Environmentally-Responsible Demand: Irresponsible Lobbying*

Olimpia Cutinelli-Rendina †

Sonja Dobkowitz ‡

Antoine Mayerowitz §

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Abstract

How do firms respond to greener household preferences? We construct a novel index of environmental willingness to act on the state-quarter level based on Google Trends search data. Relating the index to firm-level information of the US automotive sector from 2006 to 2019, we find ambiguous results. The average firm not only innovates more on electric and hybrid technologies and reduces innovation on combustion engines in the long run. But it also raises the share of anti-environmental lobbying expenditures persistently over 20 quarters. These effects are stronger and more persistent than firm responses to higher fuel prices. While greener preferences induce a shift away from polluting technologies, higher fuel prices leave patenting of combustion-engine related technologies unaffected. We interpret these results as shifts in household preferences being extremely effective in inducing a market-based green transition; yet, they entail a rise in anti-environmental lobbying thereby aggravating environmental regulation.

JEL classification: D9, D70, O3, P28, Q55

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†University of Strasbourg

‡DIW Berlin

§Formerly: Collège de France and Paris School of Economics

1 Introduction

Environmental considerations are growing more and more important as a determinant of household behavior. This has implications for firms, be it through shifts in demand to cleaner alternatives or an increased voter support for environmental regulation.[1] However, by and large, the literature on the transition to green economies focuses on tax policies.[2] In this paper we shift the focus to households: How effective are households in accelerating a green transition? To investigate this question, we not only consider the direction of innovation as a potential margin of response, but also political influence tools. Lobbying against environmental regulation, for example, may help especially dirty firms to protect their remaining profits.[3] On the other hand, firms may turn to pro-environmental lobbying to tailor environmental regulation to their newly developed clean products.[4]

In the first part of the paper, we construct a novel index of environmental willingness to act building on Google Trends search data. In contrast to commonly used survey data, the high frequency and geographic granularity of our measure allow us to exploit exogenous variation in households' willingness to act caused by natural disasters on the state-quarter level.[5] We connect our measure of willingness to act with information on anti- and pro-environmental lobbying and innovative activity of automotive firms in the US from 2006 to 2019.[6]

1. Recently, the greening of household preferences has spurred interest in the economics literature. The following non-exhaustive list of papers refers to an intrinsic willingness to pay for the avoidance of negative externalities, that is, a demand channel: Kotchen 2006; Bénabou and Tirole 2010; Bartling, Weber, and Yao 2015; Aghion et al. 2023; Kaufmann, Andre, and Kőszegi 2024. With this literature, some terminology emerged to refer to the phenomenon of an intrinsic willingness to avoid negative externalities through consumption: (Bartling, Weber, and Yao 2015; Kaufmann, Andre, and Kőszegi 2024) refer to "social responsibility" and (Aghion et al. 2023) use the term "green consumer preferences". The notion "willingness to act" is broader entailing, for example, active political participation (Falk et al. 2021). In the context of our paper, we will use "green household preferences" or "willingness to act" to underscore the two aspects of household behavior that we capture: a political and a demand channel. We distinguish the concepts "environmental concerns" or "environmental attitudes" express a state-of-mind that may occur without the intention to act.

2. An exception is the work by Aghion et al. 2023 who study interactions of green consumer preferences and competition.

3. 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). Kwon, Lowry, and Verardo 2023 show that in the status quo firms that innovate clean technologies also engage in anti-environmental lobbying to shield their current profits which depend on sales of dirty products.

4. Grey 2018 points to anecdotal evidence for polluting firms engaging in pro-environmental lobbying to develop a theoretic argument in this direction.

5. 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 an intention to change one's behavior. However, we observe similar trends comparing Google Trends data to survey data (see **??**).

6. We focus on the automotive industry for several reasons. First, transportation is a highly relevant

Equipped with this dataset, we uncover that the average firm responds to a one percent rise in our index of willingness to act with a five percent increase in clean knowledge growth over an extended period of 10 quarters, while there is a reduction in long-run growth rates of dirty knowledge. Simultaneously, however, firms increase the share of lobbying expenditures against environmental regulation. Comparing these effects to firm responses to higher fuel prices, we provide evidence that shifts in household preferences are extremely effective in redirecting resources towards cleaner technologies: Effects are an order of magnitude higher and more persistent. However, this comes with the byproduct that intensified anti-environmental lobbying aggravates stringent environmental policy making.

In more detail, we perform a shift-share instrumental variable approach where consistency of the estimand relies on the quasi-random assignment of shocks (Borusyak, Hull, and Jaravel 2022). We build an instrument from satellite data on wildfires—using only the unexpected state exposure to such fires. 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 and wildfires.[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.

Literature We contribute to several strands of the economics literature. Firstly, we add to the literature on endogenous growth which developed around the seminal paper by Aghion et al. 2005 who study interactions between competition and innovation: Firms innovate to escape competitive pressures. Empirical validation thus far focuses

sector for the reduction of greenhouse-gas emissions by accounting for 25% 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. 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). Yet, there remain other forms of externalities associated with the production of electric vehicles. Finally, 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.

