.010]	[0.025]
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Field fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country time trend	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	138,598	140,510	140,126	123,720	138,598	138,598
No. of oil fields	14,483	14,114	14,079	9643	14,483	14,483

Notes. This table presents 2SLS regression results of models using alternative measures field level performance and climate activism. In columns (1), the dependent variable is the alternative TFP variable obtained using the using Levinsohn and Petrin (2003) method (TFP-LP). In columns (2) and (3), the dependent variables are the field-level capital expenditure ((CAPEX) in U.S. dollars (2015=100)) and production (thousand barrels extracted, Kbbl/d per unit of operating expenses). In column (4), the dependent variable is the total annual volume of gas flared (billion cubic meters, bcm) within 5 km of each oil field. Column (5) presents results of regressing the baseline TFP-ACF on the severity of climate activism which is proxied by an average index taking the values 1=low, 2=medium, and 3=high, while Column (6) employs the average duration of field-targeted climate actions. All regressions include the control variables employed in the baseline regression. Standard errors are in parentheses and are clustered by field. * $p< 0.1$, ** $p< 0.05$ and *** $p< 0.01$.

5.3.3. *Accounting for lagged effects*

Our baseline model specification includes the contemporaneous impact of climate action on field-level TFP. However, the effect of activism on productivity may be delayed, as in the scenario when activism in one period initially shifts uncertainty before leading to decreased TFP in the following year. In Table 6, we investigate the delayed impact of climate activism by sequentially replacing the current values of $Activism_{it}$ with up to its third lag. The coefficients of interest remain negative, but only the first lag is statistically significant. These results imply that the prolonged productivity effect of activism appears to be completed within a year, not beyond.

5.4. *Does climate activism drive uncertainty? firm level evidence*

After establishing the effects of climate activism on plant productivity, we now address the initial/direct role of climate activism on uncertainty at the company level. To that end, we estimate Eq. (8) by regressing the company-level climate activism concern (CAC) variable on climate activism. To calculate the company-level measure of climate activism, we collapse the field-level climate activism variables into firm-year mean values.

A major problem with identifying model (8) is endogeneity bias, which may arise from omitted variable bias, caused by unobserved variables that influence both climate activism and CAC. Unobservable corporate characteristics, such as reputation and public perception, may increase the likelihood of climate activism (Adetutu et al., 2023). To address this issue, we instrument climate activism with a religious freedom variable:

$$Religious\_freedom_{it} = \sum_{j} Religious\_freedom_{jt} / N_j$$

where $Religious\_freedom_{it}$ is measured for company (i) in year (t), expressed as the mean value of religious domination across all the N_j countries of exposure where each company has oil fields, $Religious\_freedom_{jt}$. To create this instrument, we used the religion index from the International Country Risk Guide (ICRG) assessment, which assesses countries based on the extent to which a society is dominated by a particular religious group. The measure uses a scaled scoring system that ranges from 0 (religious domination) to 6 (religious freedom).

We expect a positive association between the religious freedom index and firm-level climate activism, i.e., more religiously tolerant societies will have higher levels of climate activism. Our identifying premise is based on evidence that freedom of religious engagement encourages collective action or protests (Kearns, 2011; Kikuta, 2024). Available research also implies that religious participation predicts environmentalism (Jenkins and Chapple, 2011), and nations that limit religious liberties have a reduced propensity for citizens to participate in protest activities (Arikan and Bloom, 2019). Therefore, religion has been proven to drive environmental and climatic advocacy (Koehrsen et al., 2023).

In terms of exclusion, it appears unlikely that religion across nations of operational exposure will have a direct impact on firm-level CAC, given that religious beliefs are emotional faith-based convictions anchored in family history and personal experiences, which are beyond the control of sampled firms. Furthermore, given the typical firm in our sample has oil field assets in over 20 countries, the cross-country derivation of the instrument makes it unlikely that the religious structure across such many exposure nations will directly affect company level CAC, unless through its impact on collective actions.

