Environmentally-Responsible Demand: Irresponsible Lobbying?*

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November 16, 2023

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Abstract

How do firms respond to rising environmental concerns of consumers? We investigate this question for the automotive industry in the US using a shift-share instrumental variable approach. We construct a novel dataset at the firm-level to instrument changes in household preferences with natural disasters. Our findings suggest that firms not only engage in cleaner innovation but also increase their lobbying on environmental topics. We show that the increase in environmental lobbying and clean patenting follow the same dynamics which points to a complementarity between the two strategies. These results can be understood as firms using lobbying to increase the value of clean patents: higher environmental standards tailored to the firm's new clean technologies diminish the competition the firm faces.

JEL classification: D70, D9, O3, Q55, E71

*We are grateful to Philippe Aghion, Francis Bloch, Pierre Boyer, Leonardo Bursztyn, Vincent Pons, Farzad Saidi and Thierry Verdier for their thoughtful comments. We thank Siméon Campos, Paul Chagnaud, and particularly Corentin Laffitte for excellent research assistance. Sonja Dobkowitz gratefully acknowledges financial support from the German Research Foundation (DFG) through RTG-2281 "The Macroeconomics of Inequality".

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1 Introduction

Households' environmental concerns are rising, shifting demand towards cleaner products.[1] How do firms react to such a shift in demand? The literature thus far focuses on firms' incentives to innovate clean technologies (Aghion et al. 2021). What has not been studied yet is whether firms use political influence tools to cope with a shift in demand. Lobbying against environmental regulation, for example, may help especially dirty firms to protect their remaining profits.[2] In this paper, we investigate whether a rise in green consumer preferences also implies an increase in environmental lobbying.

We use a shift-share instrumental variable approach to analyze a novel dataset linking natural disasters, environmental preferences, and firm-level data on lobbying and patents in the automotive industry. We find robust and significant evidence that automotive producers adjust in two dimensions: they increase both clean innovation and environmental lobbying expenditures. Surprisingly, it is not heterogeneity in firms' patent stocks or sales driving the results: cleaner and dirtier firms behave similarly. There is no path dependence in terms of innovation or lobbying. Furthermore, the dynamics of clean patenting and environmental lobbying comove closely. We interpret this evidence as environmental lobbying complementing clean patenting: stricter environmental regulation increases the value of new clean patents.

Our findings run counter intuitions developed from the literature. Firstly, Autor et al. 2020 show that in response to a trade shock, only those firms that are close to the technological frontier— in our case clean technologies— engage in more innovative activity. Secondly, those firms further away from the frontier turn to lobbying more in order to mitigate competitive pressures from trade (Bombardini, Cutinelli-Rendina, and Trebbi 2021). Innovation and lobbying emerge as substitutes in response to a trade shock. In contrast, we show that the two strategies are complements in response to a demand shock. We interpret this difference as a demand shock leaving less room for firms not to produce green goods as demand for dirty goods declines. When cleaner patents are realized, the firm enters a cleaner market. Higher environmental standards help shield this market from more competition, in a similar way as lobbying minimizes

1. Recently, the phenomenon of an intrinsic willingness to pay for the avoidance of negative externalities has spurred interest in the economics literature; see, for instance: Bénabou and Tirole 2010; Bartling, Weber, and Yao 2015; Aghion et al. 2021.

2. In the context of trade, earlier studies find that firms far from the technology frontier choose to lobby in response to a trade shock. Lobbying for stricter trade regulation diminishes competition in the firm's market (Bombardini, Cutinelli-Rendina, and Trebbi 2021).

competition in the trade context.

In more detail, the analysis focuses on US states over the period from 2006 to 2019. We connect several datasets into one firm-level panel to focus on a demand-led mechanism. First, we construct a novel proxy for household environmental preferences from Google Trends data. Google Trends measures the relative frequency with which certain terms, e.g. *Climate Change*, are searched. In contrast to available survey data, Google Trends comes at a high frequency and fine geographic variation which allows us to build a panel dataset at the state level at a quarterly frequency.[3]

Second, we combine our proxy for green preferences with state-level vehicle registration data of the automotive industry to construct a measure of firm exposure to green consumer preferences. While environmental awareness has increased everywhere, there is significant heterogeneity across the geographic markets of different firms; both in terms of the speed and the timing of the change. We focus on the automotive industry in the US for several reasons. First, emissions from transport account for 25% of greenhouse-gas emissions in the US (United States Environmental Protection Agency EPA 2023). Second, the industry produces highly heterogeneous goods in terms of emission standards, that are easily identifiable by consumers regarding emissions. This is an important aspect to measure the effect of consumer sentiments.[4] Third, the automotive industry is characterized by a high share of both lobbying and innovative activity: 15 out of our 17 groups lobby, and all groups file patents. Therefore, we are able to study the trade-off between these two strategies.

Finally, we link our data with a measure of natural disasters. Changes in consumer sentiments are most likely endogenous. They may be shaped by political and economic surroundings. For instance, exposure to green supply and advertisements or policies may increase environmental interest. To rule out that we measure firm responses to confounding factors, like omitted variables or reverse causality, we use exogenous variation in green preferences induced by natural disasters. Specifically, we compile a dataset of wildfires using satellite data from the NASA.[5] With this dataset, we can measure the

3. On the downside, the data does not provide information on the intention with which a term is searched so that the search data does not express concerns. However, we observe similar trends comparing Google Trends data to survey data. Figure 6 in the Appendix shows the evolution of a measure of environmental concerns from the Gallup survey. The series displays a similar trend as our index of environmental preferences derived from Google Trends presented in Figure 1. Section E.1 in the Appendix presents a state-level comparison of the two indices.

4. Questions have been raised about the environmental advantage of electric vehicles, an MIT analysis attests an emission advantage of electric vehicles also taking into account their carbon-intense production (MIT Climate Portal 2022).

5. MODIS Collection 61 NRT Hotspot / Active Fire Detections MCD14DL distributed from NASA

spatial distance of all states to a given wildfire. We use this variable to proxy consumer exposure to natural disasters at the state level.[6]

Equipped with this firm-level panel dataset, we perform an instrumental variable shift-share analysis where the identification stems from the quasi-randomness of our shocks (Borusyak, Hull, and Jaravel 2022).

We argue that our empirical strategy is valid to measure the effect of green demand on lobbying and innovation due to, first, high geographic heterogeneity in firms' sales.[7] Second, we control for a rise in environmental regulation at the federal level by including time-fixed effects.[8] Third, we include control variables to account for political adjustments at the state level in response to natural disasters such as lagged information on the political orientation of the state (republican vs. democratic), the use of public transportation, and demographics.

Our main result is that, in response to a demand shock, firms leverage lobbying and clean innovation as complementary strategies. To arrive at this conclusion, we proceed in three steps. We first show that on average firms increase their clean patenting and decrease their dirty patenting as consumer preferences become greener. A one standard deviation increase in consumer interest in the environment entails an increase in the average firm's clean patent stock (i.e. new patents) by a factor of 2.5. Dirty patent stock growth declines by a factor of 10. Environmental lobbying expenditures of the average firm, in turn, increase by a factor of 2.9 amounting to a rise of US$261K.

These findings on average firm behavior are in line with lobbying and clean innovation being substitutes at the firm level if the firms that lobby differ from those which innovate cleaner technologies. Consulting the literature, we would expect that it is only cleaner firms fostering their clean innovative activity as they have a productivity advantage in clean innovation (Autor et al. 2020) while dirtier firms turn to lobbying against environmental regulation to protect their market shares (Bombardini, Cutinelli-Rendina, and Trebbi 2021). To investigate this hypothesis and as a second step, we interact our main regressor of firm exposure to changes in consumer preferences with the

FIRMS. Available on-line at https://earthdata.nasa.gov/firms.doi:10.5067/FIRMS/MODIS/MCD14DL.NRT.0061

6. Our continuous measure of exposure assumes that all US households are affected by a wildfire, e.g. via the media. However, exposure is stronger the smaller the geographic distance between disaster and consumer. One of our robustness exercises uses extreme temperatures as an instrument instead of wildfires.

7. Also, there is a large geographic difference in the states where firms sell and produce, reinforcing the assumption that we capture a demand mechanism.

8. Note that our analysis focuses on federal lobbying activity - as opposed to state-level lobbying - which impacts environmental policymaking at the federal level.

share of dirty products in overall sales. We find no significant evidence of heterogeneity based on the dirtiness of production or innovation either on the rise in clean innovation or on the rise in environmental lobbying following the shock. We can therefore exclude that the rise in clean innovation is driven by clean firms and the rise in environmental lobbying is explained by dirtier firms: both tools appear as complements to respond to changes in consumer preferences.

Third, we use a local projection analysis to study the relation of innovation and lobbying strategies over time. This exercise, too, lends support to the interpretation that clean innovation and lobbying on environmental topics are complements at the firm level. Clean patenting and environmental lobbying move in tandem over time: more clean patenting is accompanied with more environmental lobbying. This suggests that when firms succeed in generating new knowledge to produce cleaner goods, they transition from a dirtier to a cleaner market. To prevent more firms from entering this cleaner market segment, stricter environmental regulation comes in handy.[9]

Lobbying and clean innovation most likely depend on the uncertainty of the political environment. In an additional analysis, we find that political uncertainty has a mitigating effect on the rise in clean innovation as consumer preferences become cleaner. Our intuition is that the more stringent the expected environmental regulation, the more beneficial clean innovation is for firms. This finding highlights the importance of unambiguous and persistent policies and presents additional evidence on the complementarity of environmental lobbying and clean innovation.

Literature This paper brings together two strands of literature: the literature on the relationship between competition, innovation, and lobbying and the literature on households' willingness to pay to avoid negative externalities.

The first literature developed around the seminal paper by Aghion et al. 2005 which discusses the relation between competition and innovation. Aghion et al. 2005 use a Schumpeterian model to show that firms that are able to innovate to differentiate from competition will do so when competitive pressures reach certain levels. Empirical validation thus far focuses on trade shocks to investigate firm responses to increased competition (Bloom, Draca, and Reenen 2016; Bombardini 2008; Brandt et al. 2017; Hombert

9. Unfortunately, we cannot distinguish whether lobbying activity is in favor or against more environmental regulation. The comovement of clean patenting and environmental lobbying, however, leads us to conclude that it is pro-environmental lobbying that increases. A more in-depth analysis of the quality of environmental lobbying following Kang 2016 or Kwon, Lowry, and Verardo 2023 would shed light on this important aspect.

and Matray 2018).

Autor et al. 2020 find that many firms do not have the possibility to innovate after a competition shock. Based on the intuition that other escape avenues exist in response to competitive pressures, Bombardini, Cutinelli-Rendina, and Trebbi 2021 provide evidence that US firms use innovation and lobbying as two alternative strategies to deal with trade shocks. Further confirming this intuition, Akcigit, Baslandze, and Lotti 2022 present evidence that market dominance is negatively correlated with innovation and positively correlated with political connections in the framework of Italian firms. In contrast to the existing literature, we focus our analysis on firm responses to a demand shock. Furthermore, our results point to an aggregate complementarity of clean innovation and lobbying: both, clean innovation and lobbying expenditures rise in response to increased competition in one market fragment.

More precisely, this paper connects to studies on firm capacities to modify environmental regulations through political influence. This literature attests high social costs and individual gains from anti-environmental lobbying (Kang 2016; Meng and Rode 2019).[10] Adverse environmental lobbying is particularly effective because the strength of lobbying is multiplied when targeted at maintaining the status-quo (McKay 2012), dirty firms tend to organize more than clean firms resulting in a higher impact on policies (Kim, Urpelainen, and Yang 2016), and environmental organizations lobby less than what would be considered rational (Gullberg 2008). We contribute by investigating motives for environmental lobbying. In the framework of the automotive industry, we show that while firms increase their environmental lobbying expenditures in reaction to the shift in green preferences, they also engage in a technological transition through clean innovation.

The second connected literature explores *individual social responsibility* (see, for instance, Bénabou and Tirole 2010; Bartling, Weber, and Yao 2015; Falk et al. 2021). While the phenomenon of social responsibility has been studied in the behavioral economics literature, analyses of the effectiveness of social responsibility to affect market outcomes are scarce. Aghion et al. 2021 show that clean innovation is one way to escape competition in conventional, non-green markets. Stronger environmental consumer preferences accelerate the mechanism. Other contributions highlight obstacles for social responsibility to impact actual allocations. Income inequality (Vona and Patriarca

10. A remarkable study shedding light on the positive impact of lobbying on the discrepancy between voters and legislature decisions is Giger and Klüver 2016 in the context of Swiss referenda.

2011; Dobkowitz 2022), for instance, may keep low-income households from consuming clean products. A perceived quality advantage of conventional goods, a low availability (Vermeir and Verbeke 2006), or a lack of trust in sustainability claims (Meis-Harris et al. 2021) are other reasons why demand and environmental attitudes diverge. We contribute to answering the question of whether households can shape the allocation of resources across sectors. We provide a new highly desegregated dataset of environmental preferences and find that consumers are key to defining the direction of innovation.

Outline The remainder of the paper is structured as follows. Section 2 outlines our data followed by a description of the empirical strategy in Section 3. In Section 4, we present and discuss our main results. Section 5 presents a series of robustness exercises, and 6 introduces additional results. Section 7 concludes.

2 Data and Summary Statistics

In this section, we describe the data sources, define our sample of interest, and present summary statistics.

2.1 Data Construction

Vehicle sales: S&P Global. The data on new vehicle registrations is sourced from *S&P Global* covering the years 2006 through 2019.[11] This comprehensive dataset provides quarterly registration details for each US state including information on the make, model, and engine type of each vehicle. We consider registrations in a given state to be equivalent to a sale to a resident of that state.[12] Using this dataset, we can determine the market share of each vehicle group at the state level which we use to assess a group's exposure to green consumer preferences.

Environmental preferences: Google Trends. To proxy consumers' awareness of environmental issues at the state level, we revert to Google Trends data. Google Trends is a free tool that provides time-series indices of search queries made in a certain area. Specifically, it quantifies the percentage of all searches that use a given term. To build

11. https://www.spglobal.com/mobility/en/products/automotive-market-data-analysis.html
12. It's generally forbidden to register a vehicle in another state than the state of residency in the United States. Exceptions exists for citizen that are living in multiple states, or working in another state.

our index, we use Google Trends queries on topics related to environmental issues and aggregate them using factor analysis. The selected keywords are *"Electric car"*, *"Recycling"* and *"Climate Change"*. Google Trends normalizes the index by the highest value observed within the time period and areas included in the query. However, Google Trends only allows comparing a maximum of five locations per search so that reference points of normalization vary. To solve this issue, we include the national U.S. index in each query and sequentially normalize each state by the maximum value of the US.[13] Finally, we build a composite index with principal component analysis (PCA).[14]

Previous work highlights the usefulness of Google Trends to predict near-term economic indicators (Choi and Varian 2012; Stephens-Davidowitz and Varian 2014). Vosen and Schmidt 2011 show in the context of private consumption that Google Trends outperforms survey-based indicators in forecasts.

Fires: FIRMS. We measure exogenous shocks to environmental preferences through wildfires. Data on fires comes from the Fire Information for Resource Management System (FIRMS) of the US NASA. In particular, the data divides the United States into cells of one square kilometer and documents several times a day whether there is a fire in this cell.[15] We apply the following procedure to obtain a map of all fires in the US for each week of the period of analysis. First, we collapse this highly disaggregated data at the week level, considering that a cell is alight if a fire was declared in the cell at least once over the week. Second, we determine clusters of fires using the *dbscan* algorithm (Ester et al. 1996).[16] Third, we draw a convex polygon around each cluster to determine the area of the fire.

Finally, we compute our measure of consumers' exposure in state l to fires by summing over all the fires f:

$$Fire\ Exposure_{lt} = \log\left(\sum_f \text{intensity}_{it} * \text{surface}_{ft} / \text{distance}^2_{flt}\right),$$

where the *intensity* is proxied by the fire radiative power (in Megawatts) and *surface* refers to the size of the fire. We finally divide our measure by the square of the dis-

13. See West 2020 for an extensive discussion of this issue

14. We extract the first component which accounts for 53% of the total variance.

15. We focus on "presumed vegetation fire" and drop the other types of fires.

16. We focus on clusters to exclude fires that are too small to impact environmental preferences. We choose eps=0.25 and minpts=5 as parameters for the algorithm, that is clusters are composed of at least 5 points at a maximum normalized distance of 0.25.

tance between the fire and the state to ensure that close populations are exponentially affected.[17]

Lobbying: LobbyView. Following the Lobbying Disclosure Act of 1995, all lobbyists ought to register their lobbying activity with the U.S. Senate Office of Public Records. In particular, they need to declare their client, the amount spent on lobbying, the topics lobbied, and the entity targeted by the lobbying activity. Although this information is publicly available at the Senate Office of Public Records, we use the clean version *LobbyView* provided by Kim 2018, where firms are matched to standard identifiers, such as the *gvkey* identifier for the Compustat database. In particular, we focus on clients that are firms from the automotive industry.

Using this dataset, we derive information on the topic firms lobby on by dividing lobbying expenditures into the nine groups of issues receiving the most expenditures. These groups of issues are manufacturing, trade, tax, labor, environment, consumer safety, trade, finance, innovation, and public expenditures.[18]

Innovation: Patentsview. We measure innovation through granted patents at the United States Patent and Trademark Office (USPTO). Patents are dated by their year of application to precisely represent the year of their invention. We match patents with firms in our sample using the assignee disambiguation method of PatentsView and manual inspection.[19] Following Aghion et al. 2016 we categorize patents using their Cooperative Patent Classification (CPC) into *clean*, *dirty*, and *gray* technologies. Clean patents correspond to innovation on electric and hybrid engines, gray patents correspond to technologies rendering fuel engines less polluting and dirty patents refer to the other innovations on fuel engines.[20]

However, the number of patent applications may not reflect actual investment in R&D. To bypass this issue, we weight patent applications with an estimation of its private economic value from Kogan et al. 2017 updated until 2020. Finally, following Hall 2005 and Bloom, Draca, and Reenen 2016, we compute a measure of *knowledge stock*, K_{ist}, according to the recursive identity:

17. The distance is computed between the fire's and the state's center of gravity.
18. The list of issues entering each group can be found in the appendix. We do not consider issues that are not relevant to the automotive industry, such as religion, tobacco, or firearms.
19. https://patentsview.org/disambiguation
20. The classification of patents into these three categories by their Cooperative Patent Classification code can be found in subsection E.3 in the Appendix.

$$K_{ist} = (1 - \delta)K_{ist-1} + R_{ist}.$$

Where R_{ist} represents the economic market value of new patents from firm i in technology s, with $s \in \{\text{clean, gray, dirty}\}$. The variable δ captures the depreciation of knowledge.[21] We use K_{ist} in our main analysis to measure changes in innovation activity. Using a stock instead of a flow variable is less prone to arbitrary results due to the choice of lags in the regression.[22]

State-level controls. We control for a series of state trends that may affect corporate strategies responding to shocks to consumer preferences. In particular, we control for local transportation habits (through the percentage of the population commuting by personal car, by public transportation, and by bike and the percentage of the population working remotely) and local investments in the energy transition of transports (number of alternative fueling stations). We also control for demographic information such as the employment rate; hte share of young persons in the population; the share of the rural population, and income per capita. We control for major political preferences by using the share of votes for Republicans in the past presidential election. Finally, we include state-quarter dummies (such as California-summer) to control for seasonality in the response of firms. Data on transportation habits, local infrastructure, investment in local infrastructure, and alternative fueling stations comes from the Bureau of Transportation Statistics. Demographic data comes from the Census and the share of the rural population comes from the Decennial Census. Personal income per capita comes from the Bureau of Economic Analysis. Last, election data comes from the MIT Election Data and Science Lab.

2.2 Summary Statistics

Having specified all main variables of interest, we now present a brief discussion of our sample and main variables.

21. Following the literature on depreciation of R&D (Li and Hall 2020), we set $\delta = 0.2$. Moreover, using the perpetual inventory method to compute the knowledge stock allows us to not rely on the $ln(1 + \text{Patents})$ that may bias our results.

22. We present a robustness exercise in the Appendix using the log number of new patent applications instead of the change in the value of the stock of patents. Our main results remain unchanged.

Innovation and Lobbying. Our dataset is composed of 17 groups, which are the main groups of the automotive sector offering private cars.[23] We focus on groups, which are aggregates of makes because we observe in the data that both lobbying and innovation are most often set at the group level.[24] Table 1 reports the distributions of our main outcome variables, and Table 2 reports average make characteristics.

TABLE 1: Summary statistics of the outcomes

	Mean	SD	P25	P50	P75	P95	Max
Lobby (Env. topics) K$	90.04	158.66	0.00	17.61	100.80	394.19	1236.50
Lobby (Total) K$	683.92	842.94	38.01	380.00	1040.01	2237.59	6380.00
K_{clean} (M$)	177.35	347.50	0.00	0.94	141.81	1056.28	1944.64
K_{dirty} (M$)	63.34	141.83	0.00	0.17	18.89	392.75	750.80
K_{grey} (M$)	127.69	305.98	0.00	0.33	31.95	759.65	1641.60

Notes: The table summarizes the main outcomes in our analysis. Data is quarterly average. The first is the average lobbying targeted to environmental topics in thousand of dollars. Second line is the total lobbying expenditures in thousand of dollars. The last three rows are knowledge stock for clean, dirty, and gray innovations, computed using the market value estimation of patents from Kogan et al. 2017 in million of dollars (deflated with CPI). See section 2 for a description of the dataset.

We document that green technologies represent 57% of patent applications in our period of analysis, gray technologies around 28%, and dirty technologies account for only 16% of applications. Figure 14 in the Appendix depicts the trends in the different types of patenting since 1976. There is an exponential increase in the number of patents since the late 1990s' which was mainly driven by green applications. The number of clean patents rose by a factor of five during the period.[25] The level of dirty patenting remains stable over the period with a peak around the year 2000. Gray patenting follows similar but milder trends than green patenting until 2010. Then the number of applications plateaued at an intermediate level between green and dirty applications.[26]

There is high heterogeneity in the mix of technologies patented by firms, with makes such as Mazda or Isuzu innovating mainly in gray technologies, and others focusing on green technologies. However, all firms —with the exception of Tesla —innovate in

23. We remove from the sample groups with less than 30,000 registered cars over the whole period and truck-only companies.

24. The group BMW, for instance, includes the makes BMW, Mini and Rolls-Royce. Similarly, the group General Motors includes the makes Oldsmobile, Hummer, GMC, Buick, Chevrolet, Saturn, Cadillac, and Pontiac. The whole list of groups and makes can be found in the appendix.

25. In our dataset we only observe patent applications that were accepted by the USPTO. The application process takes a few years, so all applications after 2018 have not been accepted yet. This explains the sharp decrease in patenting we observe in the last quarter.

26. These trends are congruent with trends presented in Aghion et al. 2016; Aghion et al. 2021.

all types of technologies. When studying the heterogeneity in response to consumers' environmental awareness we, therefore, do not compare *green* to *dirty* firms but use a continuous scale of *greenness*.