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.

on trade shocks to investigate firm responses to increased competition (Bloom, Draca, and Reenen 2016; Bombardini 2008; Brandt et al. 2017; Hombert and Matray 2018). Autor et al. 2020 find that many firms do not have the possibility to innovate once competition intensifies when new firms enter the market. Based on the intuition that other escape avenues exist in response to competitive pressures, Bombardini, Cutinelli-Rendina, and Trebbi 2021 provide evidence that firms use innovation and lobbying as alternative strategies. The further away a firm from the innovation frontier, the more it prefers to use political influence tools against trade to deal with heightened competition. Further confirming this intuition in a non-trade setting, Akcigit, Baslandze, and Lotti 2023 present evidence that market dominance is negatively correlated with innovation but positively correlated with political connections: Incumbents use political influence tools to complicate market entry of productive competitors instead of investing in their own productivity.

Our contribution is twofold. First, we highlight the particularity of a demand shock. Second, we differentiate the direction of innovation, while the literature cited above focuses on innovation and productivity in a Schumpeterian setting. Aghion et al. 2023 is similar to our paper in this regard. They show that competitive pressures make green demand more effective in shifting innovation to cleaner alternatives. We introduce lobbying to the analysis and highlight the role of clean sales: the ability to lobby allows especially financially distressed firms to mute the shift to clean technologies.

Secondly, this paper connects to studies on firm capacities to modify environmental regulations through political influence tools. This literature attests high social costs and individual gains from anti-environmental lobbying (Kang 2016; Meng and Rode 2019).[9] 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). Two recent papers empirically analyze pro- and anti-environmental lobbying on the firm level (Kwon, Lowry, and Verardo 2023; Leippold, Sautner, and Yu 2024). Kwon, Lowry, and Verardo 2023 is especially related in that it also focuses on the interaction of lobbying with innovation. We build on their study by using and extending their approach to classify environmen-

9. 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.

tal lobbying expenditures into pro- and against. Another distinctive feature of our work is that we look at how firms leverage lobbying and innovation in response to greener consumer preferences. In line with their finding, we show that anti-environmental lobbying is conducted even though a firm innovates a higher ratio of clean-to-dirty goods. Taking all these papers together, we add by showing that green consumer preferences intensify the use of anti-environmental lobbying with detrimental effects on the environment.

Thirdly, we contribute to a fast-evolving literature on the transition to green economies. A central topic in this literature are climate-change mitigation policies (Golosov et al. 2014; Aghion, Dechezleprêtre, Hémous, et al. 2016; Fried 2018; Barrage 2020). The novelty of our paper is that we depart from a focus on carbon taxes and research subsidies and investigate behavioral changes of consumers as the driver of a green transition.[10] We compare the effects of greener consumer preferences to the effects of higher fuel prices. Our findings suggest that greener household preferences are effective—and more so than fuel taxes—to induce a green transition. On the downside, however, firms respond with more anti-environmental lobbying complicating sound environmental policymaking.

Fourthly, the paper connects the behavior economics literature on climate change with the literature on firm responses to climate policies. In recent years, research on social responsibility or the willingness to act against climate change has abounded. This literature derives household preferences and attitudes from experiments or surveys.[11]. Recently, Kaufmann, Andre, and Kőszegi 2024 investigate market failures arising from socially responsible consumers and conduct a survey on the perceived impact on externalities through consumption and the drivers behind such behavior. We build on this literature by constructing our index of households' willingness to act and extend it by building and employing a time-series measure. By relating it to firm responses we pave the way for macroeconomic analyses of greener household preferences. Aghion et al. 2023 are one rare example which studies firm responses to green consumer preferences using country-level survey data. Our findings reach beyond this literature, as

10. Behavioral changes of consumers as the motor of a green transition is the implicit focus of behavioral economics, to which we will compare our work below. Also policymakers discuss behavioral changes of households as a potential margin to meet climate targets. For example, under its Green Deal the EU foresees to enable consumers to make informed consumption decisions (European Parliament 2024).

11. In a market setting, Bartling, Weber, and Yao 2015 show that social responsibility is relevant for households' consumption decision. Falk et al. 2021 investigate the willingness to act against climate change in a global survey and show with experiment how to increase it. Similarly, Dechezleprêtre et al. 2023 focus on support for mitigation policies

they uncover mechanisms which draw the effectiveness of consumers' willingness to spend on green goods into question.

Outline The remainder of the paper is structured as follows. We present our index of willingness to act in Section 2. Section 3 outlines our data followed by a description of the empirical strategy in Section 4. In Section 5, we present and discuss our results. Section 6 elaborates on a series of robustness exercises. Section 7 concludes.

2 A Measure of Environmental Willingness to Act

In this section, we construct and evaluate our measure of willingness to act.

2.1 Constructing an Index of Environmental Willingness to Act

To construct our index, we revert to Google Trends data. Google Trends is a free tool that provides time-series indices of search queries made in a certain geographic area. To proxy a greening of household preferences, we choose search terms that contain a notion of some willingness to change one's behavior, to pay a higher price or to make an investment to consume cleaner goods. To this end, we include *"Electric Car"*, *"Recycling"*, and *"Solar Energy"* as keywords to build our index.[12] We download time series of the relative search intensity of each individual term and combine them to an index. However, the way Google Trends provides the data complicates the downloading process and comparability of the data. The next section details how we deal with these issues.