Table 7 presents the OLS and IV regressions of the firm-level model from Eq. (8). The OLS activism coefficient is positive and statistically significant at the 5% level. The IV coefficient in column (2) remains positive and attains statistical significance at the 1%

Table 5
Field location and firm characteristics.

	Field location			Firm ownership		Env. sensitivity		Urbanization		Field type		Spatial effects
	OECD (1)	BRIC (2)	ROW (3)	SOE (4)	Public (5)	Low (6)	High (7)	Low (8)	High (9)	Onshore (10)	Offshore (11)	Co-owned field (12)
Climate activism	−0.359***	−0.416***	−0.161***	−2.300**	−0.150***	−0.046**	−0.471***	−0.230***	−0.278***	−0.206***	0.334	−0.282***
	[0.106]	[0.124]	[0.047]	[1.106]	[0.037]	[0.019]	[0.102]	[0.077]	[0.057]	[0.032]	[0.356]	[0.050]
Co-owned activism												−0.072***
												[0.017]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	54,786	33,556	37,295	46,545	91,467	23,130	114,879	48,496	89,441	100,897	37,115	138,012
No. of oil fields	5463	3766	3498	4679	9217	2517	11,711	5086	9507	9942	3954	13,896

Notes. This table presents 2SLS regression results of models estimated based on split samples based on oil field location and firm ownership characteristics. The dependent variable across all regressions is the TFP-ACF measure. Columns (1)-(3) contain regressions based on the country groups in which the oil fields are located, where OECD denotes OECD member countries, BRIC refers to the emerging economies of Brazil, Russia, India, and China. ROW refers to the rest of the world which embodies a sample of countries that are neither OECD or BRIC economies (i.e., other developing or less developed countries of the world). Columns (4) and (5) present split sample regressions based on firm ownership, where ownership refers to whether a company is a state-owned enterprise (SOE) or publicly quoted. All company incorporation information is obtained from the Thomson Reuters (Eikon) database. Columns (6) and (7) present regression estimates based on environmental sensitivity, with sample split derived using the mean value of province-level air pollution (i.e., Particulate Matter, PM2.5): high levels of PM2.5 (low sensitivity) and low levels of PM2.5 (high sensitivity). Columns (8) and (9) contain results for split sample regressions based on the mean value of province-level urbanization rate. Columns (10) and (11) relate to spilt sample regressions based on whether an oilfield is onshore or offshore. Column (12) contains an additional variable that captures the intensity of activism faced by co-owned neighbouring fields. All regressions include the control variables employed in the baseline regression. Standard errors are in parentheses and are clustered by field. * $p< 0.1$, ** $p< 0.05$ and *** $p< 0.01$.

Table 6
Specification with lagged activism.

Dep var: ln(TFP)	(1)	(2)	(3)
$Activism_{t-1}$	−0.093***		
	[0.030]		
$Activism_{t-2}$		−0.010	
		[0.023]	
$Activism_{t-3}$			−0.040
			[0.062]
All control variables	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Field fixed effects	Yes	Yes	Yes
Country-specific time	Yes	Yes	Yes
Observations	123,200	109,384	96,273
No of oilfields	13,489	13,072	12,397

Notes. This table presents 2SLS regression results of models estimated using lagged climate activism. The dependent variable across all regressions is the TFP-ACF measure. Standard errors in parentheses. * $p< 0.1$, ** $p< 0.05$, *** $p< 0.01$.

level. The results demonstrate that there is a higher level of activism-induced uncertainty and concern among companies affected by field-level activism than in other companies during the same year. This finding accords with the productivity decline reported in the field-level analysis, demonstrating that activism at the plant level also directly feed into uncertainty at the corporate level.