TABLE 2: Summary Statistics by Group (Quarterly, 2006-2019)

Group	Clean Patents	Dirty Patents	Grey Patents	Lobbying (k$)	Market Share (avg,%)
BMW	10.71	2.52	3.02	131.45	2.32
Daimler	5.12	0.92	2.29	438.45	2.09
FCA	4.46	1.15	1.90	1271.57	11.61
Ford	63.58	25.17	47.96	1786.18	15.03
Geely Automobile Hld.	3.19	0.88	1.83	334.69	0.52
General Motors	47.40	15.48	30.56	2773.49	19.61
Honda	41.50	16.02	11.35	769.56	9.82
Hyundai Kia Automotive Group	79.77	15.35	26.31	437.90	7.01
Isuzu	0.42	0.59	3.76	0.00	0.03
Mazda Motors Group	2.00	2.46	9.15	35.57	1.85
Renault-Nissan-Mitsubishi	33.79	6.35	12.58	1115.96	8.46
Subaru Group	4.00	0.38	1.00	2.50	2.45
Suzuki	3.69	2.28	0.79	0.00	0.38
Tata Group	4.56	0.68	1.26	127.92	0.45
Tesla	3.21			161.07	0.10
Toyota Group	116.10	19.15	43.31	1577.17	15.00
Volkswagen	21.77	3.46	6.67	381.64	3.34

Notes: The table summarizes patenting activity, lobbying, and market share for the make-groups that we observe in our sample. First three columns are the average number of patent applications per quarter that are categorized as clean, dirty, and gray. Lobbying is the average lobbying expenses per quarter. The last column reports the average market share of the firm over all quarters such that the column may not sum to one.

15 out of the 17 firms in our sample lobby, and lobbying expenditures are substantial.[27] The average expenditure is US$683,000 with a maximal expenditure of more than US$6,3 million.[28] Splitting lobbying expenditures according to targeted topics at the firm level, we observe that on average 13% of lobbying expenditures are directed toward environmental topics. The largest firms in terms of market shares are also the largest spender in lobbying, with General Motors spending around US$2.8 million by quarter and Ford spending on average US$1.8 million per quarter. Interestingly, the highest share of lobbying expenditures going to environmental topics are from BMW (32% of total expenditure) and Tesla (30% of total expenditures); in comparison, both General Motors and Ford allocate 18% of their lobbying to environmental issues.

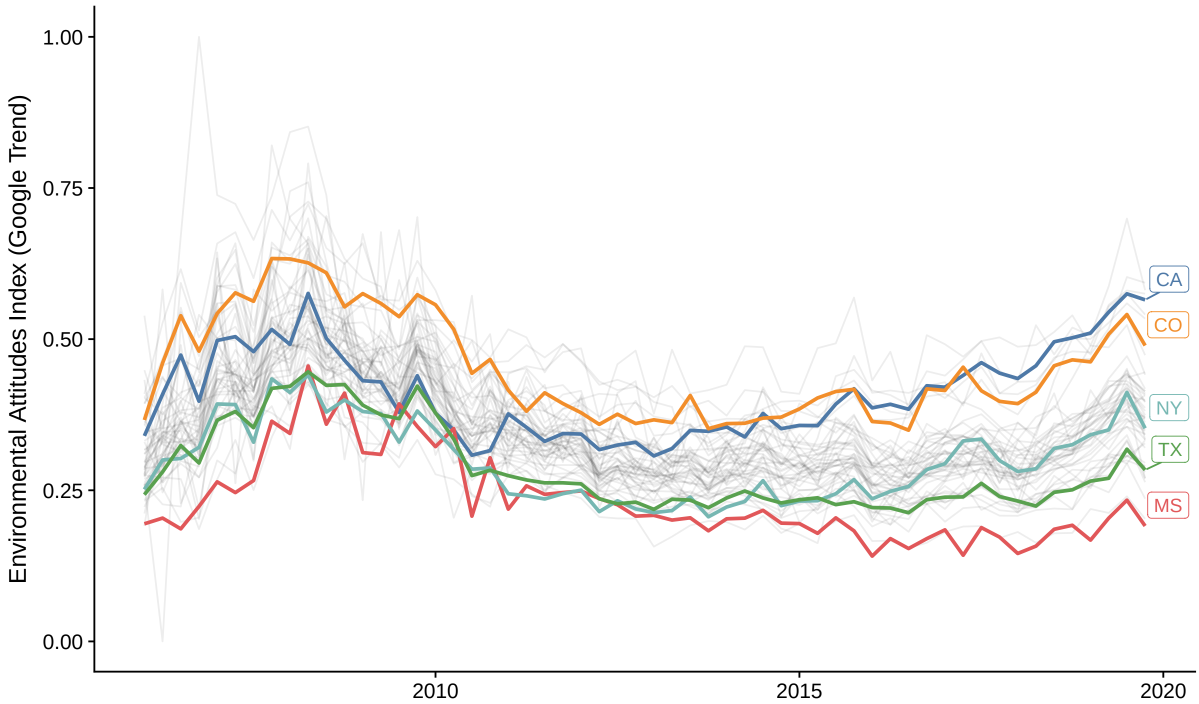
Variation in shock exposure. Figure 11 in the Appendix compares market shares across makes over the U.S. A more bluish (redish) color means that the area repre-

27. The two groups that do not lobby are Suzuki and Isuzu.

28. The order of magnitude surpasses by far campaign contributions or other political influence tools. We conjecture that adding other political influence tools would only increase the significance and magnitude of our results.

sents a more (less) important market for a given make than for other makes. There is important heterogeneity between companies: some are unexceptionably exposed to demand across the U.S. (Ford, Toyota, and Jeep, for instance), while others are particularly exposed to some regions. To Tesla, for instance, the West and Washington DC are of superior importance, New England and the West Coast are highly important to BMW, and General Motors is highly exposed to demand in the Midwest and the South. These variations in the importance of specific states for firms are at the heart of our empirical strategy. In the next step, we discuss the second crucial variation: changes in environmental attitudes across states and time.

FIGURE 1: Environmental Preferences Index



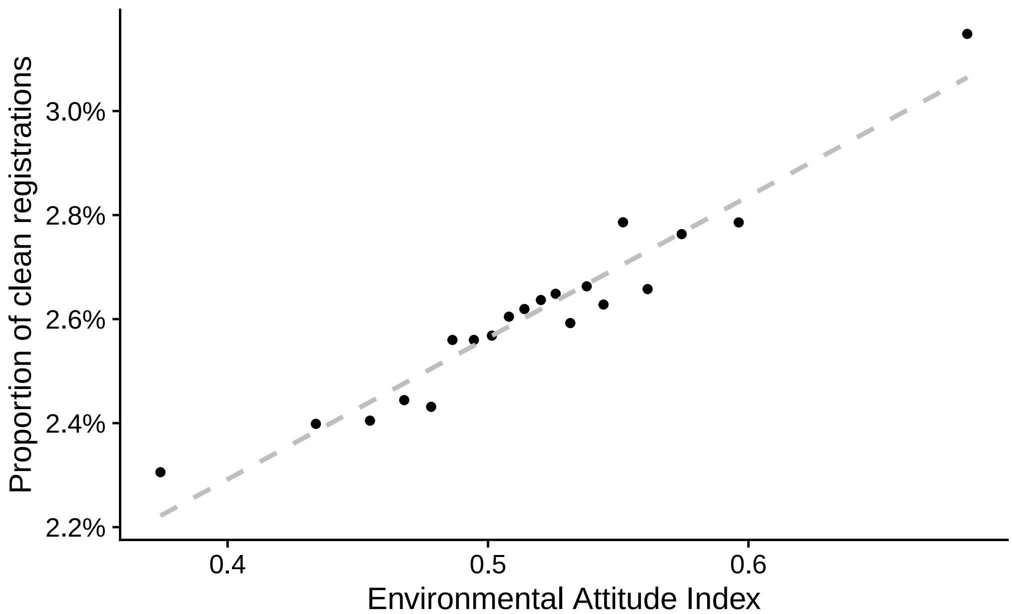
Notes: This figure shows our measure of environmental preferences built with Google Trends series at the state level discussed in section 2. The index is a composite of research popularity for terms related to popular keywords related to the environment. Those keywords are 'Climate Change', 'Recycling', and 'Electric Car'. Series are combined using the first component of a principal component analysis. The y-axis is normalized between 0 and 1 for aesthetic purposes.

Trends in environmental awareness and fires. Our standard index of environmental attitudes toward the environment is presented in Figure 1. It is characterized by a positive trend over the first years followed by a noticeable U-shape. While the decrease in environmental concerns is only somewhat discussed in the literature, our trends are congruent with the stark decline in environmental awareness presented in Aghion et al. 2021 and the trends of the Gallup survey. In our sample, we observe that the decrease started around 2008, one candidate explanation is then the drop in the salience of climate issues as a consequence of the financial crisis. Importantly for us, there is significant variation at the state level and over time.

Environmental interest and green demand A crucial assumption of our methodology is that environmental interest proxies green demand. Several results in the literature report that environmental interest induced by natural disasters affect individual behavior (Li, Johnson, and Zaval 2011; Spence et al. 2011). Furthermore, we focus on the automotive industry which produces heterogeneous goods in terms of emissions that are easily identifiable by consumers.

Figure 2 shows a binscatter at the state-level between our index of environmental interest and the share of electric vehicles in new vehicle registrations. The correlation is positive and significant suggesting our measure of environmental interest is an appropriate proxy for both green preferences and green demand.

Figure 2: Index of Environmental Interest and Electric Vehicles Sales at the State-Level



Notes: The figure plots the relationship between our index of green preferences and a proxy for green demand at the state-level. It shows the binned scatter plot correlation between our index of environmental interest (in x-axis) and the share of clean registrations (in y-axis). Each point accounts for 5% of the data. The data is a panel of US states between 2006 and 2019.

Exposure to wildfires. Because some confounders could affect consumer preferences and firm behavior, we instrument the index of environmental awareness by the exposure of populations to fires. Figure 12 pictures our index of wildfire exposure through time. The index is centered with respect to a yearly linear trend and state-quarter fixed effects, similar to our main regression. We observe a high heterogeneity both between states and across years.

3 Empirical Strategy

In this section, we introduce a quasi-experimental shift-share design to estimate the effects of changes in consumer environmental attitudes on firm behavior.

3.1 Research Design

To estimate the causal effect of environmental attitudes on lobbying and innovation, the ideal experiment would, all else equal, change random firms' consumer attitudes toward environmental issues. However, consumer preferences are an endogenous object. To approximate the ideal experiment, we employ a shift-share instrumental variable (IV) design. Therefore, we leverage two components: localized shocks to environmental concerns and pre-determined exposure shares to local markets. The analysis is run at the firm-quarter level.

Treatment. We seek to estimate the effect of a change in consumer preferences on a firm i. As discussed earlier, the index based on Google Trends ENV_{lt}^{GT}, serves as a proxy for household preferences. To derive a measure of firm exposure to consumer preferences, we weigh consumer preferences in state l with the share of firm i's sales in that state, i.e., a measure of the importance of a local market for a firm, s_{ilt}:

$$\Delta ENV_{it}^{GT} = \sum_{l}^{L} s_{ilt} \left(ENV_{lt}^{GT} - ENV_{lt-8}^{GT} \right). \tag{1}$$

Where $s_{ilt} = \frac{S_{ilt}}{S_{it}}$, $\sum_l s_{lit} \mathbb{1}[i = \iota, t = \tau] = 1$ is the share of sales of firm i in state l in total sales of firm i over the period $t - 8$ to t. Our shock is then defined as the exposure-weighted change in environmental interest over a period of 2 years (8 quarters).

Instrument. To capture a demand-led mechanism, we instrument the change in environmental preferences. As discussed in Section 2, exogenous shocks are obtained through the identification of wildfires in the US. Those shocks are aggregated at the state level l to match observed firm market shares. We measure the shocks as changes in state exposure to wildfires over a period of 8 quarters.

$$\Delta FIRE_{lt} = Fire\ Exposure_{lt} - Fire\ Exposure_{lt-8}. \tag{2}$$

The shift-share design combines this set of local shocks with variations in exposure to local markets. The exposure shares $s_{i,l,t-h}$ are computed as the share of sales in state l in total sales of firm i lagged by h quarters. Because contemporaneous shares are likely to be subject to reverse causality, we use lagged shares, measured 4 years earlier.[29] Finally, the shift-share instrument is built as the weighted average of changes in fire exposure:

$$Z_{it} = \sum_{l}^{L} s_{il,t-h} \Delta FIRE_{lt}. \tag{3}$$

Specification Outcomes, Δy_{it}, are measured as log change over two years. The endogenous variable is the change in the standardized environmental attitudes index, ΔENV_{it}^{GT}, which we instrument with the weighted change in wildfires, Z_{it}. In short, we estimate the following model by 2SLS:

$$\Delta y_{it} = \lambda_t + \alpha_i + \beta \Delta ENV_{it}^{GT} + \gamma X_{it} + \varepsilon_{it}. \tag{4}$$

Where $\Delta y_{i,t} = \log y_{i,t} - \log y_{i,t-8}$, λ_t is a time fixed effect, α_i is a firm fixed effect, and X_{it} indicates a set of controls. The coefficient of interest is β which captures the semi-elasticity of the outcome variable to a change in the index of green environmental preferences, conditional on a set of controls X_{it}.

3.2 Identification and Inference

The instrument used in this study is a combination of initial exposure shares and aggregate shocks. Previous studies on shift-share instruments have identified two possible sources of identification with this research design. The first source, as discussed by

29. Firms may strategically change their exposure to markets given the shocks, and shocks may affect a firm's market share. By using lagged exposure, we make sure to capture variation that comes only from the shocks.

Goldsmith-Pinkham, Sorkin, and Swift (2020), is the standard case where past exposure shares are thought to be exogenous. The second source, as discussed by Borusyak, Hull, and Jaravel (2022), is when exposures are non-random, but the instrumental variable identification assumption can be met through quasi-random assignment of shocks. In this paper, we argue that our study belongs to the latter category. This is natural in our setting because the shares are the equilibrium outcome of the firm's strategic decisions. However, the change in preferences triggered by wildfires can be considered as quasi-random.

In the context of a shift-share where shocks can be considered exogenous, Borusyak, Hull, and Jaravel (2022) demonstrate that the standard firm-level IV regression can be represented as an equivalent non-standard shock-level IV regression weighted by $s_{lt} = \frac{1}{N}\sum_i s_{ilt}$, the average exposure of firms to the state l. This transformation will prove particularly useful when we discuss the identification assumption and the inference in the next subsection. This state-level representation of Equation 4 is defined as:

$$\tilde{y}_{lt} = \beta \cdot \Delta E\tilde{N}V^{GT}_{lt} + \tilde{X}'_{lt}\gamma + \tilde{\varepsilon}_{lt} \tag{5}$$

where $\tilde{v}_{lt} = \frac{\sum_i s_{il,t-h} v_{it}}{\sum_i s_{il,t-h}}$ is the exposure-weighted average of variable v_{it}. This transformation has a few interesting properties: (i) The regression will recover the same coefficient $\hat{\beta}$ as the firm-level regression in Equation 4, because the shock-level regression is merely a change in the summation order. Moreover, the interpretation remains the same, that is, a firm-level estimated coefficient, (ii) this equivalent regression can be estimated with 2SLS, plugging directly the shocks $\Delta F\tilde{IRE}_{lt}$ as the instrument.

Finally, the shift-share IV estimated coefficient β is identified under the following assumptions:

Quasi-random shock assignment. This condition requires that $\mathbf{E}[\Delta FIRE_{lt}|\bar{\varepsilon}_{lt}, \tilde{X}_{lt}s_{t-h}] = \tilde{X}'_{lt} \cdot \mu$. This implies that shocks are quasi-randomly assigned conditional on shock-level unobservable $\bar{\varepsilon}$, average lagged exposure s_{t-h}, and shock-level observables $\tilde{X}_{lt}$. In our design, it means that shocks are randomly assigned, conditional on state-level characteristics and period fixed effects. Thus, a systematic relation between the occurrence of wildfires and state characteristics would not conflict with our identification strategy.

Many uncorrelated shocks. This condition states that shocks should not be concentrated in few observations and that average exposure converges to 0 as observations increase. The effective number of shocks leveraged by this research design can be estimated by the inverse of the Herfindhal index HHI of the weights $s_{l,t-h}$, where $s_{l,t-h} = \frac{1}{N}\sum_i s_{il,t-h}$. We report the related statistics in Table 11 in the Appendix. Our effective sample size is large (above 700) and our largest importance weight s_{lt} is below 1%.[30]

We next implement falsification tests of orthogonality following Borusyak, Hull, and Jaravel 2022, which provide a way of assessing the exogeneity of the shocks. We do this in two ways: first, we regress potential proxies for the unobserved residual at the state-level on the wildfires, second, we regress potential firm-level confounders directly on the shocks. The results are presented in Table 3. At the state-level we control for the exogeneity of the shocks with respect to vehicle registrations, registrations of electric vehicles and our different state-level controls. At the firm-level, we use lobbying activity and innovation measured by the log value of the knowledge stock of clean, dirty and gray technologies and the number of patents following Aghion et al. 2021. Broadly, this second set of variables reflect the political influence and innovation activity of firms. If the shocks are as-good-as-randomly assigned to firms within periods, we expect them to not predict these predetermined variables. Table 3 shows that there is indeed no statistically significant correlation within periods, consistent with the quasi-random assumption. The only exceptions are the state-level number of new electric vehicle charging stations and the share of young population, which we control for in our analysis.

Relevance Condition. The relevance condition states that the instrument has power, that is $\mathbf{E}[\Delta Y_{it} \cdot Z_{it} | X_{it}] \neq 0$. This can be checked by computing the first-stage F-statistic which we report in our tables of results. Figure 7 in the Appendix visualizes the first-stage revealing a strong positive correlation between exposure to wildfires and environmental attitudes. This finding is in line with the literature which establishes that natural disasters strongly affect local public opinion on climate change (Bergquist, Nilsson, and Schultz 2019). We present an overview of the literature on the relationship between natural disasters and environmental interest as well as some state-level evidence in Appendix D.

3.3 Treatment Correlation and Robust Standard Errors

Our wildfire shocks $\Delta FIRE_l$ generate dependencies in the instrument Z_i and residuals for automotive groups with similar exposures s_{il}. Consequently, the residuals are correlated across groups that share comparable exposures. As demonstrated by Adao,

30. This suggests that given the small number of units (17 groups) and treatment groups (50 states), the shocks are not too clustered and the frequency of observation is sufficient to reach consistency.

Table 3: Shock Balance Tests

Panel A: State-Level Balance

Balance variable	Coef.	SE
# Registrations	-0.004	(0.003)
# Clean registrations	-0.000	(0.001)
Share of republican votes	-0.007	(0.006)
Share pop. commuting by personal car	0.002	(0.004)
Share pop. commuting by public transportation	-0.001	(0.003)
Share pop. commuting by bicycle	0.004	(0.007)
Share pop. working remotely	-0.042	(0.042)
# New EV charging stations	0.026***	(0.003)
Share of active pop.	0.002	(0.003)
Share of young pop.	0.009*	(0.005)
Share of urban pop.	-0.001	(0.007)
Income per capita	0.003	(0.000)
# of state-period: 2000		

Panel B: Firm-Level Balance

Balance variable	Coef.	SE
Log total lobbying expenditures	0.315	(0.222)
Log environmental lobbying expenditures	-0.126	(0.182)
Log knowledge stock clean technologies	-0.147	(0.114)
Log knowledge stock dirty technologies	0.020	(0.049)
Log knowledge stock gray technologies	-0.077	(0.079)
Log (1+# clean patents)	-0.108	(0.154)
Log (1+# dirty patents)	-0.523	(0.427)
Log (1+# gray patents)	0.197	(0.206)
Log (1+# clean patents) - log (1+# dirty patents)	0.124	(0.221)
# of firm-period: 924		

Notes: Panel A summarize the distribution of the instrument (change in wildfire intensity exposure) across states. All statistics are weighted by the average state exposure share $s_{l,t}$. Panel B reports the *effective sample size* computed as the inverse of the Herfindahl index of the average state exposure share $s_{l,t}$. the second line reports exposures statistics in percent. Our largest average exposure share is less than 1 percent. Finally, we report the number of treatment groups, which are the 50 states (excluding DC).

Kolesár, and Morales (2019), this issue can result in over-rejection of the null hypothesis when conducting a standard SSIV regression, even when the researcher attempts to cluster the standard errors for observations with similar exposures. However, running the exposure-weighted shock-level IV regression of Equation 5 yields valid standard errors.[31] Moreover, this setting allows to further account for dependence of the errors by

31. Specifically, Borusyak, Hull, and Jaravel (2022) prove that their shock-level regression delivers the same standard errors as the procedure by Adao, Kolesár, and Morales (2019)

clustering standard errors at the shock level. In all our regressions, we run our estimations using this equivalent exposure-weighted shock-level transformation and cluster the standard errors at the level of the state.[32]

4 Results

This section details our main results and interpretation. In subsection 4.1 we discuss the point estimates. To study whether they are also complements at the firm level, we study firm heterogeneity in subsection 4.2. We then turn to the dynamics of clean innovation and lobbying in subsection 4.3.

4.1 Baseline results

Our main results are shown in Table 4. The first two panels report results for variables capturing lobbying expenditures as the dependent variable: lobbying expenditures on environmental topics, and total lobbying expenditures.[33] The following three panels use the change in the stock of clean, dirty, and gray patents in a firm, respectively measured as the knowledge stock detailed in Section 2. All outcomes are in two-year log difference and include year-quarter fixed effects, firm fixed effects, and the lagged market share at the firm level.

Table 4 separates into the OLS estimates, in columns 1 to 4, and our preferred IV estimates, in columns 5 to 8. We first turn to the OLS estimates. The first column applies a bare-bone specification that includes no covariates beyond the change in environmental awareness, the specific fixed effects, and the lagged market shares.

The OLS estimates of column 1 suggest a positive correlation between the change in consumers' environmental interest and the change in both environmental lobbying and clean patenting. Both dirty and gray patenting decline in response to greener consumer preferences. We find no significant effect on total lobbying expenditures. In column 2, we augment the long difference model with a set of demographic controls, such as population and income per capita, which test robustness and potentially elim-

32. In our analysis, we use both firm-level controls and state-level controls. This is possible by exploiting the Frisch-Waugh-Lovell theorem. The firm-level observations are first residualized on a set of firm-level controls before their state-level aggregation.

33. We focus on the intensive margin of lobbying. Lobbying activity has inherent fixed costs rendering it extremely persistent. We thus do not have enough heterogeneity in the extensive margin to measure the impact of environmental concerns on it. Details on how lobbying expenditures are aggregated between issues can be found in subsection E.2 in the appendix.

inate confounders. In the third column, we add controls for transportation habits (the share of the population commuting by personal car and state-level investments in transportation infrastructures). Finally, we control for the score for Republicans in the last presidential elections in column 4. These specifications further address the concern that firms might respond differently to different populations depending on their demographics and income level and the concern that the response of firms runs primarily through public policies and not demand. In all three specifications, the controls leave the results of similar magnitude and significance.