The data is provided as the *share* of searches relative to all searches within a given month and area including the keyword.[13] The downloaded shares are normalized by the highest share observed within the time period and areas included in a query, and only a maximum of five states can be included in a query. Consequently, the downloaded series are not directly comparable across states included in distinct queries. To deal with this issue, we ensure that the national US index is contained in each query.[14]

12. In what follows, we will also discuss alternative compositions of keywords.

13. The online tool of Google Trends only shows a subsample of the whole data which gives different results for the same keywords in repeated searches. Our data, in contrast, contains all searches as we download the data from .

14. Note that this does not imply that values are normalized with the US maximum over the time period since the data measures the share of searches dedicated to a given keyword and not amounts. Thus a a state-specific may outreach the US value.

With the same geographic benchmark included in each query, we can derive time series of search shares for each state and keyword expressed relative to the share of searches directed to the same keyword in the whole US independent of the query composition.[15]

We are now equipped with three distinct time series for each state, one for each search term. We follow Baker, Bloom, and Davis 2016 to summarize the information into one index per state by, first, dividing each series with the respective standard deviation over time, second, averaging over series at each point in time. Third, we scale the state-specific indices to have a mean of 100 over time by multiplying each value of the series with $\frac{100}{mean_{state}}$.

In a similar fashion, we derive indices for different combinations of keywords to compare their performance in the course of the paper: an index of environmental concerns which includes keywords generally related with climate change and the environment but abstracts from keywords conveying a notion of behavioral change. The considered keywords are: "Climate Change", "Climate Crisis", "Air Pollution", and "Carbon Emissions". We refer to this index as "Environmental Curiosity Index". Finally, we consider a mixed index comprising the keywords: "Electric Car", "Climate Change", and "Recycling". Table 1 presents summary statistics of the different indices over states. The environmental curiosity index has the biggest variance ranging from negative values to above 200. The willingness to act index and the mixed index are similar in terms of their variance and ranges.

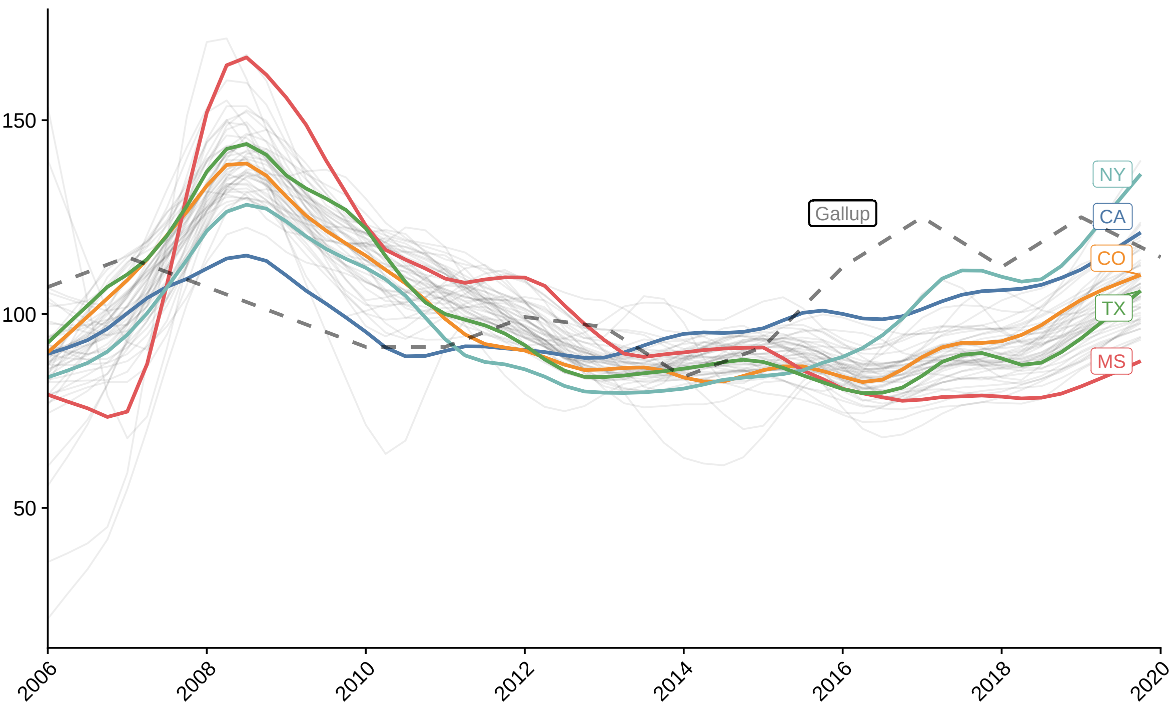
Table 1: Summary Statistics of the Indices

Index	Mean	SD	Min	Max
Social Responsibility	100.00	17.60	21.36	171.10
Environmental Concerns	100.00	27.23	-22.51	236.08
Mixed	100.00	20.54	42.50	193.01

Figure 1 presents our index of environmental willingness to act. A positive trend over the first years is followed by a noticeable U-shape. While a decrease in environmental concerns is only somewhat discussed in the literature, our trends are congruent