5.4.1. *Sensitivity of firm-level results*

Table 8 shows that the results at the firm level are robust when controlling for fixed effects and IV analysis. However, there may be concerns about the uncertainty effects reflected by our model, especially given that the CAC variable is generated via textual analysis.[33] To that end, we incorporate other data sources to validate the company-level uncertainty findings. More specifically, we use two different measures of risk and uncertainty that should capture the implications embedded in the CAC variable. These variables are the company's risk-free rate[34] or premium, as well as a measure of overall company uncertainty based on generic uncertainty-related keywords rather than the activism-specific keywords used in calculating the CAC variable.

Furthermore, we use two alternative measures of climate activism: campaign intensity and company-share of oil fields targeted. The computed coefficients in Table 8 are all positive, albeit with various degrees of statistical significance, demonstrating that the previously documented positive association between climate activism and corporate uncertainty is robust when employing alternative measures.

5.4.2. *Exploring an alternative explanation*

To rule out the possibility that the CAC variable is merely picking up corporate signals to the public rather than genuine concerns about climate activism, Table 9 presents a test conducted to rule out an alternative explanation for the results in Table 7. We use the idea that shareholders are an important public constituency for petroleum corporations, as research shows that oil companies frequently try to influence shareholder perception and ease social pressures by adapting the content and tone of various corporate reports (Neu et al., 1998; Cho et al., 2015; Megura and Gunderson, 2022; Rajan et al., 2023). If such opportunistic behaviour holds, the impact of climate activism on CAC should fade in a counterfactual scenario where shareholder effects are captured.

The prevalence of shareholder activism or revolts is well documented in academic research (Denes et al., 2017). The source of information on shareholder revolts is shareholder resolutions and votes on environmentally related proposals, which are often publicly available[35] through filings (e.g., Securities and Exchange Commission, SEC filings) outside the control of firms and their management (see Kolaric, 2024; Diaz-Rainey et al., 2024).

Hence, we augment the CAC model in Eq. (8) with environmentally motivated shareholder revolts at the firm level, as well as their interaction with climate activism. The result in Table 9 indicates that $Activism_{it}$ retains its significance, with the shareholder variable and its interaction with climate activism generally lacking statistical significance. The results rule out the potential challenge that opportunistic behaviour might have driven our CAC results.

[33] One methodological constraint is that we lack higher frequency data (e.g., daily or monthly information, as is the case with stock price data) for the CAC sentiment variable which is only available annually via textual analysis of annual reports. Nevertheless, we correlate CAC with annual values of two relevant company-level variables in years for which at least one activism event occurred. These variables are (i) environmentally related investment, and (ii) adoption of adopted environmental management practices. The correlation matrix in the online appendix (Table F3) indicates that CAC is positively correlated with both measures.

[34] We use the Weighted Average Cost of Capital (WACC) data available from the Thomson Reuters Refinitiv (Eikon API) database. We expect higher WACC to be consistent with higher activism risk captured by CAC, implying that a higher risk-free rate for such high-risk companies will raise the cost of debt and equity for them.

[35] For instance, see: https://engagements.ceres.org/

Table 7
Estimated firm-level CAC models.

Dep var: CAC	OLS (1)	IV (2)
Climate activism	0.109**	1.707***
	[0.052]	[0.622]
Firm size	0.079***	0.075***
	[0.023]	[0.023]
Firm age	0.117***	−1.193
	[0.040]	[1.151]
Country GDP per capita	−3.089*	−3.202**
	[1.628]	[1.632]
Country institutions	0.305	0.298
	[0.228]	[0.226]
Dep var: Climate activism *First-stage regression*		
Religion		0.028***
		[0.007]
Weak id test: Kleibergen-Paap F-test		17.48
Dep var: CAC *Reduced form regression*		
		0.049***
Religion		[0.015]
Year FE	Yes	Yes
Firm FE	Yes	Yes
Observations	2158	2158
Firms	166	166

Notes. This table presents the OLS and 2SLS regression results of the effect of climate activism on the firm-level climate activism concern (CAC) variable. The CAC variable is the normalised annual count of instances where a climate activism related keyword appears near a concern related keyword (i.e., both appear in the same line or one line above or below). The climate activism variable captures the incidence of climate activist campaigns targeted at the oil fields collapsed by company-year. Standard errors are in parentheses and are clustered at the firm-level. * $p< 0.1$, ** $p< 0.05$ and *** $p< 0.01$.