Table 4: Regression Estimates: Effect of Environmental Preferences on Firms Outcome

	OLS				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta_8 ln(lobby) Lobbying$ *(Environment Topics)*								
$\Delta_8 ENV^{GT}$	3.00***	2.85***	2.89***	2.90***	2.63***	3.06***	2.89***	2.87***
	(0.69)	(0.68)	(0.73)	(0.63)	(0.41)	(0.45)	(0.48)	(0.49)
$\Delta_8 ln(lobby)$ *(Total)*								
$\Delta_8 ENV^{GT}$	-0.03	-0.47	-0.64	-0.27	-1.01**	-0.42	-0.43	-0.46
	(0.72)	(0.67)	(0.67)	(0.66)	(0.47)	(0.50)	(0.50)	(0.50)
Δ_8 $ln(Clean\ Knowledge\ Capital)$								
$\Delta_8 ENV^{GT}$	3.31***	2.86***	2.66***	2.01**	1.59***	2.30***	2.51***	2.48***
	(1.01)	(0.72)	(0.70)	(0.93)	(0.46)	(0.48)	(0.44)	(0.43)
Δ_8 $ln(Dirty\ Knowledge\ Capital)$								
$\Delta_8 ENV^{GT}$	-7.44***	-7.18***	-7.15***	-6.20***	-10.11***	-10.57***	-10.12***	-10.12***
	(1.73)	(1.70)	(1.68)	(1.48)	(2.90)	(3.33)	(3.07)	(3.08)
Δ_8 $ln(Gray\ Knowledge\ Capital)$								
$\Delta_8 ENV^{GT}$	-2.07***	-1.82***	-1.74***	-1.76***	0.33	-0.07	0.11	0.13
	(0.33)	(0.32)	(0.31)	(0.37)	(0.70)	(0.76)	(0.71)	(0.70)
FE: year-quarter	X	X	X	X	X	X	X	X
FE: state-quarter	X	X	X	X	X	X	X	X
Firm Trend	X	X	X	X	X	X	X	X
Lagged Firm Controls	X	X	X	X	X	X	X	X
Lagged Demographic Controls		X	X	X		X	X	X
Lagged Transportation Controls			X	X			X	X
Lagged Political Controls				X				X
N (states - periods)	2000	2000	2000	2000	2000	2000	2000	2000
First-Stage F					97	107	116	116

Signif. codes: ***: 1%, **: 5%, *: 10%

Notes: Column (1) to (4) are OLS, (5) to (6) are Shift-Share IV. Standard errors clustered at the state level are in parentheses. All changes are in 2 years differences (8 quarters). ΔENV^{GT} represents the 8 quarters difference in the environmental awareness index that is constructed in section 2. In columns (5) to (8), it is instrumented by the change exposure to wildfire computed using satellite data from NASA's FIRMS dataset. Each line-column is the result of a different regression. Each line reports the result for a different outcome. First three rows are related to change in lobbying expenditures. Last three are net investment in innovation using patent valuation. The unit of analysis are US automotive groups. Outcomes are extensively described in the 2 section.

The following four columns repeat the same specifications instrumenting the change in the environmental interest by the change in wildfire exposure. The IV approach allows us to exclude confounding factors affecting both household preferences and firm decisions, for instance, rising supply of electric cars from competitors. Consider column 5. We observe a negative slightly significant impact of consumer awareness on total lobbying expenditures. However, lobbying on environmental topics increased as a consequence of environmental concerns. This suggests a reallocation of the lobbying activity within topics. Also, firms increase their clean patenting after a contemporaneous increase in green preferences. Dirty patenting decreases, and gray patenting does not react significantly to the change in preferences.[34] The results remain of similar magnitude after the inclusion of demographic, transportation, and political controls, with the exception of total lobbying expenditures where the estimate of the impact of environmental interest loses its significance (column 6 to 8).

The results are economically meaningful. A one standard deviation increase in environmental concerns implies a rise in environmental lobbying expenditures by a factor of 2.9, or alternatively of around US$270K. A one standard deviation increase in environmental awareness spurs green innovation on average by a factor of 2.5 and slows down dirty innovation by a factor of 10.1.

Taken together, we show that on average firms use both innovation and environmental lobbying to adjust to changing consumer preferences. On aggregate, thus, these two measures emerge as complements.

Two different interpretations could explain our results. The first interpretation is that firms leverage separately clean innovation and environmental lobbying as two different strategies to respond to rising green demand. For instance, we could hypothesize some heterogeneity in firms' response with some firms choosing one tool rather than the other. In the second interpretation, firms leverage clean innovation and environmental lobbying as two strategically related tools. A possible explanation is that firms lobby to obtain R&D subsidies for green technologies. Another explanation is that they lobby to obtain stricter environmental regulations (or environmental regulations tailored to their new technologies) once they have successfully innovated. To discriminate between these two interpretations, we turn in the next section to a heterogeneity analysis based at the firm initial level of dirtiness.

34. These results are in line with Aghion et al. 2021 who find that exposure to greener attitudes fosters clean innovation.

4.2 Heterogeneity between firms

To further interpret our results, we test the heterogeneity in the response depending on the greenness of the firm. The intuition is that we could report a positive effect on both environmental lobbying and clean innovation because some firms focus on the first and others on the latter.

Our hypothesis is that dirtier firms have an increased incentive to prevent stricter environmental regulations in response to a shift in demand toward clean products. First, those firms are affected more adversely by the shift in demand. Second, these firms need to innovate clean to catch-up with cleaner firms and eventually survive a green transition of the economy. Finally, dirtier firms are hit more by stricter environmental regulation. We therefore could report a positive effect both on clean innovation and environmental lobbying because the shock increases the revenues of greener firms enabling them to invest in more clean R&D and dirty firm, facing an adverse shock, lobby against stricter environmental regulations to protect their profits.

To test whether it is dirtier firms that lobby while clean firms focus on clean innovation, we run the following regression:

$$\begin{aligned} \Delta y_{it} = {} & \lambda_t + \alpha_i + \beta \Delta ENV_{it}^{GT} + \delta Dirty\_Ratio_{it-k} \\ & + \gamma \Delta ENV_{it}^{GT} \text{x} Dirty\_Ratio_{it-k} + \gamma X_{it} + \varepsilon_{it}. \end{aligned} \tag{6}$$

where $Dirty\_Ratio$ is the standardized share of revenues from dirty products in the total revenues of the firm.[35] With respect to the model of Equation 4, we additionally include this proxy for 'dirtiness' of the firm and a interaction term with the change in environmental preferences faced by the firm. Consistently with previous analysis, we instrument our interaction term by the interaction of the ratio of dirty sales over the total revenues of the firm, $Dirty\_Ratio$, and the weighted average of changes in fire exposure Z_{it}.

We follow Kwon, Lowry, and Verardo 2023 to define the dirtiness of a firm and base it at the firm's shares of revenues coming from dirty products. The rationale to use revenues shares from dirty products rather than the share of dirty technologies is that firms extracting revenues from polluting products might innovate green to pro-

35. We define clean products as electric and hybrid cars and dirty products as fuel cars, following our definition of clean/dirty technologies.

tect themselves against potential environmental regulation and to gain a first-mover advantage to deter competition. However, if firms' current cash flows derive more from brown-type operations, these firms could decide not to supply cleaner products. In this scenario, clean innovation would correspond to a long-term insurance rather than to a transition in production.[36]

TABLE 5: Heterogeneity Analysis by Initial Level of Share of Revenues from Dirty Sales

	(1)	(2)	(3)	(4)	(5)
	Env. Topics	Total Lobbying	Clean Innov.	Dirty Innov.	Grey Innov.
$\Delta_8 ENV^{GT}$	2.97***	-1.86+	2.70***	-7.27***	1.18
	(0.79)	(1.26)	(0.52)	(1.79)	(1.62)
$Dirty\_Ratio$	-0.07	1.91**	-0.29	-4.16***	-1.66**
	(0.34)	(0.87)	(0.54)	(1.06)	(0.64)
$\Delta_8 ENV^{GT} * Dirty\_Ratio$	87.92	-1013.62*	170.35	1950.60	674.56
	(450.09)	(563.08)	(272.91)	(1646.20)	(599.74)
FE: year-quarter	X	X	X	X	X
FE: state-quarter	X	X	X	X	X
Firm Trend	X	X	X	X	X
Lagged Firm Controls	X	X	X	X	X
Lagged Demographic Controls	X	X	X	X	X
Lagged Transportation Controls	X	X	X	X	X
Lagged Political Controls	X	X	X	X	X
N (states - periods)	2000	2000	2000	2000	2000

Signif. codes: ***: 1%, **: 5%, *: 10%
Notes: The table reports results of our regression on log change in our main outcomes, where we add the ratio of sales from dirty products at the beginning of the period and an interaction term between the ratio of sales from dirty products and the change in consumers' environmental awareness. Each coefficient corresponds to the IV estimates from our most conservative regression. Standard errors clustered at the state level are in parentheses. All changes are in 2 years differences (8 quarters). ΔENV^{GT} represent the 8 quarters difference in the environmental awareness index that is constructed in section 2. $Dirty\_Ratio$ corresponds to the the ratio of sales from dirty products at the beginning of the period.

Table 5 reports the estimated coefficients of a change in environmental interest on the lobbying and innovation activity of the firm. Every column corresponds to our most restrictive specification with controls and fixed effects.

Surprisingly, we find no significant difference between cleaner and dirtier firms. Both types of firms adjust their lobbying and innovation behavior in a similar manner. Yet, firms with a relatively high initial share of dirty sales tend to lobby more and innovate less in dirty and gray technologies. This could be explained by the overall reallocation of innovation towards cleaner technologies.

36. In our Appendix, we present a robustness exercise where we define the greenness of a firm as its share of dirty innovation on the technology mix of the firm.

The interaction between exposure to environmental interest and the ratio of dirty knowledge stock does not have a significant effect neither on the lobbying expenditures allocated to environmental issues nor on clean innovation (columns 1 and 3). This means that both cleaner and dirtier firms respond similarly to the shock.[37] The only mildly significant difference that we detect is that cleaner firms decrease their total lobbying expenditures less when facing greener demand.

Taken together, our results reject a heterogeneous effect of exposure to greener consumers' preferences based on the cleaness of production.[38] We therefore cannot conclude that previous behavior in terms of innovation and sales determines the response of firms, lending additional evidence to the complementarity between clean innovation and environmental lobbying. In contrast, recent empirical analysis of lobbying activity reports a negative relationship between innovation and lobbying (Akcigit, Baslandze, and Lotti 2020; Bombardini, Cutinelli-Rendina, and Trebbi 2021). The intuition comes from the influential analysis of Aghion et al. 2005 predicting that firms close to the technological frontier should innovate when facing high competitive pressures. When innovation over the frontier is too expensive, lobbying qualifies as a potential margin of adjustment. We conjecture that the difference in results with respect to previous literature derives from the focus on a demand shock: the demand shock leaves less room for firms not to produce green goods as demand for dirty goods declines.

To further shed light on the nature of the complementarity between clean innovation and environmental lobbying, we investigate firm responses over a longer time horizon in the next section.

4.3 Dynamics

We now focus on the shock coefficient for horizons greater than one. The local projection specification is equivalent to the unconditional model in Equation 4,

$$\Delta y_{i,t+h} = \lambda_t^h + \alpha_i^h + \beta^h \Delta ENV_{i,t}^{GT} + \gamma^h X_{i,t} + \epsilon_{i,t+h} \quad h = 0, ..., H. \tag{7}$$

37. Note that the data does not allow us to distinguish between pro-environmental and anti-environmental lobbying. We are then unable to state whether cleaner and dirtier firms lobby respectively for more or less stringent environmental regulation.

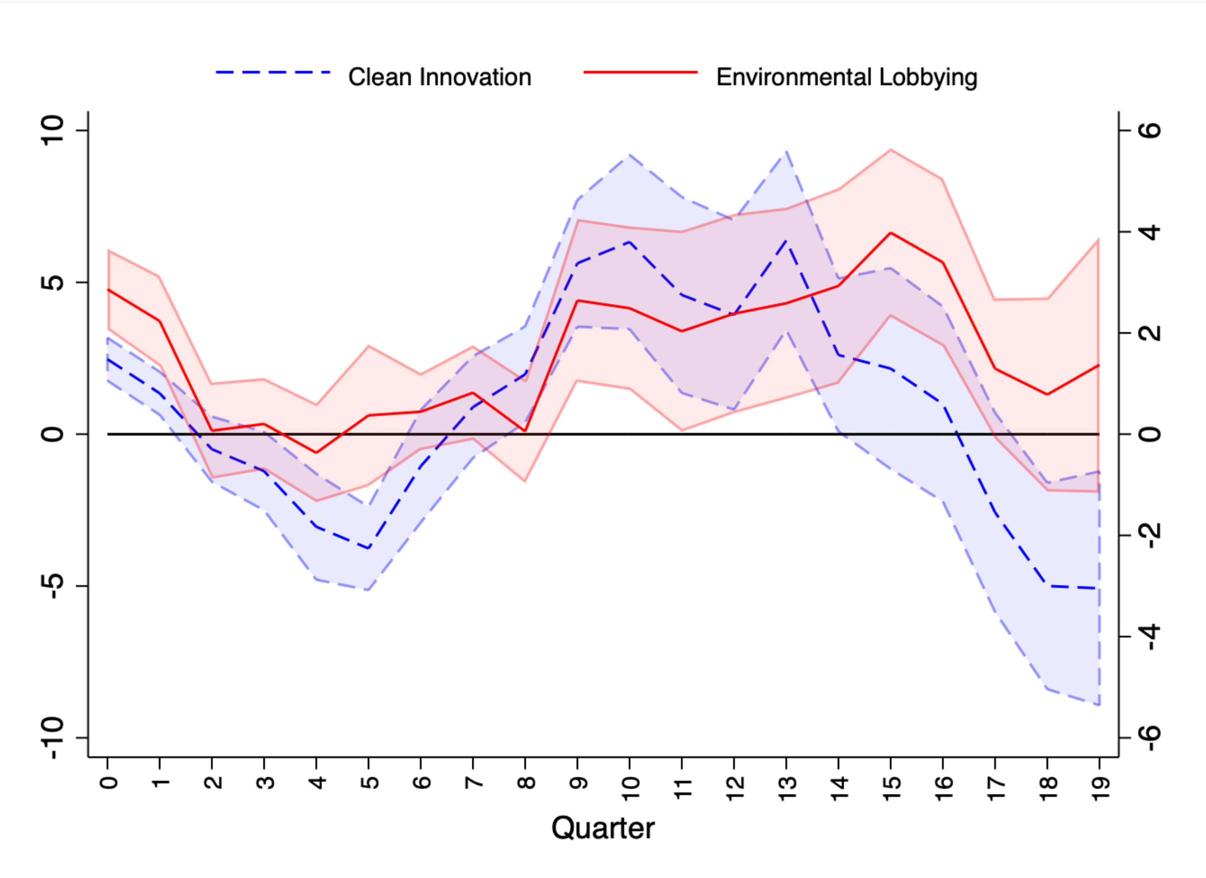
38. This result is robust to considering both the initial share of revenues coming from dirty products and the share of dirty innovation in the technology mix of the firms as proxies for dirtiness. See Table 13 in the appendix for the results using the share of dirty technologies in the technology mix of the firm as definition of dirtiness.

where $\Delta y_{i,t+h} = \log y_{i,t+h} - \log y_{i,t-8}$.

Figure 3 depicts the effects on environmental lobbying (in red) and clean innovation (in blue). We report results from our most conservative IV specification with all controls.[39]

The figure highlights that environmental lobbying and clean patenting evolve in tandem. Immediately after the shock, growth rates of clean patenting and environmental lobbying rise for around two quarters. This period is followed by a decline of new clean patents and environmental lobbying activity declines to its preshock value. Two years after the shock, we again observe an increase in both variables that lasts approximately two years.

FIGURE 3: Dynamic Effect of Environmental Preferences on Firms Outcome



Notes: This figure reports the impulse responses of environmental lobbying following an increase in environmental preference according to the specification $\Delta y_{i,t+k} = \lambda_t^h + \alpha_i^h + \beta_{i,t}^h \Delta ENV_{i,t}^{GT} + \gamma^h X_{i,t} + \epsilon_{i,t+h}$, for quarters h=0, ..., 20 after the shock. Shaded areas are 90% error bands, where standard errors are clustered at the state-level. Clean innovation is scaled according to the left axis and environmental lobbying is scaled on the right axis.

We hypothesize that the short-term increase in clean innovation is explained by firms speeding up the submission of clean patents they work on when the shock hits.

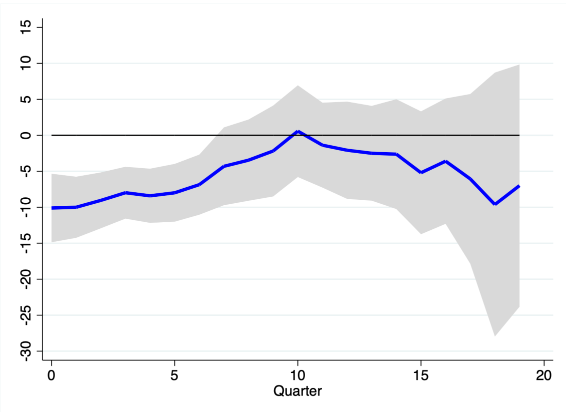
39. We present the dynamic results for all our main outcomes in Figure 17 in the Appendix.

This would allow them to profit from a first-mover advantage—in particular in a market for durable goods—and from a favorable time towards clean technologies. We interpret the interval between the short-term and the medium-term responses as the period where firms invest in clean R&D and develop new patents before submitting them.

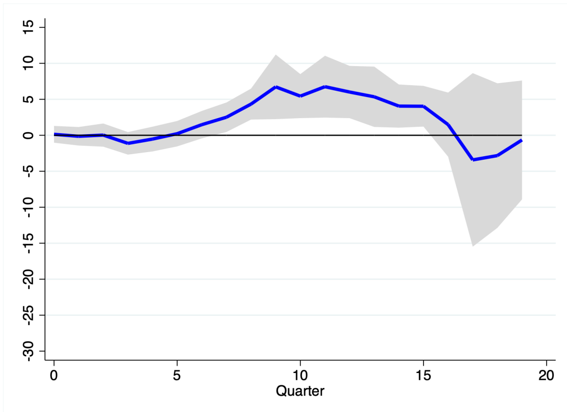
Note that the negative value of clean patenting in the figure means that new patenting is smaller than it would be without the demand shock. After a period of clean research, firms file new patents after roughly 2 years. This finding highlights the persistent effect of greener consumer preferences lasting for more than 3 years.

All in all, on average firms leverage clean innovation and environmental lobbying simultaneously.

The dynamic responses of dirty and gray patenting are consistent with this interpretation. In particular, Figure 4 reports that gray patenting responds similarly to clean innovation and environmental lobbying in the medium-term, but not in the short-term (right panel). Also, firms decrease their dirty innovation immediately after the shock, and the effect of the change in environmental awareness remains negative and significant for around two years (left panel).[40]



Dirty Innovation



Gray Innovation

Figure 4: Dynamic response of firm outcome to changes in environmental preferences

Notes: This figure reports the impulse responses of gray and dirty patenting following an increase in environmental preference according to the specification $\Delta y_{i,t+k} = \lambda_t^h + \alpha_i^h + \beta_{i,t}^h \Delta ENV_{i,t}^{GT} + \gamma^h X_{i,t} + \epsilon_{i,t+h}$, for quarters h=0, ..., 20 after the shock. Shaded areas are 90% error bands, where standard errors are clustered at the state-level.

The strong correlation of the responses of clean innovation and environmental lobbying to greener consumers' preferences points to a complementarity of the two strate-

40. Note that the decrease in the knowledge stock of clean and dirty technologies comes from the depreciation of existing knowledge stock and not from a negative measure of innovation.

gies. These results can be understood as firms using lobbying to increase the value of clean patents. When cleaner patents are realized, the firm enters a cleaner market.[41] Then, firms strategically engage in lobbying activities to shape environmental standards in a way that favors their clean technologies and shields the market from more competition. They can gain a competitive advantage by reducing the number of rival products or technologies in the market, ultimately increasing the value of their clean patents. Importantly, our result implies that a demand shift leaves less room for firms not to innovate than a supply shift.

4.4 Limitations

Results from our research design have some limitations. Our emphasis is on the automotive sector due to its production of goods with differing emission standards. Consumers ability to distinguish products based on their emission levels is crucial for our analysis. In many industries however, distinguishing cleaner products from dirtier ones can be more challenging (we can for instance think of the textile industry). Therefore, we perceive our estimates as representative for scenarios where there is more transparency on the environmental footprint of goods.

Second, the automotive industry is particularly concentrated with only 17 international groups. This reduced number of firms offers some particularities in terms of lobbying activity. We conjecture that firms lobby more for individual advantages than for industry advantages relatively to some more dispersed industries. The external validity of our analysis is threatened in less concentrated industries where firms gather in trade associations to lobby for industry-level advantages.

Finally, our estimates gauge the microeconomic responses of firms to changes in consumers' environmental preferences without considering the broader general equilibrium effects that arise when different firms are simultaneously affected. For instance, if different firms are treated simultaneously, each individual firm might have increased incentives to innovate clean in order to protect its market from treated competitors. Similarly, the lobbying activity of firms can be thought as a strategic game, where firms respond optimally to their competitors' strategies.

41. Another possible explanation is that firms lobby to obtain R&D subsidies for green technologies. In our additional analysis, we report that lobbying expenditures allocated to issues related to innovation decrease as a result of the shock. This suggests that R&D subsidies do not explain the rise in environmental lobbying.

5 Robustness Exercises

5.1 Alternative Measure of Demand

Our main analysis aims at estimating the effect of a change in green demand on lobbying and innovation outcomes. As demand is not measurable, we proxy it by environmental interest.[42] In this section and as a robustness exercise, we propose an alternative proxy of green demand based on observed vehicle registrations.

One naive approach would be to use direct sales of clean vehicles as a proxy for clean demand. This approach has a major drawback: some makes do not sell any electric vehicle, therefore the measured demand would be null, even if consumer were willing to buy electric vehicle from the manufacturer if they could. To solve this issue, we can estimate demand using all sales made within the same market segment. If we define a segment (hereby called a *cell*) as a tuple of location and vehicle type, then the change in clean demand in this cell is the change in the number of clean vehicles sold in this cell. Here is an example of what the change in demand for a cell in symmetric percent change looks like: [43]

$$\Delta N_{ct}^{clean} = \frac{N_{ct} - N_{ct-h}}{\frac{1}{2}(N_{ct} + N_{ct-h})}$$

With N_{ct} the number of clean vehicles sold in a cell c at time t.[44]

To compute the firm specific change in clean demand similarly to our main specification, we weigh the change in demand in cell c with the share of firm i's sales in that cell (that is, its exposure),

$$\Delta Demand_{it}^{clean} = \sum_{c \in C} s_{ict} \Delta N_{ct}^{clean}$$

We use this measure as a direct alternative to the one based on google trends, and we leverage the exact same instrument. The estimated coefficients are presented in Table 6 are both qualitatively and quantitatively unchanged. Focusing on our most restrictive specification in column (8), the coefficients are statistically indistinguishable from the coefficients estimated in our main regression in Table 4.