15. To see this more clearly, consider transforming the value of the downloaded series in period t, keyword k, and state a. The downloaded value is given by $\frac{share_{a,t,k}}{\max_{i,t}\{share_{i,t,k\in q}\}}$, where $q \in Q$ denotes the specific query. Dividing by the US value of the same query yields: $\frac{share_{a,t,k}}{share_{US,t,k}}$. The share of searches directed to keyword k in state s at time t relative to the share of searches directed to the same keyword in the same time period in the US. Note that this expression is independent of the composition of states included in the query leaving us with time series comparable across queries. See West 2020 for a more extensive discussion of this issue

Figure 1: Index of Environmental Willingness to Act



Notes: This figure shows our measure of willingness to act built with Google Trends data at the state level. The index is a composite of research popularity for terms relevant for aspects of consumption and behavior to mitigate climate change. Those keywords are "Solar Energy", "Recycling", and "Electric Car".

with the stark decline in environmental awareness presented in Aghion et al. 2023 and the trends of the Gallup survey on concerns about climate change. 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 our empirical exercise, there is significant variation at the state level and over time.

2.2 Evaluating the Index

Using search frequency for keywords as a measure of greener household preferences entails caveats. An online search does not convey the intention of the search, while survey data does. To shed light on how our measure compares to survey data, we contrast it to survey data from the Gallup. Furthermore, we explore the relation with immediate measures of environmentally-friendly changes in consumption behavior drawing from the Consumer Expenditure Survey from the Bureau of Labor Statistics and with support for environmental policies drawing from the American National Election Studies. If our index indeed captures a notion of willingness to act, we expect to observe changes in consumption behavior associated with a lower environmental burden and heightened support for environmental protection.

A second potential caveat is representativeness of our measure. While access to the internet is widespread and Google is the most popular search engine in the US, the types of household using it could be limited and self-selected.[16]

Comparison to Survey Data To shed light on the proximity of our index to survey data on the state level, we turn to the Gallup survey. Gallup conducts and provides surveys on public opinion. The caveat with Gallup data is that it comes at a yearly frequency and questions regarding an environmental willingness to act are recorded only in a limited number of years[17]. Therefore, we use a broader measure of environmental concerns, which is available at a higher frequency, to compare our indices. This comparison, albeit measuring distinct aspects, remains informative to get an idea about how reasonable our index is to measure a greening of preferences which is closely related with environmental concerns. The precise question we consider from the Gallup reads: "How worried are you by climate change?". We use the share of participants that answer "A great deal" to construct a survey-based index following the same steps as for our google trends index.

Figure 2 contrasts for highly populated states[18]—California, New York, and Texas—our indices of willingness to act, environmental curiosity, and the mixed index to the survey-based index based on environmental concerns. There is a remarkable similarity of our index and the survey-based index both over time and across states. In the cases of California and New York the index based on Gallup mimics our indices for willingness to act and the mixed version, while it seems less closely related to the broader measure of general environmental curiosity. As regards the state of Texas, we observe a timely wedge of approximately 2.5 years between the Google Trends and the Gallup-based indices with the latter foreshadowing the former.

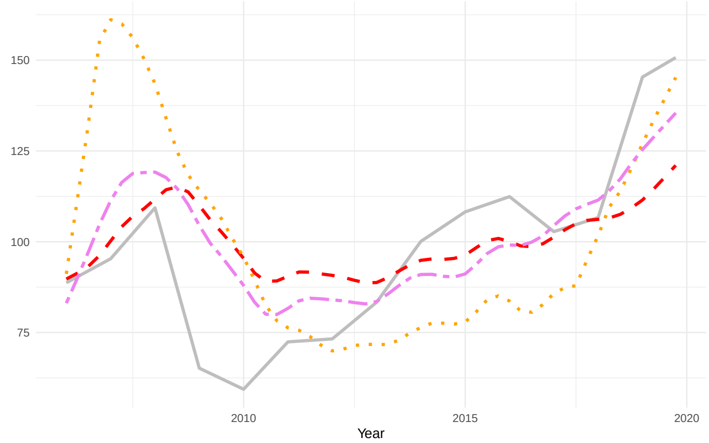
Even though the graphs suggests that the Gallup-based index more closely corre-

16. This selection into treatment may imply a stronger correlation of willingness to act and demand for cleaner cars, if it is especially "doers" who search the web. Our estimates would be upward biased. Conversely, our measures would be downward biased, if a web search mutes the willingness to act. On the other hand, the elderly may be less prone to use google but act socially responsible. We would then overestimate the effect of greener household preferences on firms.

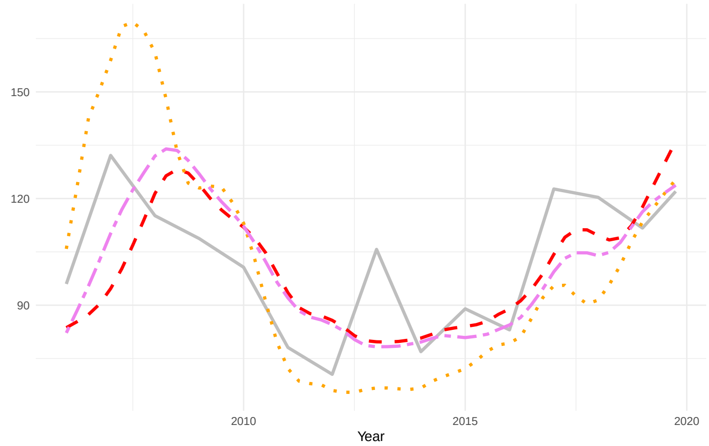
17. Questions concerning a willingness to act, such as, do you recycle, do you adjust your consumption, are only asked in a few years and do not allow for a comparison over time.