Table 8
Sensitivity analysis of company-level results.

	Alternative dependent variables		**Alternative independent variables**	
Dep var>>>	Risk premium (1)	General Uncertainty (2)	CAC (3)	CAC (4)
Climate activism	0.380*	0.344**		
	[0.221]	[0.147]		
Climate activism (intensity)			1.563***	
			[0.516]	
Share of oil fields affected				0.041***
				[0.014]
Year fixed effects	Yes	Yes	Yes	Yes
Company fixed effects	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes
Observations	2158	2158	2158	2158
No. of companies	166	166	166	166

Notes. This table presents 2SLS regression results of models estimated based on alternative dependent variables namely risk premium, and a broader measure of uncertainty (columns 1–2) and alternative independent variables namely intensity of climate activism (column 3) and share of oil fields attacked (column 4). All regressions include the control variables employed in the baseline regression. Standard errors are in parentheses and are clustered by field. * $p< 0.1$, ** $p< 0.05$ and *** $p< 0.01$.

Table 9
Ruling out alternative explanations.

Dep var.: CAC	(1)	(2)	(3)
Climate activism (count)	1.623***		
	[0.583]		
Climate activism (intensity)		1.597***	
		[0.532]	
Climate activism (share of field attacked)			1.593***
			[0.524]
Shareholder revolts	0.276*	0.160	0.161
	[0.147]	[0.116]	[0.121]
Climate activism X Shareholder revolts	0.206	−0.018	−0.002
	[0.131]	[0.203]	[0.024]
Baseline controls	Yes	Yes	Yes
Firm-FE	Yes	Yes	Yes
Year-FE	Yes	Yes	Yes
Observations	2158	2158	2158
No of Firms	166	166	166

Notes This table presents the 2SLS regression results of the effect of climate activism on the firm-level climate activism concern (CAC) variable. The CAC variable is the normalised annual count of instances where a climate activism related keyword appears near a concern related keyword (i.e., both appear in the same line or one line above or below). The climate activism variable captures the climate activism incidence or intensity or share of oil fields targeted by company-year. Shareholder revolts is the total number of shareholders environmentally related resolutions/votes pushing back against firm environmental damage. Standard errors are in parentheses and are clustered at the firm-level. * $p< 0.1$, ** $p< 0.05$ and *** $p< 0.01$.

5.5. *Accounting for indirect effects*

Our analyses have separately established the direct local disruptive effect of climate activism on hydrocarbon extraction, as well as its role in increasing managerial or investor uncertainty. While we found strong evidence supporting these two pathways, one major unanswered question is the indirect impact of company-level uncertainty on field-level performance. Given the ownership linkages between oil fields and companies, we investigate the impact of company-level uncertainty on field-level performance. In Table 10, we augment the baseline oil field TFP model in Eq. (7) with the CAC variable,[36] as well as its interaction with the activism variable: $Activism_{it} \times CAC_{it}$

The results in Table 10 shows that $Activism_{it}$ loses statistical significance, while the coefficients on CAC ($p< 0.01$) and its interaction with activism ($p< 0.10$) have negative statistically significant effects. Our coefficient of interest is the $Activism_{it} \times CAC_{it}$ interaction, which captures the above-mentioned indirect effect. The estimated interaction coefficient of −0.080 indicates that, for each given level of company level uncertainty, oil fields that eventually face a one standard deviation rise in activist attacks lose an additional 0.25% of productivity.[37] These results show the presence of an uncertainty channel in which activism increases management or investor uncertainty, limiting investment and productivity at the field level.