42. Because we merely observe the realized equilibrium of supply and demand, and not the demand curve of consumers

43. Using a symmetrical percentage change has the great advantage of limiting the risk of having a denominator = 0.

44. Examples of cells are (SUV, Ohio) or (Compact, Florida).

Table 6: Heterogeneity Analysis by Level of Economic Policy Uncertainty

	(1) $log(1+\#clean) - log(1+\#dirty)$	(2) $log(1+\#clean)$	(3) $log(1+\#dirty)$	(4) $log(1+\#gray)$
$\Delta_8 ENV^{GT}$	5.96***	6.42**	0.46	0.34
	(2.15)	(2.47)	(1.11)	(1.33)
$Dirty\_Ratio$	-0.17***	-0.04	0.13***	-0.16***
	(0.06)	(0.07)	(0.03)	(0.04)
$\Delta_8 ENV^{GT} * Dirty\_Ratio$	1317.35	1802.53*	485.18	192.70
	(815.76)	(901.16)	(323.91)	(5 53.79)
FE: year-quarter	X	X	X	X
FE: state-quarter	X	X	X	X
Firm Trend	X	X	X	X
Lagged Firm Controls	X	X	X	X
Lagged Demographic Controls	X	X	X	X
Lagged Transportation Controls	X	X	X	X
Lagged Political Controls	X	X	X	X
N (states - periods)	2000	2000	2000	2000
First-Stage F	5	5	5	5

Signif. codes: ***: 1%, **: 5%, *: 10%

Notes: The table reports the results of our regression on log change in our main outcomes. Each coefficient corresponds to the IV estimates from our most conservative regression. Standard errors clustered at the state level are in parentheses. All changes are in 2 years differences (8 quarters). ΔENV^{GT} represents the 8 quarters difference in the the registration of electric cars in the market segments of the firm that is constructed as specified in the text and is instrumented by exposure to wildfires as in the main specification.

5.2 Alternative Instruments

Table 7: Effect of Environmental Preferences of Firms Outcome

	Env. Topics	Env. Agencies	Total Lobbying	Clean Innovation	Dirty Innovation	Grey Innovation
$\Delta_8 ENV^{GT}$	1.01	3.18***	-3.56***	1.54**	-4.55**	-1.47*
	(1.42)	(0.81)	(1.15)	(0.69)	(2.08)	(0.77)
FE: year-quarter	X	X	X	X	X	X
Lagged Firm Controls	X	X	X	X	X	X
Lagged Demographic Controls	X	X	X	X	X	X
Lagged Transportation Controls	X	X	X	X	X	X
Lagged Political Controls	X	X	X	X	X	X
First-Stage F	24	24	24	24	24	24
N (states - periods)	2000	2000	2000	2000	2000	2000

Signif. codes: ***: 1%, **: 5%, *: 10%

Notes: The table reports results of our regression on log change in our main outcomes. Each coefficient corresponds to the IV estimates from our most conservative regression. Standard errors clustered at the state level are in parentheses. All changes are in 2 years differences (8 quarters). ΔENV^{GT} represent the 8 quarters difference in the environmental awareness index that is constructed in section 2 and is instrumented by different measure of extreme temperatures and extreme precipitations as described in the text.

Table 7 reports results using extreme temperatures and droughts as alternative instruments for environmental interest. In our baseline instrument, we considered every state to be affected by all the wildfires in the United States. We now assume that environmental interest is only affected by extreme temperatures that take place in the state of consideration. The main advantage of the former strategy was to allow consumers to be influenced by large and distant wildfires, for instance through media. On the contrary, the latter strategy ensures that households are directly affected by the meteorological event.

We use both extreme temperatures and precipitations as instruments. We construct the yearly distribution of temperature over the period 1960-2000 and count the number of days in our period of analysis above where the temperature is above the ninety fifth percentile or below the fifth percentile. We also include three variations of the Palmer Index for extreme precipitations that are the Palmer "Z" index, the Palmer hydrological drought index, and the Palmer drought severity index.[45] The first stage F-statistics of 24 suggests that, while these instruments have less power than wildfires, the relevance condition is met.

Our results are qualitatively very similar to the estimated coefficients of our benchmark regression reported in Table 4. In particular, we confirm that environmental interest spurs clean innovation and results in a decrease of dirty innovation. We report a negative effect on total lobbying expenditures, similarly to the one reported in the dynamic results presented in Figure 17.

In contrast to our baseline results, we find that the increase in environmental preferences involves a decrease in gray innovation which is significant at the 10 percent confidence level (column 6). The estimated impact of a change in environmental preferences on environmental lobbying is positive but non-significant (column 1). For further robustness, we additionally present the estimate on lobbying expenditures where we consider expenditures targeted at institutions treating environmental topics (column 2). We detect a positive effect of green preferences using this alternative definition of environmental lobbying.[46]

Our estimates remain economically meaningful, yet, the estimated coefficient on clean innovation falls from 2.5 to 1.5, the coefficient on dirty innovation decreases from -10.5 to -4.5, and , the estimated coefficient on environmental lobbying declines from 2.9

45. More details on the data can be found in subsection E.4 in the Appendix.

46. Subsection C.2 of the Appendix presents a robustness exercise where we use institutions rather than the topics to define environmental lobbying. The section also discusses the similarities and differences between the two definitions.

to 1. As the alternative instrument has less power than wildfires, we conjecture a bias towards 0 in this specification.

5.3 Alternative Keywords in Google Trends

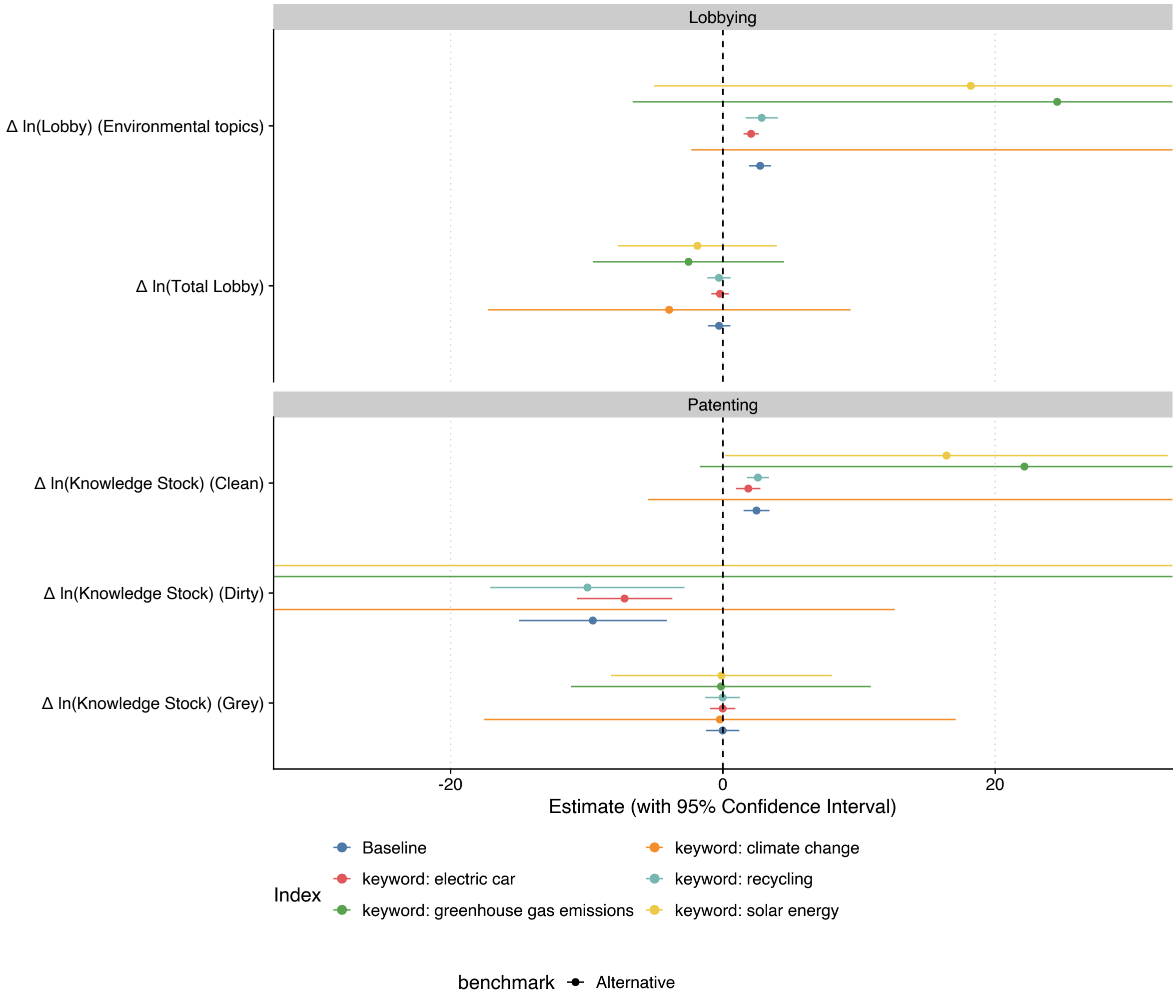


FIGURE 5: Shift share IV estimates: Robustness to alternative measurements of environmental interest

Notes: The figure summarizes estimates of shift-share IV regressions of environmental interest on lobbying and patenting behavior of firms with different hypothesis for the measurement of environmental interest. Each point is the result of a separate regression following the specification in section 3. The benchmark specification is presented in dark blue. Bars represent 95% confidence intervals using clustered standard errors. Index of environmental interest are constructed using Google Trends data. *"Benchmark"* is the index of environmental interest constructed using the first component of a PCA decomposition using the keywords "Climate Change", "Recycling", and "Electric Car". We additional present the estimates from specification where we use individually the keywords "Climate Change", "Electric Car", "Recycling", "Solar Energy", and "Greenhouse Gas Emissions".

Our measure of environmental interest is constructed using the first component of a PCA decomposition based the Google Trends keywords "Climate Change", "Recycling", and "Electric Car". An alternative approach is to consider each keyword individually as a proxy for environmental interest. We present results of these alternative proxies in Figure 5. The upper panel focuses on lobbying outcomes, and the lower panel presents the estimates on innovative activity. We additionally include the results using two alternative keywords that are "Greenhouse Gas Emissions" and "Solar Energy".

The results using both "Recycling" (in teal) and "Electric Car" (in red) as only keywords are remarkably similar to our baseline results for all lobbying and patenting outcomes, both qualitatively and quantitatively. The estimated coefficients based on the keywords "Climate Change" (in orange), "Greenhouse Gas Emissions" (in green), and "Solar Energy" (in yellow) are much larger and less precisely estimated.

Using these alternative definitions of environmental interest allows us to distinguish the effect of a specific interest impacting consumers' behavior from the effect of a more general and wide interest. In the first case, firms react to the change in preferences reallocating their innovation efforts towards clean technologies and through environmental lobbying. In the second case, the estimates are around ten times larger, but statistically not distinguishable from zero, suggesting a much larger heterogeneity in the response of firms.

In sum, Figure 5 strongly suggests that firms respond to specific changes in consumers' green preferences. Importantly, our results are not driven by the keyword "Electric Car".

6 Additional Analysis

We turn in this section to some additional results and robsutness exercises. Subsection 6.1 analyses the effect of the change in preferences on lobbying expenditures targeted at a variety of topics. We present a heterogeneity analysis based on economic policy uncertainty in subsection 6.2. Subsections 5.2 and 5.3 present robustness exercises with respectively an alternative instrument and measure of environmental interest.

6.1 Other Lobbying Topics

Our results suggest that while total lobbying expenditures do not increase at the firm level, there is a reallocation within issues towards environmental topics. In this section, we look at broader set of issues that firms lobby on.[47]

47. subsection C.2 provides an analysis of the institutions targeted by the lobbying activity as a robustness exercise.

Table 8 presents the results for the different groups of issues, where the dependent variables in the different panels are the lobbying expenditures targeted at environmental topics, taxation, trade, innovation, finance, manufacturing, labor, and public expenditures.

Apart from environmental topics, firms reallocate their lobbying expenditures towards taxation (panel 2), trade (panel 3), finance (panel 5), and manufacturing (panel 6). The reallocation effect is particularly pronounced for trade and manufacturing, The reported estimates are twice and sixty percent larger than for environmental topics and these two topics receive a significant share of total lobbying as they respectively represent 12% and 25% of total expenditures. In contrast, expenditures targeted at topics related to innovation (panel 4) and labor issues (panel 7) decline in response to a rise in green consumer preferences.

The decrease in innovation-related lobbying seems contradictory to the hypothesis that firms increase their environmental lobbying activity to obtain R&D subsidies for green technologies. We therefore conjecture that the rising environmental lobbying aims at obtaining stricter environmental regulations tailored to the new technologies of the firm.

The increase in lobbying on other topics shows that firms also resort to lobbying to protect their profits. We do not observe a large and significant decrease in the expenditures allocated to other specific topics, indicating that there is a high heterogeneity in the topics from which firms reallocate expenditures.

6.2 Policy Uncertainty

Our key result —firms rely on both clean innovation and environmental lobbying to respond to a rise in environmental interest of consumers—may depend on the uncertainty of new economic policy. The intuition is that we could report a positive effect on both environmental lobbying and clean innovation because firms leverage both clean innovation and environmental lobbying to respond as substitutes choosing the best strategy relatively to the policy climate.

The direction in which uncertainty should impact lobbying activity is unclear. Cooper and Boucher 2019 distinguish two different categories of political uncertainty : *policy objectives* and *issue-information* uncertainty. The first kind of uncertainty relates to political decision makers' intentions. The second type results from the lack of necessary infor-

Table 8: OLS and Shift Share IV of Firms Lobbying by Topic

	OLS				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta_8 ln(Lobby)$ $(Environment)$								
$\Delta_8 ENV^{GT}$	3.00***	2.85***	2.89***	2.90***	2.63***	3.06***	2.89***	2.87***
	(0.69)	(0.68)	(0.73)	(0.63)	(0.41)	(0.45)	(0.48)	(0.49)
$\Delta_8 ln(Lobby)$ $(Taxation)$								
$\Delta_8 ENV^{GT}$	2.06***	2.00***	1.44***	1.36***	1.25**	1.49***	1.89***	1.91***
	(0.47)	(0.42)	(0.26)	(0.23)	(0.48)	(0.50)	(0.46)	(0.45)
$\Delta_8 ln(Lobby)$ $(Trade)$								
$\Delta_8 ENV^{GT}$	2.12***	2.27***	2.32***	1.92***	6.04***	5.76***	5.56***	5.57***
	(0.39)	(0.43)	(0.46)	(0.50)	(0.92)	(0.90)	(0.92)	(0.91)
$\Delta_8 ln(Lobby)$ $(Innovation)$								
$\Delta_8 ENV^{GT}$	-0.49***	-0.50***	-0.52***	-0.41***	-0.33*	-0.31*	-0.37**	-0.37**
	(0.11)	(0.11)	(0.11)	(0.10)	(0.16)	(0.16)	(0.17)	(0.17)
$\Delta_8 ln(Lobby)$ $(Finance)$								
$\Delta_8 ENV^{GT}$	0.16***	0.19***	0.21***	0.18**	0.84**	0.79**	0.81**	0.82**
	(0.05)	(0.06)	(0.06)	(0.08)	(0.34)	(0.34)	(0.34)	(0.34)
$\Delta_8 ln(Lobby)$ $(Manufacturing)$								
$\Delta_8 ENV^{GT}$	0.96***	0.95***	0.90***	0.76***	5.14***	4.96***	4.59***	4.59***
	(0.12)	(0.11)	(0.15)	(0.11)	(0.45)	(0.43)	(0.41)	(0.41)
$\Delta_8 ln(Lobby)$ $(Labor)$								
$\Delta_8 ENV^{GT}$	-0.98***	-1.03***	-0.99***	-0.79***	-0.40**	-0.31	-0.44**	-0.43*
	(0.27)	(0.28)	(0.28)	(0.26)	(0.19)	(0.21)	(0.22)	(0.22)
$\Delta_8 ln(Lobby)$ $(Public\ Expenses)$								
$\Delta_8 ENV^{GT}$	-0.25***	-0.26***	-0.27***	-0.23***	-0.14	-0.16	-0.22	-0.22
	(0.07)	(0.08)	(0.09)	(0.05)	(0.19)	(0.20)	(0.16)	(0.16)
FE: year-quarter	X	X	X	X	X	X	X	X
FE: state-quarter	X	X	X	X	X	X	X	X
Firm Trend	X	X	X	X	X	X	X	X
Lagged Firm Controls	X	X	X	X	X	X	X	X
Lagged Demographic Controls		X	X	X		X	X	X
Lagged Transportation Controls			X	X			X	X
Lagged Political Controls				X				X
N (states - periods)	2000	2000	2000	2000	2000	2000	2000	2000
First-Stage F					97	107	116	116

Signif. codes: ***: 1%, **: 5%, *: 10%

Notes: The table reports results of our regression on log change in lobbying expenses categorized by topic. Column (1) to (4) are OLS, (5) to (6) are Shift-Share IV. Standard errors clustered at the state level are in parentheses. all changes are in 2 years differences (8 quarters). ΔENV^{GT} represent the 8 quarters difference in the environmental awareness index that is constructed in section 2. In columns (5) to (8), it is instrumented by the change exposure to wildfire computed using satellite data from NASA's FIRMS dataset. Each line-column is the result of a different regression. Each line report the result for a different outcome. First three rows are related to change in lobbying expenditures. Last three are net investment in innovation using patent valuation. The unit of analysis are US automotive groups. Outcomes are extensively described in the 2 section.

mation available to policymakers to make an informed decision. Here we focus on economic policy objectives uncertainty. The theoretical framework developed by Cooper and Boucher 2019 predicts that a sudden increase in policy objective uncertainty decreases lobbying activity. The intuition is that policy uncertainty raises uncertainty on the results of lobbying. Building on this insight, we conjecture that firms might respond to rising green preferences by innovating in clean technologies when policy uncertainty is high, and lobbying to protect their revenues when policy uncertainty is low.

We use the economic policy uncertainty index developed by Baker, Bloom, and Davis 2016 which is based on three components: (i) a newspaper-based component capturing the presence of news articles discussing economic policy uncertainty, (ii) an annual dollar-weighted number of tax code provisions scheduled to expire over the next 10 years, and (iii) the dispersion between individual forecasters' predictions about economic indices.[48] We include both the level of policy uncertainty and an interaction with the change in environmental interest.

Table 9: Heterogeneity Analysis by Level of Economic Policy Uncertainty

	(1) Env. Topics	(2) Total Lobbying	(3) Clean Innov.	(4) Dirty Innov.	(5) Grey Innov.
$\Delta_8 ENV^{GT}$	2.27***	-0.76	-1.32	-5.22 **	1.16
	(0.65)	(1.86)	(1.92)	(2.50)	(0.89)
$Policy\_Uncertainty$	0.01	0.01	-0.02***	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.03)	(0.01)
$\Delta_8 ENV^{GT} * Policy\_Uncertainty$	-1.49	-4.28***	-4.24**	6.70	1.86
	(1.25)	(1.60)	(1.82)	(4.75)	(1.46)
FE: year-quarter	X	X	X	X	X
FE: state-quarter	X	X	X	X	X
Firm Trend	X	X	X	X	X
Lagged Firm Controls	X	X	X	X	X
Lagged Demographic Controls	X	X	X	X	X
Lagged Transportation Controls	X	X	X	X	X
Lagged Political Controls	X	X	X	X	X
N (states - periods)	2000	2000	2000	2000	2000

Signif. codes: ***: 1%, **: 5%, *: 10%

Notes: The table reports the results of our regression on log change in our main outcomes, where we add the level of policy uncertainty at the beginning of the period and an interaction term between the level of policy uncertainty and the change in consumers' environmental awareness. Each coefficient corresponds to the IV estimates from our most conservative regression. Standard errors clustered at the state level are in parentheses. All changes are in 2 years differences (8 quarters). ΔENV^{GT} represent the 8 quarters difference in the environmental awareness index that is constructed in section 2. $Policy\_Uncertainty$ represents the index of economic policy uncertainty by Baker, Bloom, and Davis 2016.

Table 9 reports the estimated effect of a change in environmental interest conditional on the initial level of policy uncertainty. Every column corresponds to our IV specification including the different fixed effects and state-level controls. We find that the

48. More information can be found at https://www.policyuncertainty.com/methodology.html.

level of policy uncertainty does not impact lobbying activity but results in lower clean innovation (columns 1 to 3). The coefficient on the interaction term between changes in environmental interest and policy uncertainty is negative and significant for clean innovation (column 3) and negative and non-significant for environmental lobbying (column 1). This suggests that the higher policy uncertainty is, the less firms respond to responsible demand by innovating, but that they do not increase their environmental lobbying as an alternative strategy. Furthermore, we find a strong and negative effect of the interaction term on total lobbying expenditures (column 2) in line with Cooper and Boucher 2019.

We conclude that firms do not decide whether to leverage clean innovation or lobbying to respond to the shock depending on the different policy regimes but rather that policy uncertainty mitigates the response of firms.

7 Conclusion

Climate change and environmental pollution raise household solicitude about the environment. As a result, demand may shift to greener goods. How do firms react to an increase in green preferences? The literature points to the innovation of cleaner technologies as a response (Aghion et al. 2021). We show that there exists another margin of adjustment: environmental lobbying.

More precisely, we examine firm responses in the automotive industry to exogenous changes in household concerns about the environment in the U.S. from 2006 to 2019. To this end, we compile a novel dataset set combining information on natural disasters, a measure of household interest in the environment based on Google Trends, and firm information. Our findings suggest that automotive firms not only innovate cleaner technologies but also increase their lobbying on environmental topics. We provide evidence that firms use clean patenting and environmental lobbying as complements. Not only in the short run but also over a longer horizon of approximately 14 quarters, clean patenting is accompanied by a rise in environmental lobbying expenditure of the average firm. We rule out that it is firm heterogeneity in the cleanness of production that drives the average behavior, that is, some firms lobby and others engage in clean innovation.

We close by briefly discussing routes for future research. Our estimates measure microeconomic responses not taking into account general equilibrium effects originating from all firms being affected simultaneously. Spillover effects are not included in our estimates. or instance, when two firms are treated simultaneously, we would expect a stronger effect on clean innovation due to strategic considerations to secure market shares. To infer firm responses in a general equilibrium setting, we plan to embed our micro-estimates into a macroeconomic model.

Natural disasters are only one mechanism through which consumer preferences may change. Most likely, they are themselves formed by firm behavior through advertisement, the type of products offered, or firms actively engaging in shaping the social perception of their goods (we can think of the massive investments from the tobacco industry to improve its image). However, the literature studying this relation is scarce. Given that our paper finds an economically relevant effect of environmental preferences, we would like to further investigate the role of firms in shaping these.

One may interpret our results as attesting a double dividend to green demand. On the one hand, greener demand increases the use of clean technologies. On the other hand, this increase is accompanied with firms' pushing for stricter environmental regulation. However, to assess the overall effect, one would need to take into consideration that the resources used to lobby are no longer available for R&D investment. Furthermore, a lack of competition in markets due to regulation may curb innovative activity (Aghion et al. 2021). A macroeconomic model would allow us to investigate the overall effects of a change in green demand on aggregate emissions.