18. Since the Gallup is not representative on state level, we focus on the most populated states only.

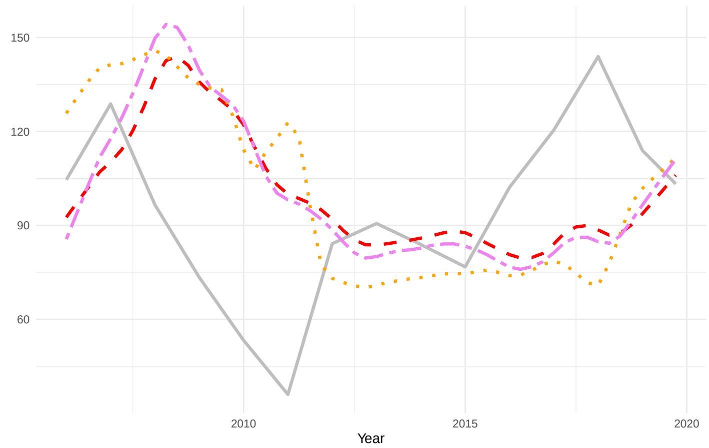
FIGURE 2: Comparison to Survey Data



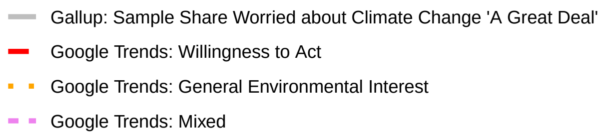
(A) California



(B) New York



(C) Texas



Notes: This figure shows different indices built with Google Trends series at the state level in comparison to an index based on data from the Gallup survey. The Gallup data depicts the share of sample participants answering to the question "How worried are you by climate change?" with the strongest answer, that is "a great deal".

lates with our index of environmental willingness to act, at least for New York and California, it only achieves a 30% correlation for the the four most populated states (California, Texas, New York, and Florida). With a maximum of 63% for New York and a minimum of -30% for Texas. The negative correlation for Texas is explained by the shifts in time. The average correlation increases to 41% when only terms reflecting a general interest in the environment are included. A higher correlation is sensible as the Gallup measure is about environmental worries and not a willingness to act. The maximum correlation here is 76% for New York.

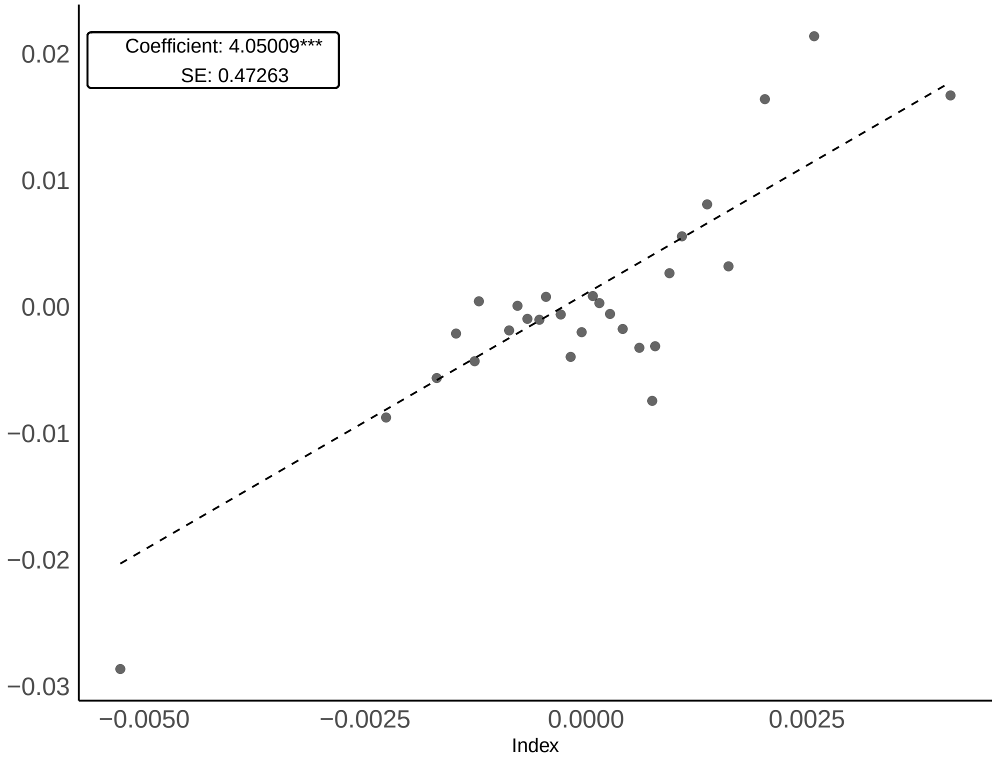
Finally, we depict the federal-level data from the Gallup, which is supposedly representative as a gray dashed graph in Figure 1. Dynamics are similar yet shifted to the left relative to our state-level measures. The Gallup is also characterized by a decline in the share of households worried around the financial crisis with a resurge starting around 2015. On average, the Gallup suggests to foreshadow our measure of willingness to act: Environmental concerns foster a willingness to act.