6. Concluding remarks and study implications

The world is seeing an increase in the frequency and intensity of climate activism because of significant shifts in social views towards global warming and a feeling that authorities are acting too slowly to address climate change dangers. Various activists are now targeting petroleum firms by disrupting their production processes and pressuring them to reduce their environmental effect. Yet, little is known about the quantitative effects of climate advocacy on the supply side of the hydrocarbon economy.

Using a global data set, we present comprehensive empirical evidence on two distinct but interconnected mechanisms by which climate activism affects petroleum industry performance. First, there is a local disruption mechanism in which activists disrupt production operations at the oil field level while increasing uncertainty at the parent company level. In this study, we also identified a second-order effect, which indicates that, for any given level of company-level uncertainty, oil fields that eventually face activist attacks experience further productivity losses. This second-order effect is a previously untested empirical effect of climate activism. Given that climate activism is fueled in part by the public's perception that policymakers are not acting quickly enough to address climate change (Daubanes and Rochet, 2019; Besley and Persson, 2023), our findings are consistent with previous research indicating

[36] In the model specification in Table 9, we employ an instrument for CAC using a proxy for the risk perception of the board of directors: the average probability across all board directors that there was conflict/war involving the individual's country of origin at some point in the period before the individual reached adulthood. Our identifying assumption is that wars during the period before people reach adulthood represent big shocks that will shape the formative experiences of board directors and their level of risk perception (Malmendier et al., 2011; Benmelech and Frydman, 2015).

[37] We arrive at this by using the standard deviation of CAC (i.e., 0.031 as presented in Table 1): 0.031 x 0.080 x 100%.

Table 10
Conditional effect of company-level uncertainty on field performance.

Dep var.: ln(TFP)	
Climate activism	0.177
	[0.188]
CAC	−0.112***
	[0.020]
Climate activism × CAC	−0.080*
	[0.042]
Year fixed effects	Yes
Field fixed effects	Yes
Country trend	Yes
Baseline controls	Yes
Observations	138,012
No. of oil fields	13,896

Notes. This table presents 2SLS regression results of the effect of climate activism on field-level productivity. The dependent variable is total factor productivity (TFP) computed following the Ackerberg et al. (2015) (ACF) method, and the activism variable is the number of climate actions targeted at oil fields in each given year. CAC is the activism induced uncertainty variable. The model specifications control for field and year fixed effects, and a range of field, company, province, and country (of field location)-specific variables. Standard errors are clustered at the field level. * $p< 0.1$, ** $p< 0.05$ and *** $p< 0.01$.

the contingent role of weak climate policy[38] as a trigger for climate movements. As a result, climate activists may see the mechanisms described in our study as compensating for such policy weaknesses.

We can envision some potential extensions to our analysis. For example, a promising area for future research is a policy analysis to investigate how productivity losses caused by climate action translate into national welfare losses. Other interesting paths include studies of (a) whether climate activism has contributed to advances in institutional structures; (b) the degree and speed with which climate advocacy drives the green transition at the company and country level.

Data statement

Our two main datasets are constructed at oil field and firm level using raw data from Rystad Energy U-Cube and Thomson Reuters (Eikon) databases, respectively. The information from both databases are proprietary data, obtained under terms and conditions that expressly state that "The client cannot distribute data sets from the products to third parties". Specifically, authors obtained a single access license to Rystad UCube.

CRediT authorship contribution statement

Morakinyo O. Adetutu: Writing – review & editing, Writing – original draft, Visualization, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Anthony J. Glass:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Abbi Kedir:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Karligash Kenjegalieva:** Writing – review & editing, Writing – original draft, Visualization, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

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[38] Adetutu et al. (2023) showed that fossil-rich countries with weak environmental policies have higher incidence of climate activism relative to those with stringent regulations. This is consistent with the positive coefficient on the environmental policy variable within our TFP model.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jce.2026.07.003.

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