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Appendix

A Additional Summary Statistics

Table 10: Firm lobbying expenditures by target

	Mean	SD	P25	P50	P75	Max
Total Lobbying	683.92	842.94	38.01	380.00	1040.01	6380.00
Topics						
– Environment	90.04	158.66	0.00	17.61	101.37	1236.50
– Tax	85.01	113.90	0.00	22.25	138.85	509.29
– Trade	79.51	101.02	0.00	46.58	131.70	528.67
– Innovation	43.33	84.18	0.00	0.00	65.11	612.00
– Finance	45.23	84.69	0.00	0.00	63.86	612.00
– Manufacturing	171.39	168.54	17.36	131.17	279.95	1013.00
– Labor	63.27	135.75	0.00	0.00	37.50	938.00
– Public Expenditures	35.09	69.10	0.00	0.00	33.67	612.00
Institutions						
– Environmental Institutions	33.72	77.89	0.00	0.00	26.62	962.93
– Political Group	555.15	729.38	30.00	261.67	742.51	5224.97
– Senate	253.25	298.55	13.33	136.60	405.14	1725.81
– White House	16.55	41.62	0.00	0.00	5.00	514.61
– House of Representatives	255.33	299.22	13.12	144.93	415.75	1725.81
– Dpt. of Commerce	11.23	23.23	0.00	0.00	10.02	140.91
– Dpt. of Energy	16.33	42.43	0.00	0.00	6.17	531.61
- Agencies	123.03	217.59	0.00	24.44	145.63	1374.44
– EPA	18.61	35.95	0.00	0.00	27.20	431.31
– NHTSA	14.36	30.72	0.00	0.00	10.00	205.86
– USTR	12.38	25.23	0.00	0.00	17.05	347.98

Notes: The table summarizes the distribution of quarterly lobbying expenses for a list of target in thousand of dollars. The first row reports the total lobbying. On average, groups spend 684k$ on lobbying each quarter.

Table 11: Shocks and Shares Summary Statistics

Panel A: Shocks Summary Statistics

	Mean	Std. dev.	p5	p95
$\Delta FIRE_{lt}$	-0.04	0.01	-0.02	0.03
$\Delta FIRE_{lt}$ (w. period FE)	0.00	0.01	-0.01	0.01

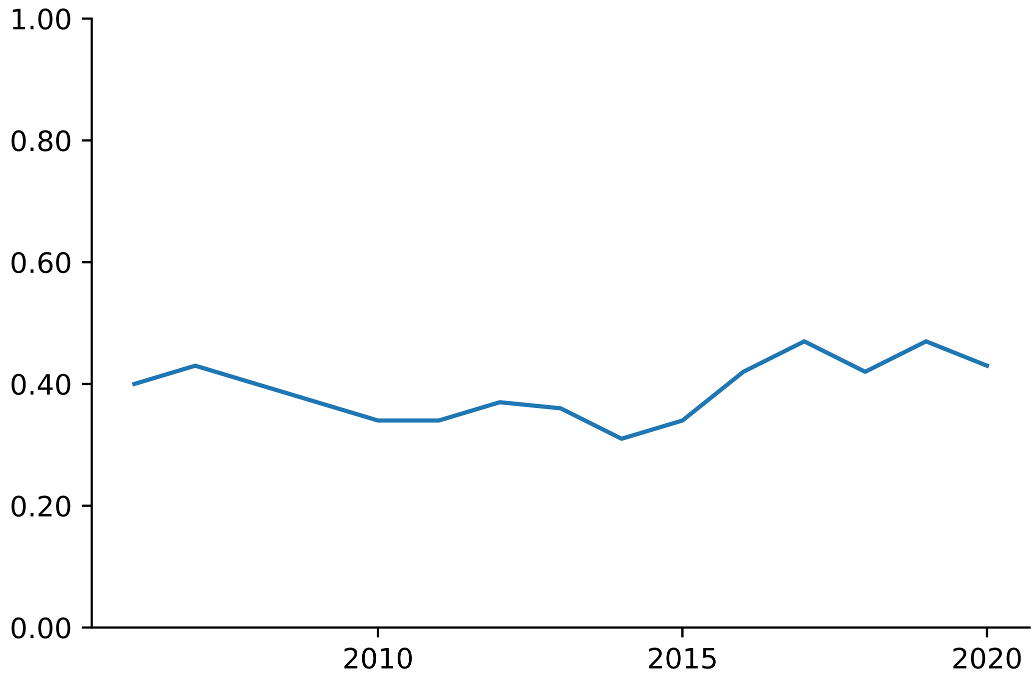
Panel B: Shares Summary Statistics

	Mean	Max
$1/HHI$	719.56	719.56
s_{lt} (pct)	0.05	0.44
Treatment Groups	50.00	50.00

Notes: Panel A summarizes the distribution of the instrument (change in wildfire intensity exposure) across states. All statistics are weighted by the average state exposure share $s_{l,t}$. Panel B reports the *effective sample size* computed as the inverse of the Herfindahl index of the average state exposure share $s_{l,t}$. the second line reports exposures statistics in percent. Our largest average exposure share is less than 1 percent. Finally, we report the number of treatment groups, which are the 50 states (excluding DC).

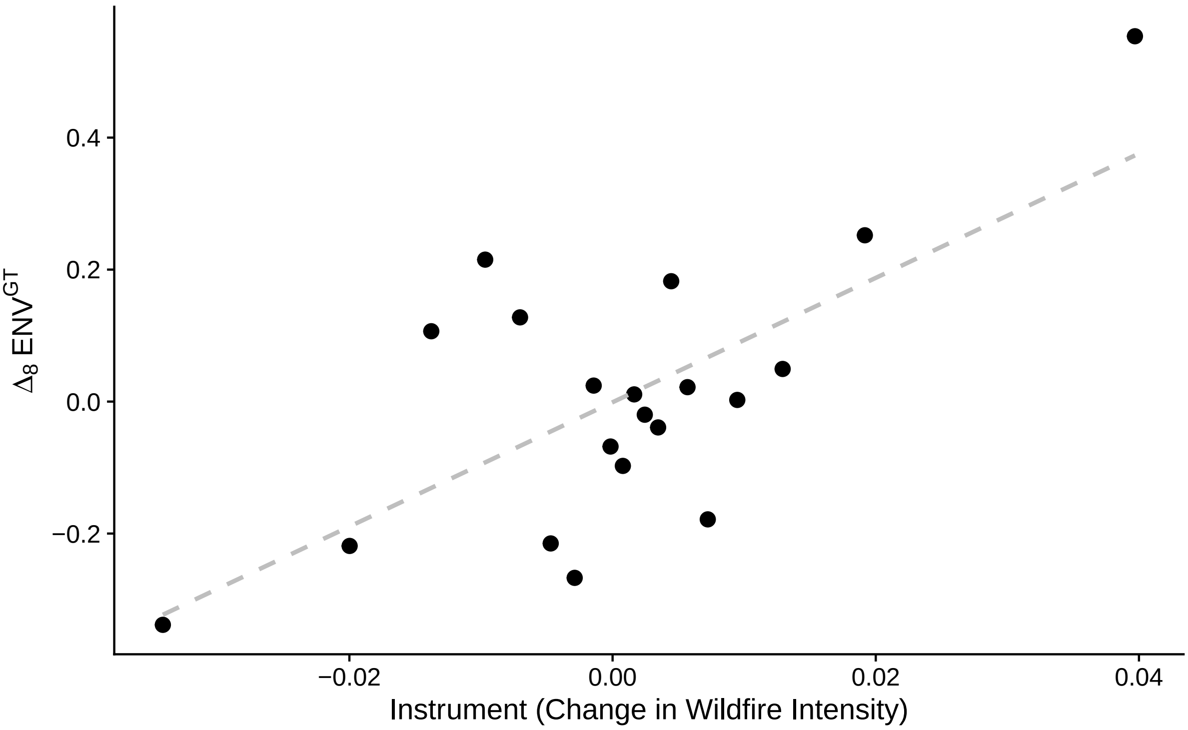
B Additional Figures

Figure 6: Gallup Survey Data: Solicitude about the environment



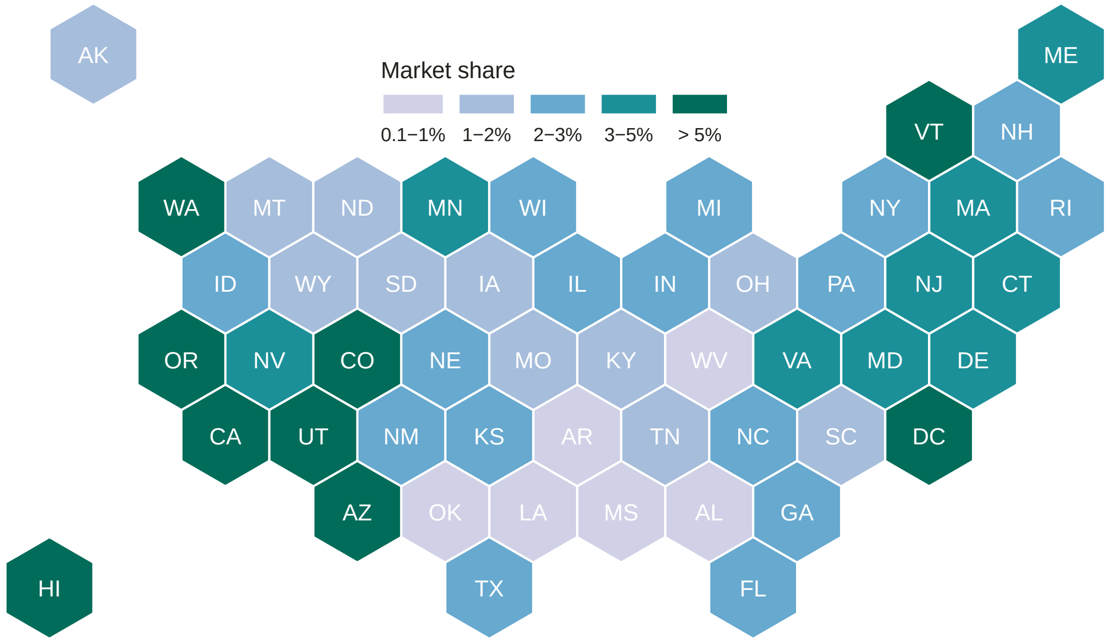
Notes: This figure shows the share of surveyed people responding that they are worried a "great deal" about the quality of the environment. Data comes from the Gallup annual survey for the US (https://news.gallup.com/poll/391547/seven-year-stretch-elevated-environmental-concern.aspx). The precise question asked reads: "For each one, please tell me if you personally worry about this problem a great deal, a fair amount, only a little, or not at all? First, how much do you personally worry about. The quality of the environment" The graph shows the share of participants that worry "a great deal".

Figure 7: First-stage estimation, shift-share IV



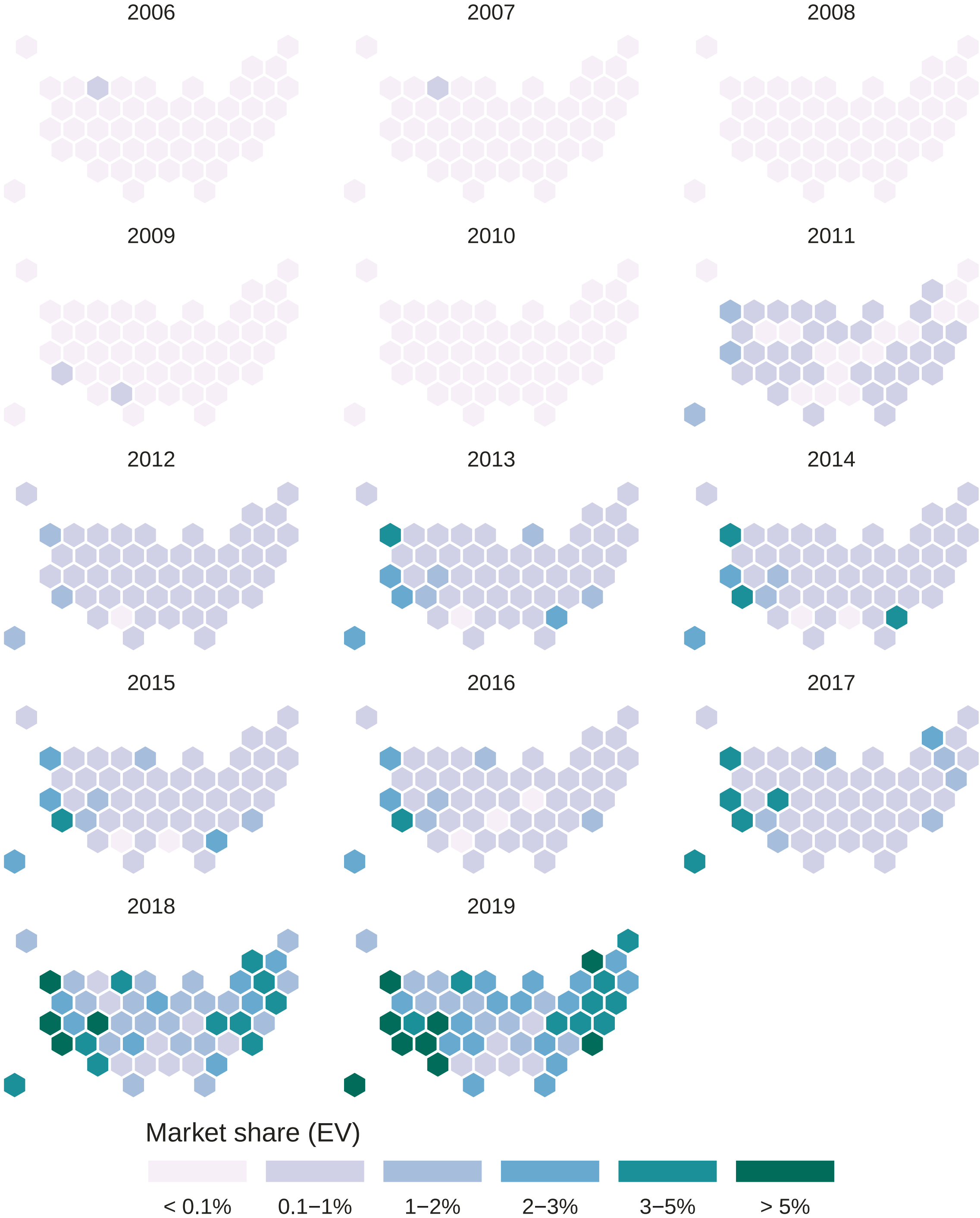
Notes: The figure plots the reduced-form relationship underlying our shift-share IV design. It plots the correlation between our instrument (in x-axis) and change in the environmental preferences index (in y-axis). Each point accounts for 5% of the data. The data is first residualized on a set of firm controls and period fixed-effects. Observation are weighted by the average treatment group exposure share s_{lt}.

Figure 8: Market Share of Electric Vehicles in 2019



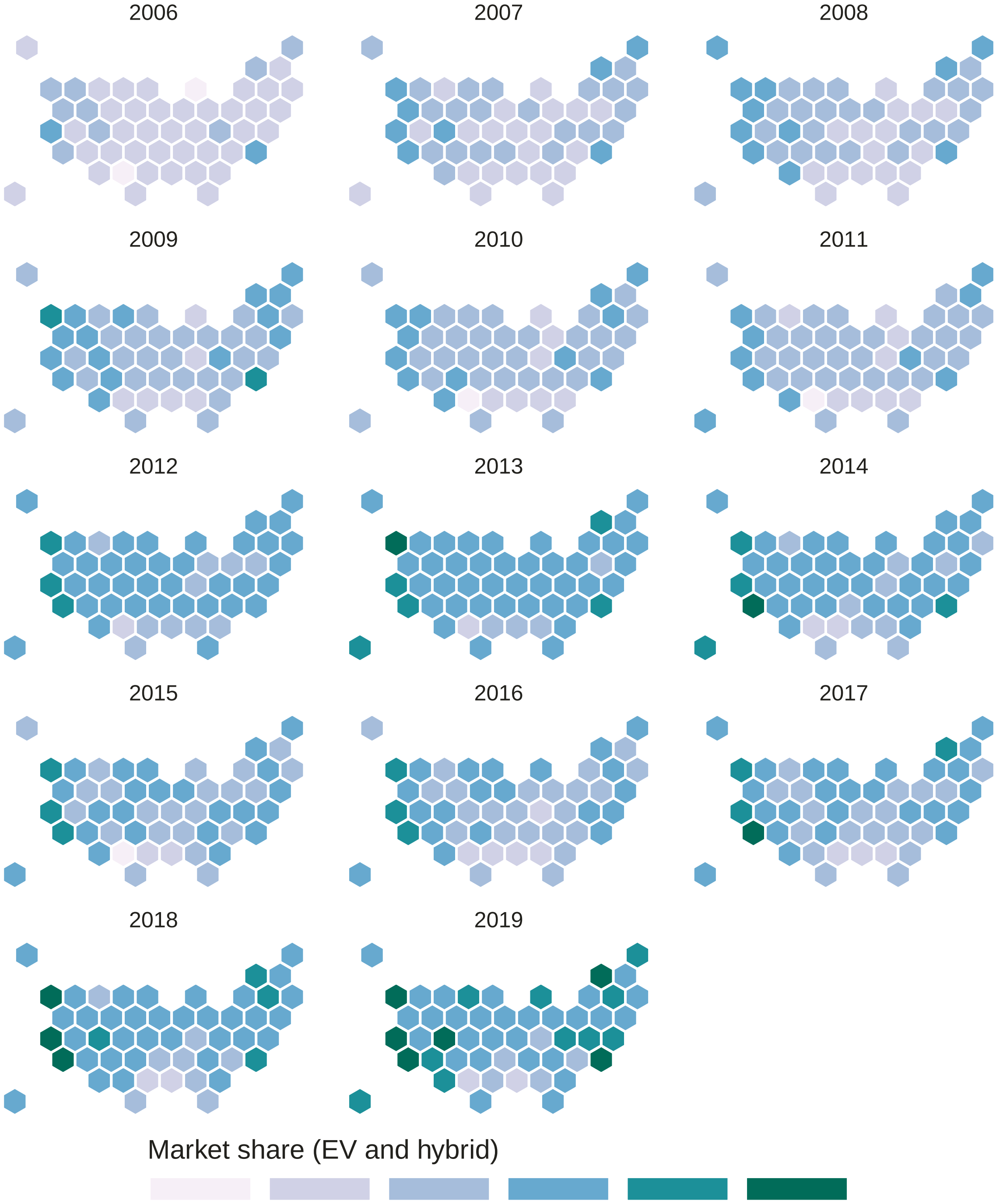
Notes: The figure shows the market share of electric vehicles in each U.S. states for vehicle registrations in 2019. The market shares are computed as the fraction of clean passenger cars registered over total passenger cars registrations in the state.
Source: S&P Global, authors' calculation.

Figure 9: Market Share of Electric Vehicles



Notes: The figures show the market shares of electric vehicles in each U.S. states between 2006 and 2019. The market shares are computed as the fraction of clean cars registered over total passenger cars registrations in the state.
Source: S&P Global, authors' calculation.

FIGURE 10: Market Share of Low Emission Vehicles

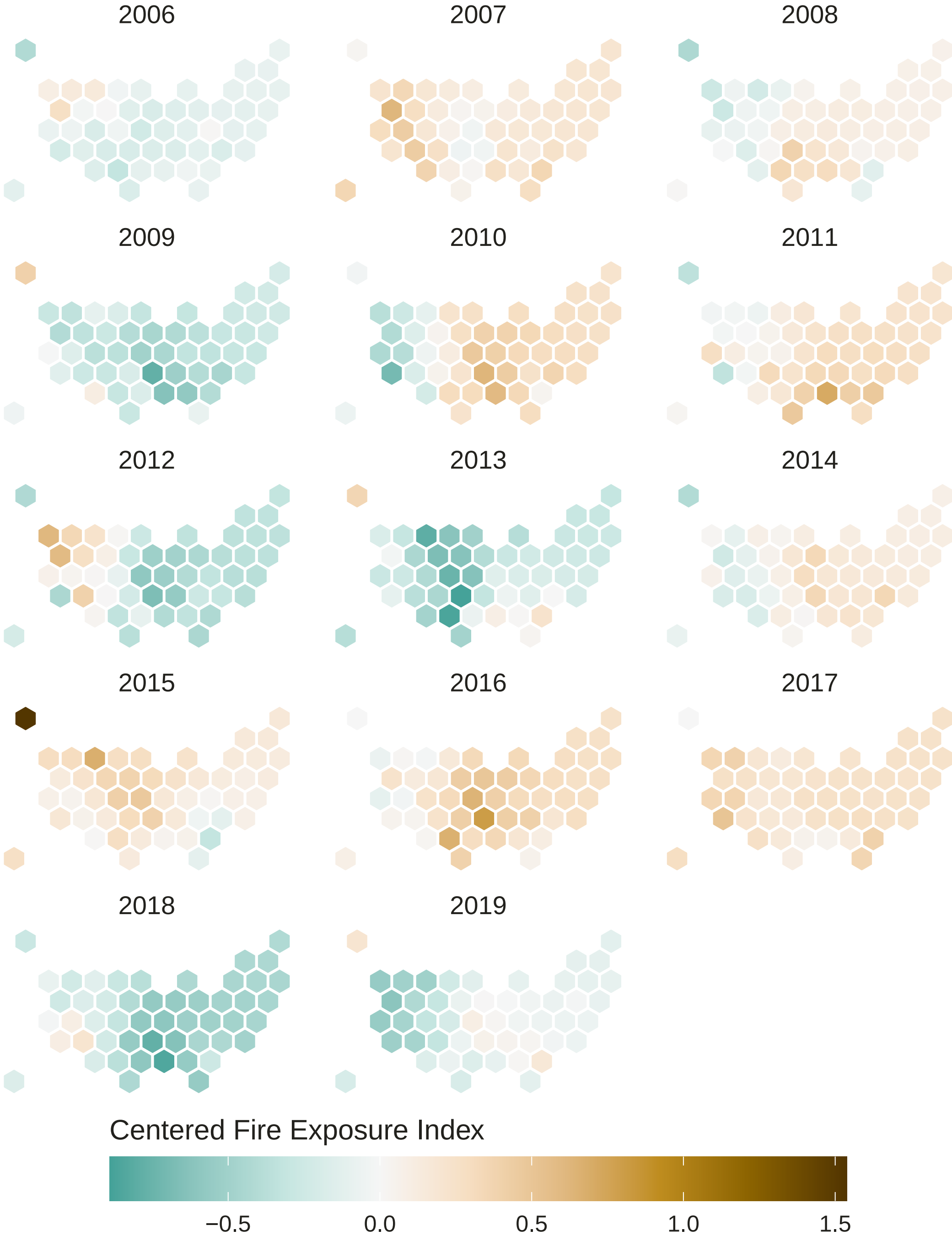


Notes: The figures show the market shares of low emissions vehicles in each U.S. states between 2006 and 2019. The market shares are computed as the fraction of clean cars registered over total passenger cars registrations in the state.
Source: S&P Global, authors' calculation.