Our Index and Consumption Having discussed how our measure compares to survey data, we now turn to explore its relation with supposedly climate-friendly consumption behavior. While the previous analysis was suggestive of our index being closely related or even fostered by environmental concerns, this section focuses on whether our measure predicts environmentally-friendly behavior. To this end, we draw from the CEX Survey data provided by the BLS and data on new vehicle registration provided by S&P Global which we describe in more detail in section 3.

Electric Vehicle Consumption on the State Level Figure 3 shows a binned scatter at the state level between our index and the share of electric vehicles in new vehicle registrations. The estimation accounts for time and state fixed effects. The correlation is strongly significant and economically meaningful: A 1 percentage increase in the index is associated with a 0.04 percentage point increase in the share of electric vehicle registrations. This corresponds to roughly 1.2% relative to the weighted average over states of 3.4 percent.

Probability to consume green energy Having looked at correlations on state level, we now turn to the household level. This degree of granularity allows us to account for other household characteristics and to compare their relevance. We focus on the

Figure 3: Index of Willingness to Act and Electric Vehicle Sales at the State Level



Notes: Binned scatter plot depicting the relation of the share of electric vehicles in new registrations on the log-transformed index of willingness to act (demeaned over time and states). One bin represents 1% of the sample. The y-axis shows the demeaned share of electric vehicles in new registrations. Regression line results from fitting a fixed-effects model with state and year-quarter fixed effects. State-level population weights are applied. The number of observations is 2,800.

probability to either spend on electric vehicle charging or having solar panels, which we refer to as a measure of green energy consumption.

Table 2 depicts the results. The index is strongly significant at the 1% significance level for all model specifications. The first model in column (1) is a simple OLS regression. When adding fixed effects for state and time in column (2), coefficient remains significant but its size reduces by more than 50%. Subsequently adding age of the reference person, column (3), a dummy for whether the household lives in a rural area, column (4), and a dummy of whether the household head has a minimum of some college education, column (5), leaves the importance of our index of environmental willingness to act unchanged. Adding a measure of per-capita after-tax income of the household[19] (in 1,000$US per month), raises the size of our index slightly, pointing to a negative correlation between income and our index.

In our preferred specification with all controls, column (6), a one percent increase in

19. The modified OECD equivalence scale is applied.

the index is associated with a 0.04 percentage point increase in the probability to either use electric vehicles or solar panels. This is a meaningful effect equivalent to 1.6% of the observed sample share of 2.8%. The effect size is comparable in magnitude to a 100$US increase in monthly per-capita income which is associated with a 0.03 percentage point increase in the probability to consume electric cars or solar energy.

Table 2: CEX Consumption and Willingness to Act lagged by 6 Months

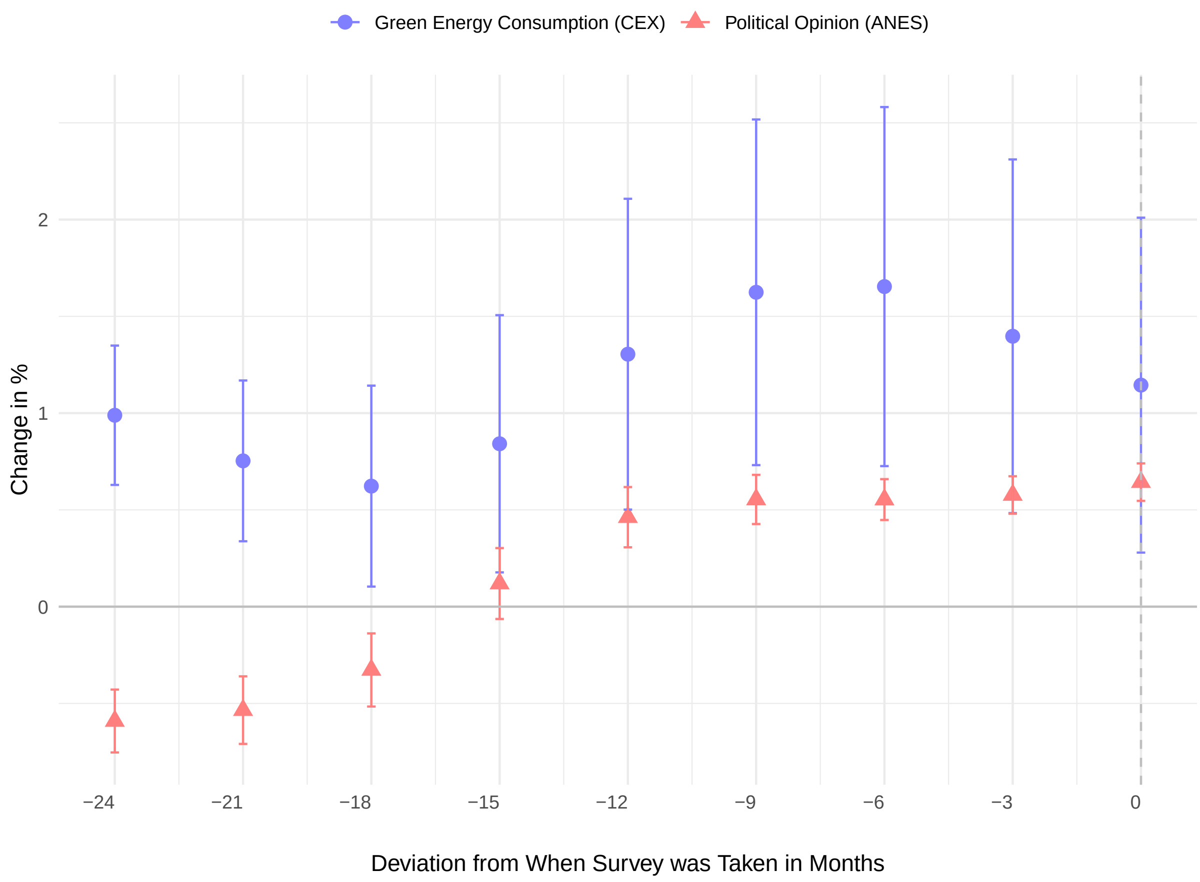
	(1)	(2)	(3)	(4)	(5)	(6)
	Probability to spend on Solar energy or EV					
$\log(\text{Index}_{-6Months})$	0.0858 ***	0.0357 ***	0.0358 ***	0.0357 ***	0.035 ***	0.0393 ***
	(0.0031)	(0.0134)	(0.0134)	(0.0134)	(0.0134)	(0.0134)
Age			2e-04 ***	2e-04 ***	3e-04 ***	3e-04 ***
			(0)	(0)	(0)	(0)
Rural Area				-0.0055 ***	-0.0034 ***	2e-04
				(9e-04)	(0.001)	(0.001)
Education					0.0094 ***	0.004 ***
					(6e-04)	(6e-04)
Income in 1k$US						0.003 ***
						(1e-04)
FE: year-month		X	X	X	X	X
FE: state		X	X	X	X	X
N:	178,262	178,262	178,262	178,262	178,262	177,590