Figure 11: Relative Market Shares (log Odds-Ratio)

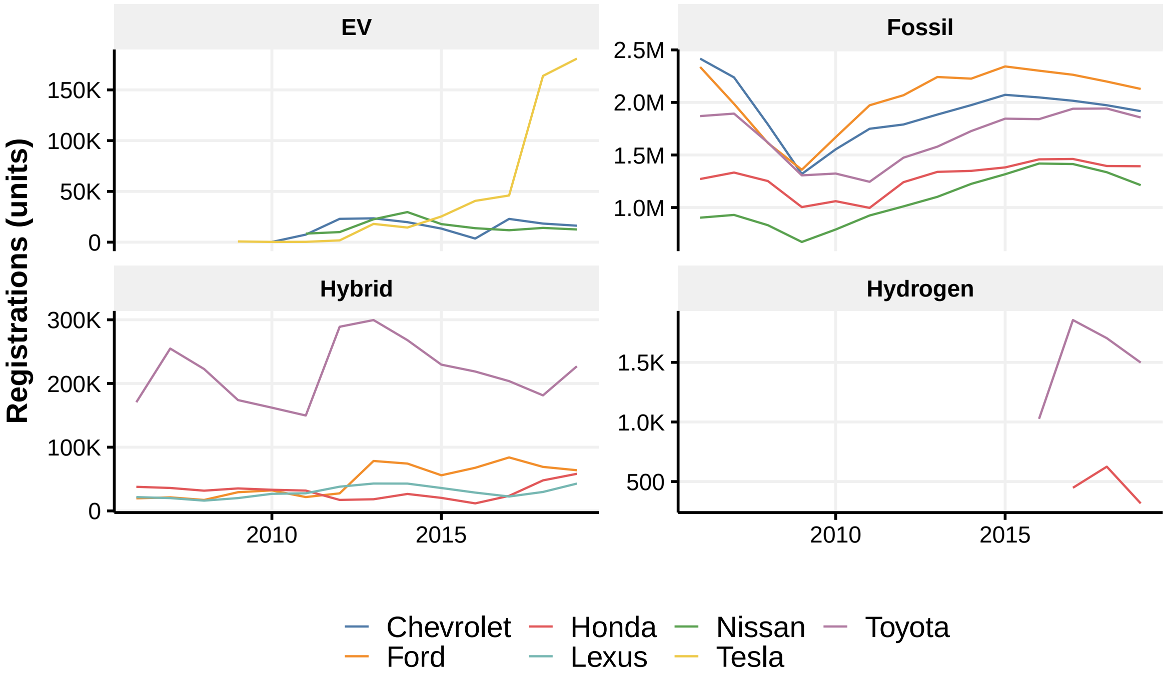
Notes: The figures show the relative market share of each make, compared to the other makes. We define $p_{il} = P(l|i)$ the proportion of vehicles registered in state l for a make i, and $p_{0l} = P(l|\neg i)$ the proportion of vehicles not made by i registered in state l. Then the log odds-ratio is $r_{li} = log\left(\frac{p_{il}/(1-p_{il})}{p_{0l}/(1-p_{0l})}\right)$. The ratio is positive if a make is over-represented in a state l and negative if it is under-represented in the state.
Source: S&P Global, authors' calculation

Figure 12: Centered Fire Exposure Index (yearly average)



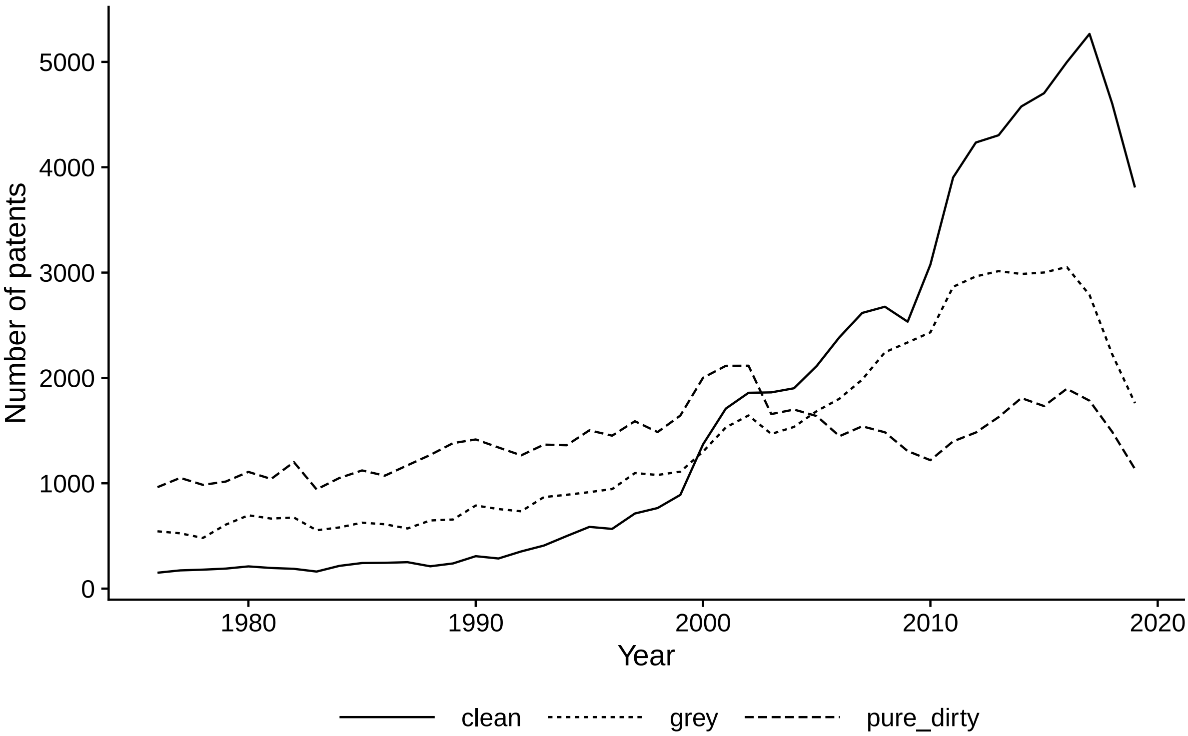
Notes: The figures show the centered wildfire measure. The measure is centered with respect to a yearly linear trend and state × quarter fixed effects. We report annual average for each state. Brown shade indicates over-exposure. Blue shades indicates under-exposure.
Source: NASA's FIRMS, authors' calculation.

FIGURE 13: Number of vehicle registrations in the U.S. for makes with at least 5% market share in a segment.



Notes: This figure shows the number of registered units by quarter in the U.S. Only makes with more than 5% market share in a engine segment are plotted. Top left are Electric Vehicles (EV), top righ are Fossil Fuel vehicles, bottom left are Hybrid, including plug-in hybrid, finally bottom right are Hydrogen.
Source: S&P Global, authors' calculation

FIGURE 14: Number of Clean, Dirty, and Gray Patents 1976-2019



Notes: This figure illustrates the number of patent applications filed for 'clean', 'gray', and 'dirty' technologies over time in the U.S. patent office. Dirty patents are defined as innovations related to internal combustion engine while clean innovations are related to electric, hybrid, and hydrogen vehicle patents. Gray patents are innovations that aim to reduce emissions from fossil fuel vehicles.
Source: USPTO, authors' calculation

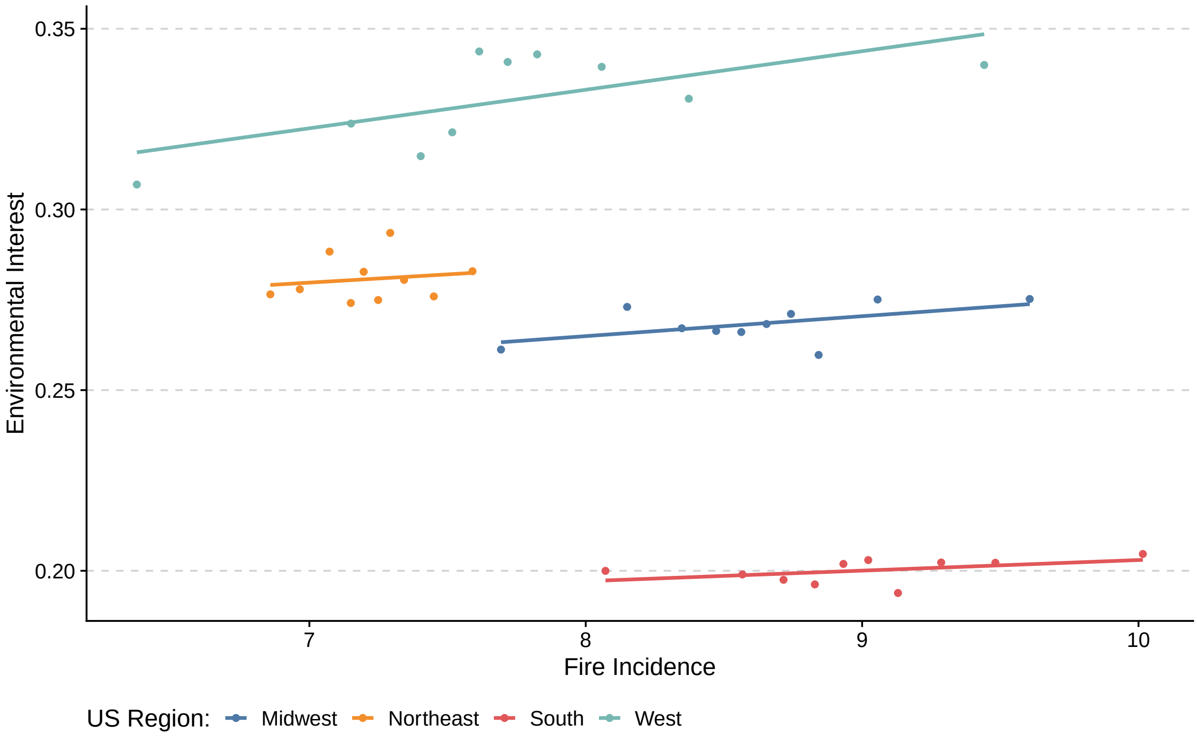


Figure 15: Fire incidence and environmental interest by US region, binned scatter plot

Notes: This figure reports the relation between wildfire incidence and environmental interest by US region as a binned scatter plot by US regions. The data is a panel of US states between 2006 and 2019. The observations are weighted by the population of the state in each year. The observation are first residualized on state-quarter and time fixed effects. Observations in each region are plotted with 10 bins. The wildfire incidence is measured using NASA's FIRMS satellite data. The environmental interest is measured using a PCA decomposition of Google Trends research interest for the following topics: ”climate change”, ”recycling”, and ”electric car”. The index is then normalized between 0 and 1. Fitting lines are estimated using an OLS regression.

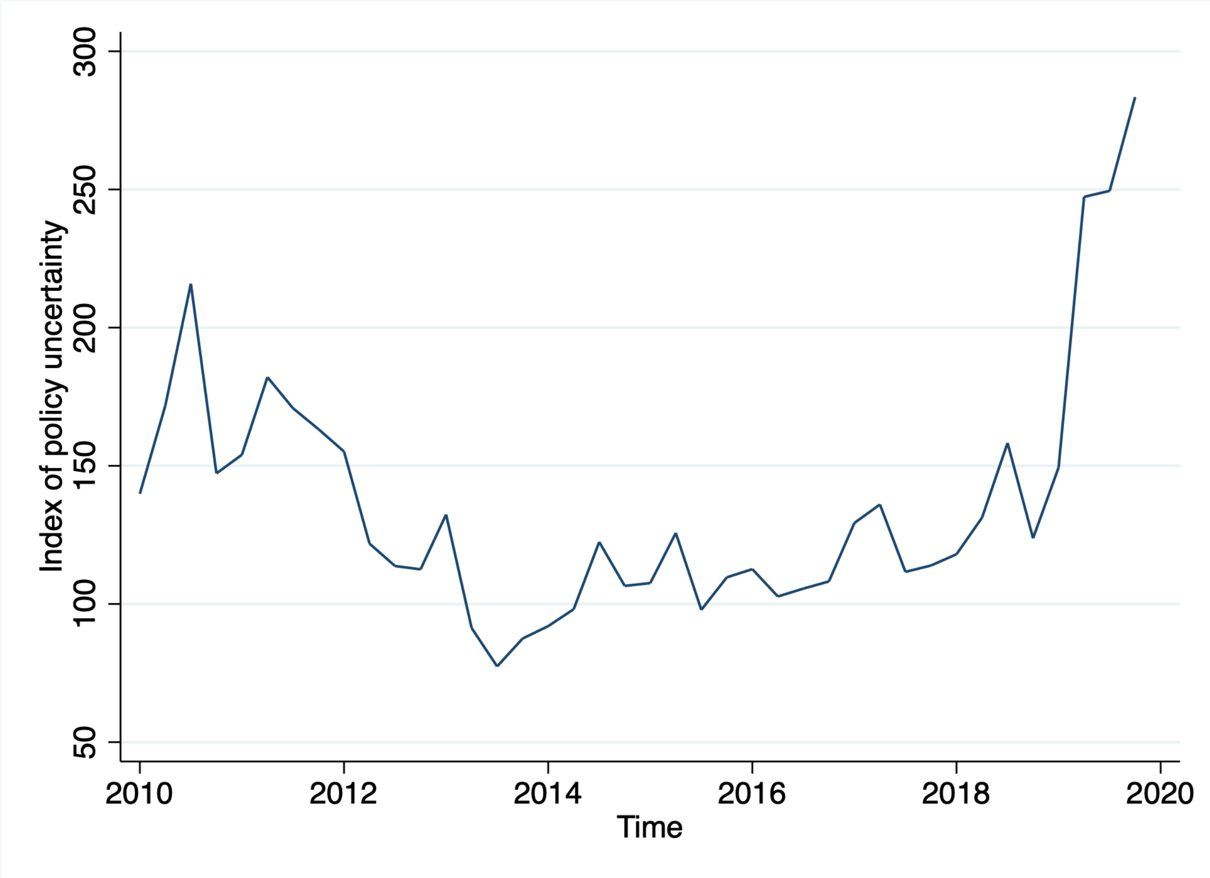


Figure 16: Economic policy uncertainty over time

Notes: This figures reports the index of economic policy uncertainty developed by Baker, Bloom, and Davis 2016. More information about the construction of the index can be found at https://www.policyuncertainty.com/.

C Additional Results and Robustness Exercises

C.1 Additional Robustness Exercises

Falsification test To ensure that our results capture the period-specific effects of exposure to consumers' environmental awareness, and not some long-run common causal factor behind both the rise in awareness and technological change or lobbying, we conduct a falsification exercise by regressing past changes in innovation and lobbying expenditures on future changes in environmental awareness. The results of the pre-trend falsification tests are presented in Table 12, where the first two panels focus on lobbying activity and the three following panels on patenting, similarly to our main table of results. Across our specifications on environmental lobbying, total lobbying and clean innovation, we cannot reject that there is no relationship between the shocks and our lagged dependent variables on lobbying expenditures and clean innovation, lending credibility to a causal interpretation of these estimates. Interestingly, we note a positive and significant relationship between the increase in environmental interest and lagged gray and dirty innovation suggesting that dirtier firms face a higher shift in environmental interest in our period of analysis.

TABLE 12: Falsification test for the IV regression on lagged outcomes

	(1)	(2)	(3)	(4)
Lagged $\Delta_8 ln(lobby) Lobbying$ *(Environment Topics)*				
$\Delta_8 ENV^{GT}$	-1.214	-1.157	-0.833	-0.935
	(1.143)	(0.914)	(0.994)	(1.048)
Lagged $\Delta_8 ln(lobby)$ *(Total)*				
$\Delta_8 ENV^{GT}$	0.459	0.556	1.023	0.738
	(0.684)	(1.038)	(1.227)	(1.306)
Lagged Δ_8 *Clean Knowledge Capital*				
$\Delta_8 ENV^{GT}$	0.370	0.525	0.211	-0.0940
	(0.683)	(1.197)	(1.164)	(1.227)
Lagged Δ_8 *Dirty Knowledge Capital*				
$\Delta_8 ENV^{GT}$	13.27**	12.80***	13.16***	13.32***
	(6.401)	(4.252)	(4.252)	(4.338)
Lagged Δ_8 *Gray Knowledge Capital*				
$\Delta_8 ENV^{GT}$	2.575	2.484*	2.438*	2.574**
	(1.702)	(1.324)	(1.259)	(1.271)
FE: year-quarter	X	X	X	X
FE: state-quarter	X	X	X	X
Firm Trend	X	X	X	X
Lagged Firm Controls	X	X	X	X
Lagged Demographic Controls		X	X	X
Lagged Transportation Controls			X	X
Lagged Political Controls				X
First-Stage F	94	105	103	99
N (states - periods)	1500	1500	1500	1500

Signif. codes: ***: 1%, **: 5%, *: 10%

Notes: The table reports coefficients from the shift-share IV falsification tests. We regress the two-year change in the environmental preferences index on changes in the outcomes lagged by ten quarters. The change in environmental preferences index is instrumented with the change in wildfire intensity computed from NASA's FIRMS dataset. Clustered standard errors at the state level are in parentheses.

Table 13: Heterogeneity Analysis by Initial Level of Share of Dirty Technology

	(1)	(2)	(3)	(4)	(5)
	Env. Topics	Total Lobbying	Clean Innov.	Dirty Innov.	Gray Innov.
$\Delta_8 ENV^{GT}$	2.13	-3.49	2.46*	5.06	3.94
	(1.72)	(2.95)	(1.36)	(10.69)	(3.27)
$Dirty\_Ratio$	0.05+	0.05	0.09**	-0.09	-0.05
	(0.03)	(0.06)	(0.04)	(0.17)	(0.05)
$\Delta_8 ENV^{GT} * Dirty\_Ratio$	6.15	25.88	-0.23	-130.05	-32.50+
	(12.70)	(24.95)	(10.78)	(97.80)	(20.40)
FE: year-quarter	X	X	X	X	X
FE: state-quarter	X	X	X	X	X
Firm Trend	X	X	X	X	X
Lagged Firm Controls	X	X	X	X	X
Lagged Demographic Controls	X	X	X	X	X
Lagged Transportation Controls	X	X	X	X	X
Lagged Political Controls	X	X	X	X	X
N (states - periods)	2000	2000	2000	2000	2000

Signif. codes: ***: 1%, **: 5%, *: 10%
Notes: The table reports results of our regression on log change in our main outcomes, where we add the ratio of dirty technologies in the overall technology mix of the firm, both in levels and as in interaction term with the change in consumers' environmental awareness. Each coefficient corresponds to the IV estimates from our most conservative regression. Standard errors clustered at the state level are in parentheses. All changes are in 2 years differences (8 quarters). ΔENV^{GT} represent the 8 quarters difference in the environmental awareness index that is constructed in section 2. $Dirty\_Ratio$ the ratio of dirty technologies in the overall technology mix of the firm at the beginning of the period. Our result that the increase in clean innovation and environmental lobbying is not driven by heterogeneity of firms' initial level of dirtiness is robust to this alternative definition of dirtiness.

Table 14: Response of innovation using Aghion et al. 2021 measures of innovation

	(1) $log(1+\#clean)$ $-log(1+\#dirty)$	(2) $log(1+\#clean)$	(3) $log(1+\#dirty)$	(4) $log(1+\#gray)$
$\Delta_8 ENV^{GT}$	4.04***	3.79***	-0.25	-0.04
	(1.21)	(1.07)	(0.49)	(0.52)
FE: year-quarter	X	X	X	X
FE: state-quarter	X	X	X	X
Firm Trend	X	X	X	X
Lagged Firm Controls	X	X	X	X
Lagged Demographic Controls	X	X	X	X
Lagged Transportation Controls	X	X	X	X
Lagged Political Controls	X	X	X	X
N (states - periods)	2000	2000	2000	2000
First-Stage F	97	107	116	116

Signif. codes: ***: 1%, **: 5%, *: 10%
Notes: The table reports results of our regression on log changes on environmental interest on innovation activity. Innovation activity if defined following Aghion et al. 2021 as the number of patents, rather than the as the knowledge stock of the firm. The first column reports the effect of the change in environment interest on the relative clean innovation measured as $log(1 + \#cleanpatents) - log(1 + \#dirtypatents)$. The second, third and fourth columns respectively reports the effect on the log number of clean, dirty and gray patents. Each coefficient corresponds to the IV estimates from our most conservative regression. Standard errors clustered at the state level are in parentheses. Changes in environmental difference are in 2 years differences (8 quarters). ΔENV^{GT} represent the 8 quarters difference in the environmental awareness index that is constructed in section 2.

TABLE 15: Heterogeneity of response of innovation using Aghion et al. 2021 measures of innovation

	(1)	(2)	(3)	(4)
	$log(1+\#clean)$ $-log(1+\#dirty)$	$log(1+\#clean)$	$log(1+\#dirty)$	$log(1+\#gray)$
$\Delta_8 ENV^{GT}$	5.96***	6.42**	0.46	0.34
	(2.15)	(2.47)	(1.11)	(1.33)
$Dirty\_Ratio$	-0.17***	-0.04	0.13***	-0.16***
	(0.06)	(0.07)	(0.03)	(0.04)
$\Delta_8 ENV^{GT} * Dirty\_Ratio$	1317.35	1802.53*	485.18	192.70
	(815.76)	(901.16)	(323.91)	(553.79)
FE: year-quarter	X	X	X	X
FE: state-quarter	X	X	X	X
Firm Trend	X	X	X	X
Lagged Firm Controls	X	X	X	X
Lagged Demographic Controls	X	X	X	X
Lagged Transportation Controls	X	X	X	X
Lagged Political Controls	X	X	X	X
N (states - periods)	2000	2000	2000	2000

Signif. codes: ***: 1%, **: 5%, *: 10%

Notes: The table reports results of our heterogeneity analysis of the regression of log changes on environmental interest on innovation activity. Innovation activity if defined following Aghion et al. 2021 as the number of patents, rather than the as the knowledge stock of the firm. The first column reports the effect of the change in environment interest on the relative clean innovation measured as $log(1+\#cleanpatents) - log(1+\#dirtypatents)$. The second, third and fourth columns respectively reports the effect on the log number of clean, dirty and gray patents. Each coefficient corresponds to the IV estimates from our most conservative regression. Standard errors clustered at the state level are in parentheses. Changes in environmental difference are in 2 years differences (8 quarters). ΔENV^{GT} represent the 8 quarters difference in the environmental awareness index that is constructed in section 2.

Comment: Using the number of new patent applications instead of the change in the technology stock of the firm, we find that firms initially dirtier tend to innovate more in dirty technologies. This is consistent with the path dependency highlighted in Aghion et al. 2021. As in our main specification, we find no path dependency for clean innovation. Taken together, these two specifications point to the fact that dirty firms tend to patent more in dirty technologies but also decrease relatively more their dirty innovation. We confirm that the cleaner and dirtier firms react similarly to the shock as the coefficient of the interaction term is only significant at the 10% level for the clean innovation outcome.

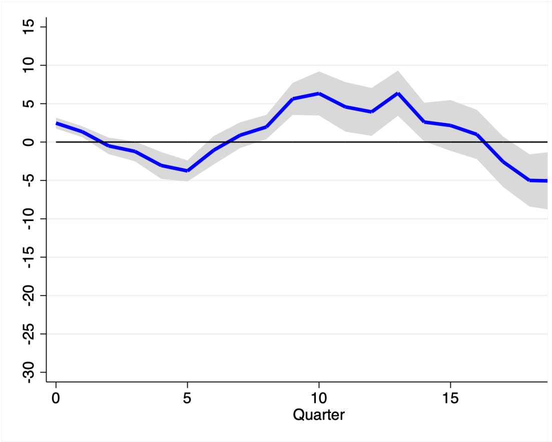
C.2 Additional Results

Table 16: Impact of environmental interest on revenues

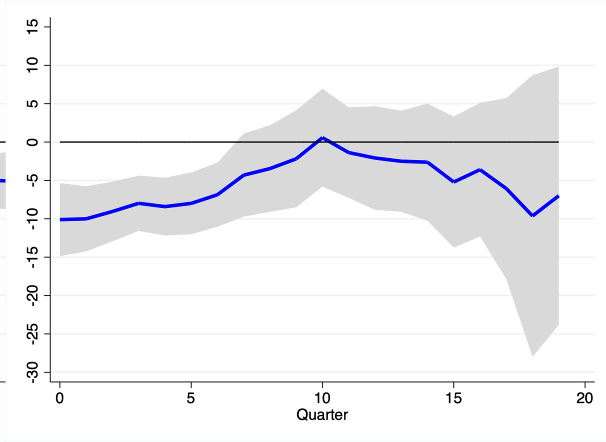
	OLS				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta_8 ln(Revenues)$								
$\Delta_8 ENV^{GT}$	0.03	-0.04	-0.16	0.93	-3.65**	-3.28**	-3.04**	-3.02**
	(1.66)	(1.69)	(1.83)	(1.98)	(1.43)	(1.40)	(1.36)	(1.36)
FE: year-quarter	X	X	X	X	X	X	X	X
FE: state-quarter	X	X	X	X	X	X	X	X
Firm Trend	X	X	X	X	X	X	X	X
Lagged Firm Controls	X	X	X	X	X	X	X	X
Lagged Demographic Controls		X	X	X		X	X	X
Lagged Transportation Controls			X	X			X	X
Lagged Political Controls				X				X
N (states - periods)	2000	2000	2000	2000	2000	2000	2000	2000
First-Stage F					97	107	116	116

Signif. codes: ***: 1%, **: 5%, *: 10%

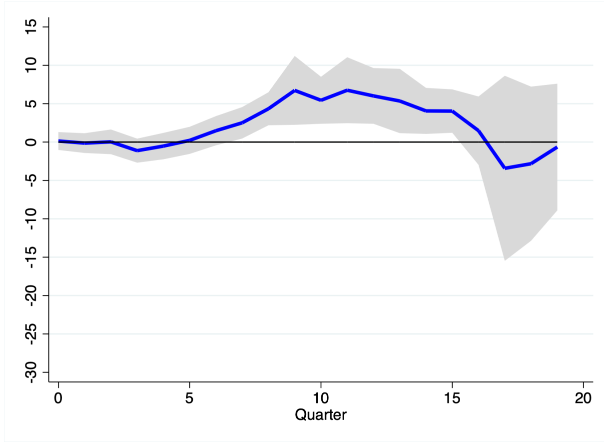
Notes: The table reports results of our regression on log changes on environmental interest on innovation activity on the total revenues of the firm. Standard errors clustered at the state level are in parentheses. Changes in environmental difference are in 2 years differences (8 quarters). ΔENV^{GT} represent the 8 quarters difference in the environmental awareness index that is constructed in section 2. The table reports an average negative effect of an increase in environmental interest on firm revenues.



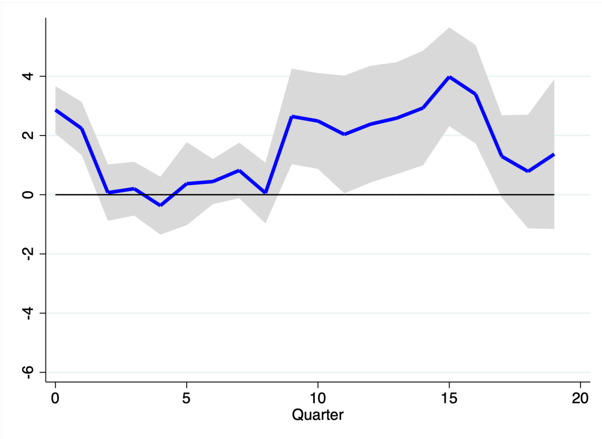
Clean Innovation



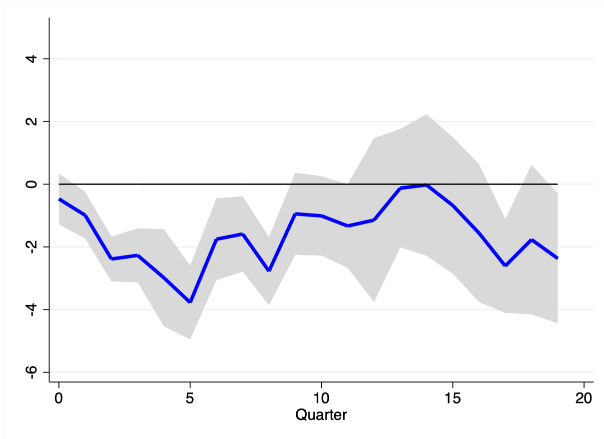
Dirty Innovation



Gray Innovation



Environmental Lobbying



Total Lobbying

FIGURE 17: Dynamic response of firm outcome to changes in environmental preferences

Notes: This figure reports the impulse responses of firm outcomes following an increase in environmental preference according to the specification $\Delta y_{i,t+k} = \lambda_t^h + \alpha_i^h + \beta_{i,t}^h \Delta ENV_{i,t}^{GT} + \gamma^h X_{i,t} + \epsilon_{i,t+h}$, for quarters h=0, ..., 20 after the shock. Shaded areas are 90% error bands, where standard errors are clustered at the state-level.

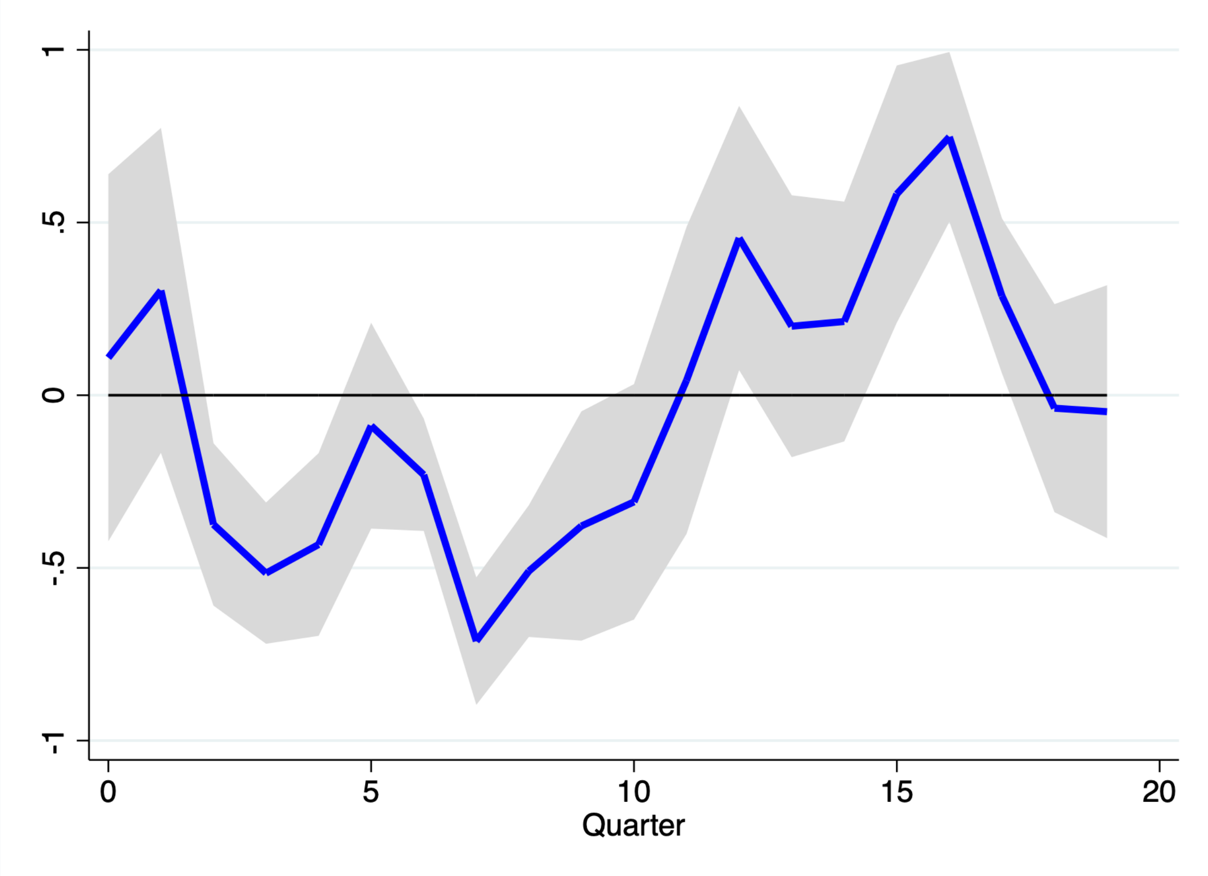


Figure 18: Dynamic response of share of lobbying expenditures allocated to environmental topics to changes in environmental preferences

Notes: This figure reports the share of lobbying expenditures allocated to environmental topics following an increase in environmental preference according to the specification $\Delta y_{i,t+k} = \lambda_t^h + \alpha_i^h + \beta_{i,t}^h \Delta ENV_{i,t}^{GT} + \gamma^h X_{i,t} + \epsilon_{i,t+h}$, for quarters h=0, ..., 20 after the shock. Shaded areas are 90% error bands, where standard errors are clustered at the state-level. *Comment:* The figures report that the share of lobbying expenditures allocated to environmental topics decreases after the shock for around two year. The share then increases between year 3 and year 5 after the shock. This period of increase roughly corresponds to the period where clean patenting increases (see Figure 3). This result points again towards a complementarity of clean innovation and environmental lobbying.

Using institutions lobbied instead of topics Lobbying declarations provide information on the expenditures paid by the firm to the lobbyist for the lobbying activity, the topics and the institutions targeted by the lobbying activity. In our main analysis, we use the topics targeted by the activity to define environmental lobbying. We here focus on the institutions targeted. Our sample of firms targets over eighty institutions and we here as consider environmental lobbying all the activity targeting directly the following institutions: the Department of Energy, the Environmental Agency Protection, the Council of Environmental Quality, and the Federal Energy Regulatory Commission. We additionally focus on the eight institutions which are the most intensively lobbied by the automotive industry.

We present in Table 17 the results of the main specification focusing on the institutional targets. We interpret our results taking into account the absence of effect of environmental interest on the total amount of lobbying expenditures.

The first panel gathers expenditures at all the targets whose main mandate is related to environmental institutions. The second panel focuses on political institutions - that is institutions where representatives are elected - in opposition to independent agencies.[49] The following panels focus on the eight institutions subject to the most lobbying which are the Department of Energy, the Environmental Protection Agency (EPA), the National Highway Traffic Safety, the Department of Commerce, the Trade Representative, the House of Representatives, the Senate, and the White House.

Panel 1 presents a positive causal relationship between environmental interest and lobbying expenditures on environmental institutions. This result is in line with the previous results on environmental topics. However, we note that the estimates are twice as large, implying that a one standard deviation increase in the salience of environmental topics results in an increase in lobbying expenditures on these targets by a factor of 5.3.

Decomposing, we find a modest causal effect of consumers' attitudes on expenditures targeted at the Department of Energy (panel 3) and no effect on expenditures targeted at the EPA (panel 4). These results could be explained by an effect on the extensive margin we do not capture, that is that firms start lobbying on a higher number of environmental institutions after the shock.[50] Alternatively, the lack of significant es-

49. The list of political institutions can be found in subsection E.2 of the Appendix.

50. Recall that our analysis focuses on the intensive margin. For instance, if we consider a firm lobbying continuously one environmental institution and only every other quarter another environmental institution, we will observe the difference in lobbying expenditures for the first institution, for the group of environmental institutions, but not for the second institution.

timates could be explained by the fact that lobbying expenditures on each individual issue are too noisy to measure the impact of our shocks.

Panel 2 focuses on lobbying targeted at political institutions. Changes in consumers' environmental concerns can be understood as changes in public opinion, and therefore as changes in the salience of environmental issues for voters. Politicians therefore have incentives to adapt to new concerns. On the contrary, independent agencies do not rely on public support and do not see their incentives shift with public opinion. Interestingly, our estimate suggests that lobbying on political institutions responded positively to contemporaneous exposure to greener consumers. This confirms the intuition that firms are concerned with new environmental regulations, after the shift of our index of environmental attitudes toward the environment. The political institutions targeted the most by lobbyists are the House of Representatives, the Senate, and the White House. We observe no simultaneous effect on the expenditures targeted at the Senate but report a positive, statistically significant and of meaningful magnitude causal impact of environmental attitudes on lobbying on the White House and the House of Representative. Last, Panel 7 exhibits a positive effect of environmental concerns on lobbying expenditures targeted at the Trade Representative, in line with our analysis of the topics targeted by the activity in Table 8. This result highlights one more time the result that firms lobby for a variety of topics in order to protect their profits.

Table 17: OLS and Shift Share IV of Firms Lobbying by Targeted Agency

	OLS				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta_8 ln(Lobby)$ (*All env. Targets*)								
$\Delta_8 ENV^{GT}$	0.48***	0.61***	0.70***	0.65***	6.01***	5.61***	5.33***	5.36***
	(0.09)	(0.11)	(0.18)	(0.15)	(0.91)	(0.95)	(0.92)	(0.90)
$\Delta_8 ln(Lobby)$ (*All Political Inst.*)								
$\Delta_8 ENV^{GT}$	0.99*	0.76	0.67	0.80*	0.53	0.99*	0.87*	0.85*
	(0.52)	(0.46)	(0.47)	(0.42)	(0.59)	(0.50)	(0.45)	(0.44)
$\Delta_8 ln(Lobby)$ (*Dpt. of Energy*)								
$\Delta_8 ENV^{GT}$	0.16***	0.17***	0.16***	0.13***	0.23**	0.22**	0.24**	0.24**
	(0.03)	(0.03)	(0.03)	(0.04)	(0.11)	(0.10)	(0.10)	(0.10)
$\Delta_8 ln(Lobby)$ (*EPA*)								
$\Delta_8 ENV^{GT}$	-0.29	-0.25	-0.27	-0.24	0.34	0.28	0.28	0.28
	(0.17)	(0.17)	(0.17)	(0.15)	(0.40)	(0.40)	(0.38)	(0.38)
$\Delta_8 ln(Lobby)$ (*NHTS*)								
$\Delta_8 ENV^{GT}$	0.35**	0.41***	0.48***	0.40***	0.15	0.11	0.10	0.10
	(0.15)	(0.14)	(0.10)	(0.12)	(0.47)	(0.46)	(0.49)	(0.49)
$\Delta_8 ln(Lobby)$ (*Dpt. of Commerce*)								
$\Delta_8 ENV^{GT}$	0.04	0.04	-0.02	-0.01	1.11**	1.06**	1.14**	1.14***
	(0.18)	(0.18)	(0.16)	(0.13)	(0.46)	(0.43)	(0.42)	(0.42)
$\Delta_8 ln(Lobby)$ (*Trade Representative*)								
$\Delta_8 ENV^{GT}$	-0.27**	-0.26**	-0.25*	-0.19	2.25***	2.12***	1.95***	1.96***
	(0.11)	(0.12)	(0.13)	(0.12)	(0.29)	(0.27)	(0.26)	(0.26)
$\Delta_8 ln(Lobby)$ (*House of Representatives*)								
$\Delta_8 ENV^{GT}$	1.09*	0.82*	0.70	0.73*	0.63	1.12*	1.08*	1.06*
	(0.55)	(0.44)	(0.43)	(0.40)	(0.63)	(0.64)	(0.61)	(0.60)
$\Delta_8 ln(Lobby)$ (*Senate*)								
$\Delta_8 ENV^{GT}$	0.65	0.37	0.28	0.43	-0.75	-0.21	-0.26	-0.28
	(0.58)	(0.44)	(0.45)	(0.36)	(0.80)	(0.77)	(0.75)	(0.73)
$\Delta_8 ln(Lobby)$ (*White House*)								
$\Delta_8 ENV^{GT}$	0.54**	0.52**	0.47**	0.45**	2.35***	2.34***	1.98***	1.98***
	(0.21)	(0.21)	(0.23)	(0.19)	(0.42)	(0.44)	(0.37)	(0.37)
FE: year-quarter	X	X	X	X	X	X	X	X
FE: state-quarter	X	X	X	X	X	X	X	X
Firm Trend	X	X	X	X	X	X	X	X
Lagged Firm Controls	X	X	X	X	X	X	X	X
Lagged Demographic Controls		X	X	X		X	X	X
Lagged Transportation Controls			X	X			X	X
Lagged Political Controls				X				X
N (states - periods)	2000	2000	2000	2000	2000	2000	2000	2000
First-Stage F					46	49	50	50

Signif. codes: ***: 1%, **: 5%, *: 10%
Notes: Regression on log change in lobbying expenses categorized by target. (1) to (4) are OLS, (5) to (6) are Shift-Share IV. Standard errors clustered at the state level are in parentheses. Independent variable is th change in environmental preferences instrumented in columns (5) to (8) by the change in exposure to wildfire computed using NASA's FIRMS dataset. Each line-column is the result of a different regression.

D Natural disasters and environmental interest

There are two main concerns about estimating our baseline regression Equation 4 as an OLS. First, a reverse causality concern: we would measure an increase in environmental interest driven not only by changes in demand but also by changes in supply. In short, identifying supply and demand side effects jointly. Second, some confounding factors could affect both consumer preferences and firm behavior. We use an instrument for consumer preferences to mitigate these concerns.

In our instrumentation strategy, we follow a strand of the psychology literature which analyzes the relationship between personal experience with extreme weather events and both individual beliefs about climate change, and intentions to take actions to mitigate one's impact on the environment (Joireman, Truelove, and Duell 2010; Bergquist, Nilsson, and Schultz 2019). This approach is grounded in the understanding that climate change is usually seen as a distant and abstract issue, often disconnected from our daily well-being (Ornstein and Ehrlich 1991; Gifford 2011). However, during extreme weather events, the tangible effects of climate change become readily apparent.

The literature reports in different countries and settings that people connect extreme weather events to the broader narrative of climate change in the aftermath of the event (Lang and Ryder 2016), that experience of extreme weather events results in higher environmental concerns, increased salience of climate change, greater perceived vulnerability to climate change, and more favorable attitudes toward climate-protecting politicians (Rudman, McLean, and Bunzl 2013; Demski et al. 2017; Donner and McDaniels 2013). Also, experience of extreme weather events appear to change behaviors. For instance, Li, Johnson, and Zaval 2011 report that residents in the US and Australia are more likely to make pro-environmental donations under extreme temperatures. Similarly, Spence et al. 2011 show, in the context of 2010 flooding in the UK, that first-hand experience of flooding was positively linked to environmental concern and even greater willingness to save energy to mitigate climate change.

We now discuss how natural disasters impact environmental interest in our specific framework. To do so, we regress our measure of environmental interest on our measure of wildfire intensity up to 10 quarters before. One crucial assumption is that the exogeneity of wildfires is conditional on state and period fixed effects. This is intuitive as wildfires are not randomly distributed across states and some year are more prone to wildfires than others. Including those fixed effects implies that we leverage the within-state variations in wildfires to identify the effect of wildfires on environmental interest. The estimated linear relation is given by:

$$E\tilde{N}V_{l,t} = \alpha_{l,q} + \lambda_t + \sum_{k=0}^{10} \beta_k \tilde{W}_{l,t-k} + \epsilon_{l,t} \tag{8}$$

Where $\tilde{x}_{lt}$ denotes the variable x weighted by the population of state l at time t. $\alpha_{l,q}$ and λ_t are state-quarter and time fixed effects respectively.

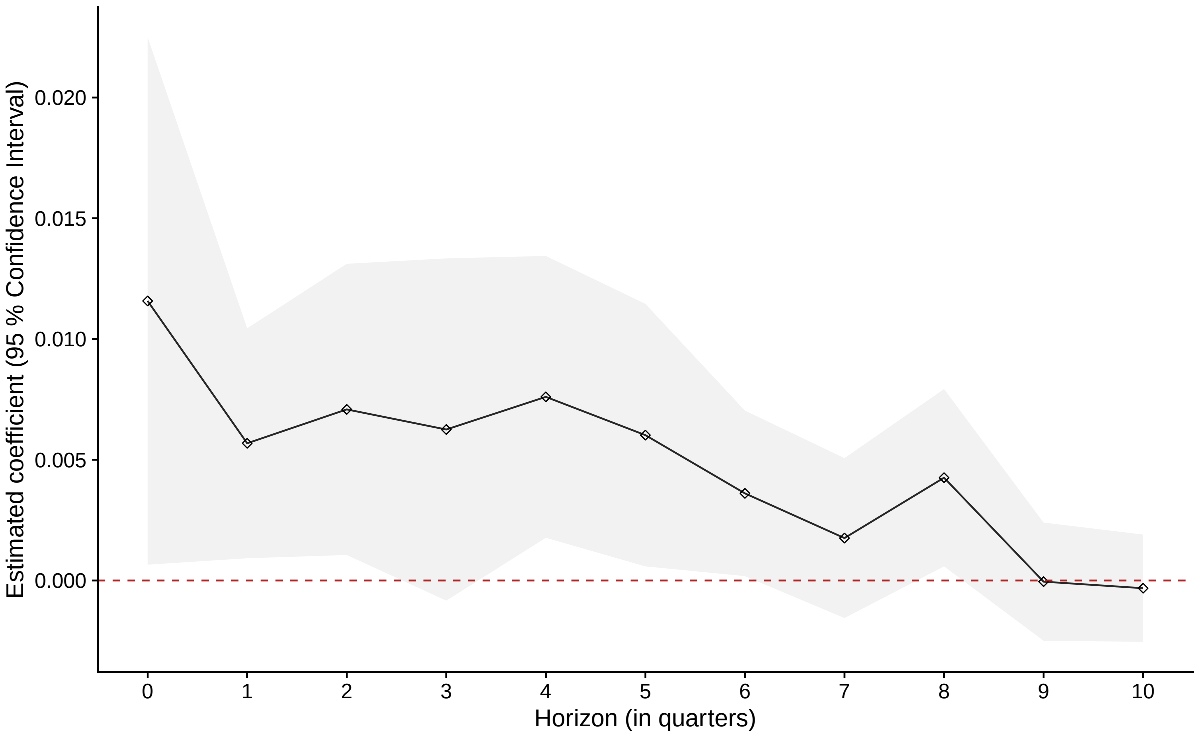


FIGURE 19: Dynamic relationship between wildfires and environmental interest by quarters

Notes: The figure reports the dynamic effect of wildfires on environmental interest within US states. The data is a panel of US states between 2006 and 2019. The regression is weighted by the population of the state in each year. The figure is the result of a linear regression including contemporaneous wildfire incidence and lagged wildfire incidence up to 10 quarters before. The regression includes state-quarter and time fixed effects. The shaded area represents the 95% confidence interval. The wildfire incidence is measured using NASA's FIRMS satellite data. The environmental interest is measured using a PCA decomposition of Google Trends research interest for the following keywords: "climate change", "recycling", and "electric car".

Figure 19 shows the long lasting effect of wildfires on environmental interest. The estimated coefficients are positive and mostly significant for up to 2 years (8 quarters) after the wildfire. The effect is stronger at the time of the shock and then decreases linearly over time. A natural question is whether this effect is driven by western states that often makes the headlines when wildfires occur. To test this hypothesis, we plot the correlation split by US regions [51]. Figure 15 in the Appendix shows that the relationship is robust between US regions, with a slightly higher slope for western states.