Notes:

Finally, the blue circles in Figure 4 depict the coefficients of Model (6) expressed in percent of the average probability to consume green energy which is at 2.36 percent for different lags of our measure of willingness to act. The vertical lines indicate 10% confidence intervals. The horizontal axis shows the lags relative to the consumption measure. For example, a value of -18 indicates the coefficient of a regression of energy consumption today on the value of our index measured 18 months before. All coefficients are positive and significant at the 10% level indicating that a rise in our index predicts green energy consumption.

Correlations with Political Support of Environmental Protection Having shown that our index robustly predicts higher probabilities of environmentally-friendly forms of energy consumption, we now turn to investigate how it relates with support for environmental protection, another channel through which greener household preferences may affect firm behavior. We use data from the American National Election Studies (ANES) which surveys political opinions of US citizens around election dates. The

FIGURE 4: Coefficients on Index prior of green energy consumption and environmental policy support



Notes: This figure shows regression coefficients of the share of participants supporting an increase in the budget share on environmental protection on different leads and lags of our index of environmental concerns. The x-axis indicates the time structure: at zero the index is measured at the time of the survey. Positive values on the x-axis mean that our index is measured after the survey. Conversely, a negative value means the index precedes the survey.

survey is representative on the federal level. We construct a time series of the reoccurring question on whether a survey participant supports an increase of the federal budget share spent on environmental protection. Alternative answers are ”keep about the same”, ”decrease” or ”don’t know”.[20] The final time series contains 3 years: 2008, 2012, and 2016. Given the variation in the exact month when a survey is conducted the time series contains nine distinct month-year combinations. [21]

As before, we run a linear prediction model of the probability to support a higher environmental budget share and our index of willingness to act with varying lags. The results given in percent relative to the share of households supporting an increase in the environmental budget (48.90 percent) are shown by the red triangles in Figure 4. Again, a higher index predicts a higher share of environmental policy support, but only up to 1 year (12 months) prior to the survey. Values lagged further into the past predict a reduction in the probability to support more environmental protection. Thus, greener household preferences may affect firm strategies through a political channel constituting an additional channel. Looking at the size of the effects, however, the results suggest that our index is more important a predictor of green energy consumption (the blue circles) indicating that the demand channel is more relevant a mechanism relating firm decisions and green household preferences.

The comparisons to survey data, to green energy consumption, and to political opinions jointly suggest that our measure of environmental willingness to act is an appropriate proxy for the greening of household preferences that foster behavioral change. Previous work also 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. Since our index predicts both, consumption and voting behavior, we will have to examine in more depth the importance of either channel in shaping firm strategies.

20. We code refusal to respond and don’t know as missing values. Thus, we consider the share of participants opting for an increase in the set of participants who express a clear opinion.

21. As a concern, perhaps, the considered months are September, October, and November, so that we cannot account for seasonality in political opinions. Then again, it is exactly the time when political opinions matter most for actual policy, namely, around election times.

3 Other Data and Summary Statistics

In the rest of the paper, we will study how firms respond to a greening of household preferences. We now detail the remaining data sources we exploit and provide summary statistics.

Vehicle sales: S&P Global. The data on new vehicle registrations is sourced from *S&P Global* covering the years 2006 through 2019.[22] 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.[23] 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.

Fires: FIRMS. In the main analysis, 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.[24] 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).[25] 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-

22. https://www.spglobal.com/mobility/en/products/automotive-market-data-analysis.html

23. 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.