E Data Construction

E.1 Google Trends and Environmental Interest Index

E.1.1 Data

We utilize data from Google Trends, a publicly available online tool provided by Google that allows users to explore and analyze the popularity of search queries over time. Google Trends provides insights into the relative search interest for specific terms or topics based on the frequency of searches conducted on the Google search engine. The data encompasses a wide range of search categories and geographical regions. Google Trends provides search interest data on a relative scale, with values ranging from 0 to 100. A value of 100 indicates the peak popularity of a search term or topic during the specified time period, while a value of 0 indicates the lowest observed popularity. The tool allows to compare either multiple search terms or topics, or a single search term over multiple geographical regions. However, the tool does not permit to compare more than 5 geographical regions at a time. In order to compare the search interest for a single search term over multiple geographical regions, we pull data for four states along with the US as a whole to serve as a normalization factor. We then renormalize each state's search interest data by dividing it by the maximum search interest of the US. This way we end up with and index that is not bounded by 100, but that is comparable across states.

We pull monthly data for the US states from January 2006 to December 2019. Figure 20 shows the raw data for the search terms we use in the paper. Two striking features emerge from the raw data. First, the search interest for some keywords is highly volatile due to the fact that the search volume for some keywords is too low. Second, the search interest for some keywords exhibits strong seasonality.

51. We use the US Census Bureau definition of US regions: Northeast, Midwest, South and West.

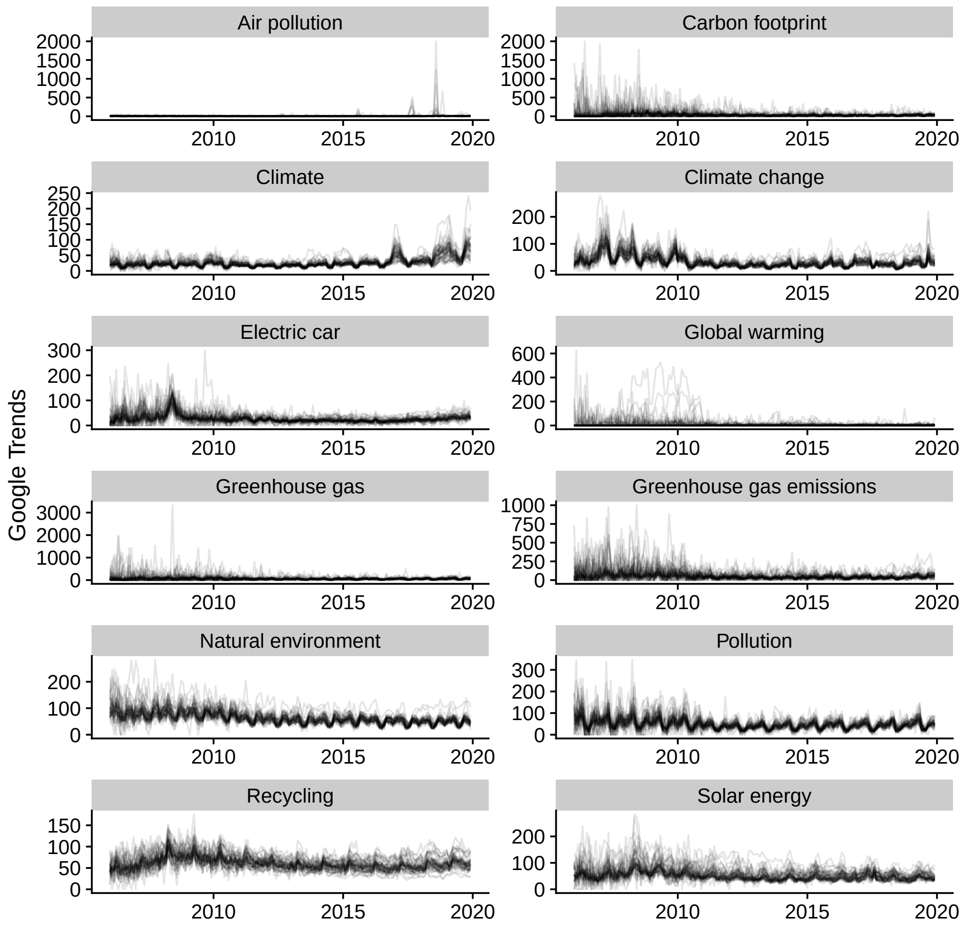


FIGURE 20: Google Trends series for keywords related to the environment

Notes: The figure shows the raw Google Trends series for a selection of keywords related to environmental questions. The series are renormalized relative to the US to allow the comparison of multiple geographical regions. Each subplot shows one line per state.

E.1.2 Construction of the Index

We use a Principal Component Analysis (PCA) to construct an index of environmental interest. The index is constructed using the following topics: ”climate change”, ”recycling”, and ”electric car” for their broad coverage of environmental questions and their high search volume. The resulting index is shown in Figure 1. Here, we present alternative specifications of the index. First, we select alternative keywords to construct the index, such as ”Natural environment”, ”Greenhouse gas emissions”, ”Carbon Footprint”, and ”Solar Energy” [52]. Figure 21 (and Figure 22) shows that the index is robust to the choice of the keywords.

52. We discard ‘Pollution’ because of its straightforwardly link to wildfires, which would make the index trivially predicted by the shock.

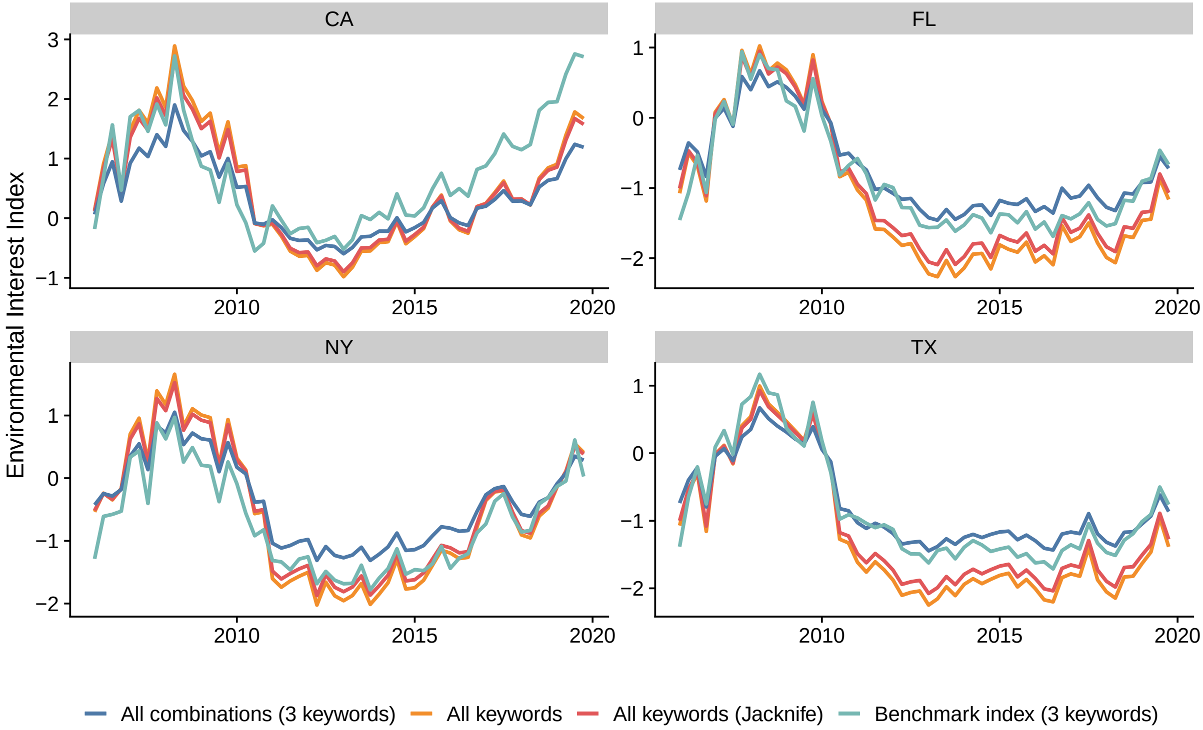


FIGURE 21: Environmental interest index, comparison of the benchmark to alternative computations

Notes: This figure shows our measure of environmental interest built with Google Trends series at the state level discussed in section 2 along with three alternative measures of the index. The figure is focusing on 4 states for readability purposes. The index is a composite of research popularity for terms related to popular keywords related to the environment. In the benchmark, those keywords are 'Climate Change', 'Recycling', and 'Electric Car'. Series are combined using the first component of a principal component analysis. To build the other indexes, we also include the following keywords: 'Natural Environment', 'Greenhouse Gas Emissions', 'Carbon Footprint', and 'Solar Energy'. **All combinations** is the index build as an average of all the PCA factorization of 3 keywords. **All keywords** is the index build with the PCA factorization of all the keywords alltogether. **All keywords (Jackknife)** is computed using a leave-one-out (jackknife) procedure.

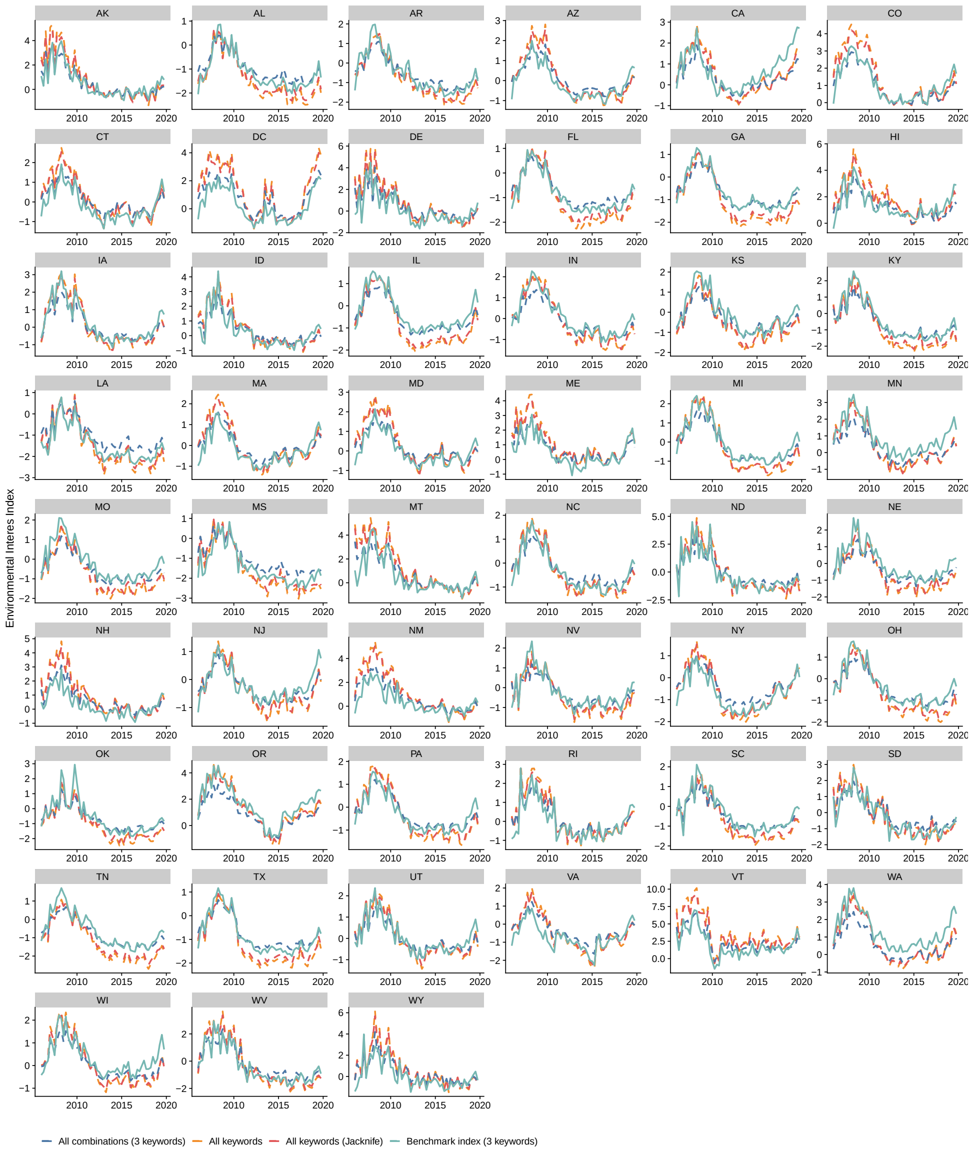


FIGURE 22: Environmental interest index, comparison of the benchmark to alternative computations

Notes: This figure shows our measure of environmental interest build with Google Trends series at the state level discussed in section 2 along with three alternative measures of the index. The index is a composite of research popularity for terms related to popular keywords related to the environment. In the benchmark, those keywords are 'Climate Change', 'Recycling', and 'Electric Car'. Series are combined using the first component of a principal component analysis. To build the other indexes, we also include the following keywords: 'Natural Environment', 'Greenhouse Gas Emissions', 'Carbon Footprint', and 'Solar Energy'. **All combinations** is the index build as an average of all the PCA factorization of 3 keywords. **All keywords** is the index build with the PCA factorization of all the keywords alltogether. **All keywords (Jackknife)** is computed using a leave-one-out (jackknife) procedure.

E.1.3 Google Trends and the Gallup Survey

To assess the external validity of our data, we compare our index of environmental interest with an index built from the Gallup survey. In particular, the environmental index we build from the Gallup survey is the share of population reporting to worry "a great deal" about climate change.[53]

The main difficulty with traditional surveys, and the Gallup survey in particular, is that it is representative only at the level of the US, and not a more disaggregated level. The survey is conducted every year, and 1000 adults are surveyed across all 50 states and the District of Columbia using a dual-frame design, which includes both landline and cellphone numbers. Gallup samples landline and cellphone numbers using random-digit-dial methods.[54] While the survey should be representative at the aggregate level, we cannot expect it to be representative at the state level. On the contrary, Google Trends data is based on thousands - generally millions - of searches in each state.

Figure 23 presents our index of green preferences and the proxy of environmental awareness built from the Gallup survey for the four states with the largest average number of respondents. On average, 100 people are surveyed each year in California, the most populated US state, 68 in Texas, 62 in New York state and 59 in Florida. The index plotted in the figure are demeaned and normalized to a unit variance for better comparability. Overall, the index built from the Gallup survey is more noisy but the general trend is the same for the two indices in California, Florida and New York. Texas shows a different evolution of the two indices in the second period of the sample. Table 18 presents a positive and significant correlation between the two indices.

53. The question is: "I'm going to read you a list of environmental problems. As I read each one, please tell me if you personally worry about this problem a great deal, a fair amount, only a little, or not at all. First, how much do you personally worry about [...] the "greenhouse effect" or global warming or climate change?

54. Refer to https://www.gallup.com/175307/gallup-poll-social-series-methodology.aspx for more details on the methology of the Gallup survey.

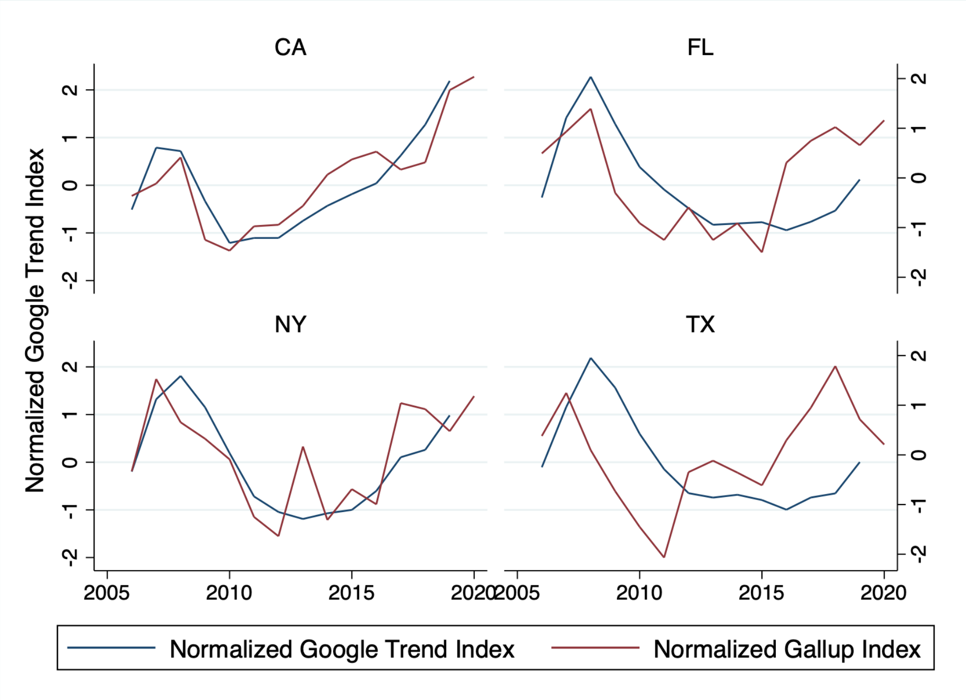


Figure 23: Google trends index of environmental interest and Gallup survey.

Notes: This presents our measure of environmental interest built from Google Trends series at the state level discussed in section 2 and the share of surveyed people reporting to be worried "a great deal" by climate change in the Gallup survey. We report both variables over time for California, Florida, New York and Texas, the four states with the higher average number of respondents in the Gallup survey.

	GT Index	GT Index	GT Index	GT Index
Gallup Index	0.14***	0.15***	0.04***	0.04***
	(0.04)	(0.04)	(0.02)	(0.02)
FE: state		X		X
FE: year			X	X
N (states-year)	686	686	686	686

Table 18: State-level correlation of environmental index in Google Trends data and Gallup survey

Signif. codes: ***: 1%, **: 5%, *: 10%
Notes: State-level regression of the level of the share of surveyed people reporting to be worried "a great deal" by climate change in the Gallup survey on the environmental interest built from Google Trends series as discussed in section 2. The sample includes all the state-year observations present in the Gallup survey.

E.2 Lobbying Expenditures and Environmental Lobbying

E.2.1 Lobbying Expenditures by Targeted Issue

We find a total of 79 different targets in the lobbying data. We group the relevant issues into the nine following categories:

- Manufacturing: AUT, AVI, TRA, AER, TRU, CPI, MAN.
- Trade: TRD, TAR, FOR.
- Taxes: TAX.
- Environment: ENV, ENG, CAW, FUE.
- Finance: FIN, BAN, BNK, INS.
- Labor: HCR, LBR, IMM MMM, RET.
- Public Expenditures: BUD, DEF, GOV, HOM, ROD, RRR.
- Innovation: CPT, SCI.
- Consumer, Safety Product: CSP.

E.2.2 Lobbying Expenditures by Targeted Branch

We split lobbying expenditures equally over all the targets present in a single report.

We first focus on the eight main targets, then separate them between political and independent, and finally, between branches focusing on environmental issues and other branches.

The eight main institutions targeted by lobbying are: House of Representatives, Senate, White House, Department of Commerce, Environmental Protection Agency, Department of Energy, National Highway Traffic Safety Administration, and Trade Representative.

The list of political branch is the following: House Of Representatives, Senate, Department Of Transportation, Department Of Energy, Department Of Commerce, Department Of The Treasury, White House, Department of State, Department of Defense, Department of Labor, Office Of Management And Budget, Council on Environmental Quality, National Economic Council, Council on Economic Advisers, Federal Highway Administration, Department of Homeland Security, Occupational Safety And Health

Administration, Federal Railroad Administration, Department of Education, National Security Agency, Department Of Agriculture, Executive Office of the President, Federal Transit Administration, Patent and Trademark Office, Internal Revenue Service, Department of Veterans Affairs, Food and Drug Administration, Transportation Security Administration, National Telecommunications and Information Administration, Army, Navy, Air Force, International Trade Administration, Customs And Border Protection, Administration for Children and Families, Technology Administration, Federal Aviation Administration, Science Office. All the other targets are considered as independent agencies.

Last, we divide lobbying expenditures depending on whether the target focuses mainly on environmental issues. The targets that do so are the following: Department of Energy, Environmental Agency Protection, Council of Environmental Quality, Federal Energy Regulatory Commission.

E.3 Patents classification

Table 19: Patent classification into clean, gray, and dirty by CPC code

CPC code	Label
Clean Patents	
B60K1	Arrangement or mounting of electrical propulsion units
B60K6	Arrangement or mounting of plural diverse prime-movers for mutual or common propulsion, e.g. hybrid propulsion systems comprising electric motors and internal combustion engines
B60L3	Electric devices on electrically-propelled vehicles for safety purposes; Monitoring operating variables, e.g. speed, deceleration or energy consumption
B60L15	Methods, circuits, or devices for controlling the traction-motor speed of electrically-propelled vehicles
B60W10	Conjoint control of vehicle sub-units of different type or different function (for propulsion of purely electrically-propelled vehicles with power supplied within the vehicle)
B60W20	Control systems specially adapted for hybrid vehicles
H01M8	Fuel cells; Manufacture thereof
Y02T10/60	Other road transportation technologies with climate change mitigation effect.
Y02T10/70	Energy storage systems for electromobility
Y02T10/72	Electric energy management in electromobility
Dirty Patents	
F02B	Internal-combustion piston engines; combustion engines in general
F02D	Controlling combustion engines
F02F	Cylinders, pistons or casings, for combustion engines; arrangements of sealings in combustion engines
F02M	Supplying combustion engines in general with combustible mixtures or constituents thereof
F02N	Starting of combustion engines; starting aids for such engines, not otherwise provided for
F02P	Ignition, other than compression ignition, for internal-combustion engines; testing of ignition timing in compression-ignition engines
Grey Patents	
Y02T10/10-40	Climate change mitigation technologies related to transportation : internal combustion engine [ICE] based vehicles
Y02T10/80-92	Technologies aiming to reduce greenhouse gasses emissions common to all road transportation technologies
Y02E20	Combustion technologies with mitigation potential
Y02E50	Technologies for the production of fuel of non-fossil origin (e.g. biofuels, bio-diesel, synthetic alcohol)

Notes: The table reports the Cooperative Patent Classification (CPC) used to classify patents into clean, gray, and dirty technologies.

E.4 Alternative instrument

As a robustness test, we present in Table 7 the results of our main regression using alternative instruments of environmental interest based on extreme temperatures and precipitations. In this section, we detail how these instruments are built.

Extreme temperatures come from the National Climatic Data Center (NCDC) of the National Oceanic and Atmospheric Administration (NOAA)[55]. The data presents daily information on temperatures at the meteorologic station level. We first merge weather stations to counties and collapse temperature levels to the mean by county. We use the period 1960-2000 as baseline period and build the distribution of temperatures at the month/county level. Our measure of extreme temperatures is then the number of days in our period of analysis below the first percentile and above the ninety-fifth percentile. We then aggregate this county measure at a state-quarter level weighting each county by its population and summing the number of days with extreme temperatures across months.

We use three variations of the Palmer Index as proxies for extreme precipitations that come from the NOAA Monthly U.S. Climate Divisional Database (NClimDiv).[56] These three variations are the palmer "Z" index, the Palmer hydrological drought index, and the palmer drought severity index.

55. https://www.ncei.noaa.gov/cdo-web/
56. https://www.ncei.noaa.gov/access/metadata/landing-page/bin/iso?id=gov.noaa.ncdc:C00005