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

25. 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.[26]

Lobbying: LobbyView and US Senate Lobbying Disclosure Act Reports. Following the Lobbying Disclosure Act of 1995, all lobbyists ought to register their lobbying activity with the US 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.[27]

To classify environmental lobbying into pro- and anti-environmental, we follow Kwon, Lowry, and Verardo 2023 and use political leaning of hired lobbyists to proxy the intention behind environmental lobbying. The idea is that a firm would rather hire a republican lobbyist to lobby against environmental regulation and a democrat-leaning lobbyist to argue for more environmental regulation. To determine whether a lobbyist is republican or democrat, we use information on campaign contribution by lobbyists and past relationships with legislators. We exploit information on lobbyist-firm linkages on a report basis from raw lobbying reports provided by the US Senate Lobbying Disclosure. In the end, pro-environmental lobbying includes all lobbying activities on environmental issues for which democrat lobbyists are hired, and symmetrically, anti-environmental lobbying is the activity relying on republican democrats targeting environmental issues.

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

26. The distance is computed between the fire's and the state's center of gravity.

27. 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.

manual inspection.[28] Following Aghion, Dechezleprêtre, Hémous, 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.[29]

Finally, following Hall 2005 and Bloom, Draca, and Reenen 2016, we compute a measure of *knowledge stock*, K_{ist}, according to the recursive identity:

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

Where R_{ist} represents the number of new patents from firm i in technology s, with $s \in \{\text{clean, gray, dirty}\}$. The variable δ captures the depreciation of knowledge.[30] 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.[31]

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; the 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 Trans-

28. https://patentsview.org/disambiguation
29. The classification of patents into these three categories by their Cooperative Patent Classification code can be found in subsection E.2 in the Appendix.
30. 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 $ln(1+$ Patents) that may bias our results.
31. The number of patent applications may not reflect actual investment in R&D. To bypass this issue, we present a robustness exercise weighting patent applications with an estimation of its private economic value from Kogan et al. 2017 updated until 2020 and with their respective citations. Our main results remain unchanged.

portation 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.

3.1 Summary Statistics

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

Innovation and Lobbying. Our dataset is composed of 17 groups, which are the main groups of the automotive sector offering private cars.[32] 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.[33] Table 3 reports the distributions of our main outcome variables, and Table 4 reports average make characteristics.

TABLE 3: 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 3 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 13 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

32. We remove from the sample groups with less than 30,000 registered cars over the whole period and truck-only companies.
33. 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.

patents rose by a factor of five during the period.[34] 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.[35]

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

TABLE 4: 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.[36] The average expenditure is US$683,000 with a maximal expenditure of more than US$6,3 million.[37] Splitting lobbying expenditures according to targeted topics at

34. 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.

35. These trends are congruent with trends presented in Aghion, Dechezleprêtre, Hémous, et al. 2016; Aghion et al. 2023.

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

37. 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.

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 10 in the Appendix compares market shares across makes over the US A more bluish (redish) color means that the area represents 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 US (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.

Exposure to wildfires. Because some confounders could affect consumer preferences and firm behavior, we instrument the index of green preferences by the exposure of populations to fires. Figure 11 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.

4 Empirical Strategy

In this section, we introduce a quasi-experimental shift-share design to estimate the causal effects of changes in consumers' willingness to act on firm behavior. We elaborate on the construction of our instrument, the model specification, and the assumptions underlying identification of the desired effect.

4.1 Research Design

We seek to estimate the effect of a change in consumers' willingness to act on firms. The ideal experiment would, all else equal, change random firms' consumers' willingness to act. However, such willingness is an endogenous object. To approximate the ideal experiment, we only consider changes in consumer attitudes that are as good as randomly assigned across firms by employing a shift-share instrumental variable (IV) design. Therefore, we leverage two components: localized shocks to consumer attitudes and firm predetermined exposure shares to local markets. The analysis is conducted at the firm-quarter level.

Firm Treatment. We employ our index on consumer attitudes derived from Google Trends, ENV_{lt}^{GT}, (see section 2) as a proxy for household willingness to act. We weigh this index 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}. We specify our model in changes over a two year horizon (eight quarters) in our baseline estimation. This gives us a measure of firm exposure to local consumer attitudes:

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

Where $s_{ilt} = \dfrac{S_{ilt} - S_{ilt-h}}{S_{it} - S_{it-h}}$ is the share of sales of firm i in state l over the period $t-8$ to t relative to total sales of that firm in that period. Shares sum to one over states for a given time and firm.[38]

Instrument. Regressing firm behavior on changes in consumers' willingness to act by ordinary least squares would suffer from, first, reverse causality, for example because firm innovation behavior may affect consumer attitudes through the supply of cleaner goods. Second, omitted variables may coincide with changes in attitudes and move firm behavior, such as state-level environmental policies. Therefore, we only use the variation in our index that follows unexpected changes in wildfires—henceforth referred to as "shocks". More precisely, we measure shocks as changes in states' exposure to

38. Note that these shares are not predetermined while the instrument is build using predetermined shares. This is possible because the instrument and not firm exposure to environmental attitudes require uncorrelatedness to the error term for the validity of our methodology.

wildfires (see section 3) over a period of 8 quarters

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

Based on these state-level shocks, we construct our instrument for firm exposure to green consumer attitudes. To this end, we rely on predetermined shares from firm local sales lagged by 8 quarters; similarly to the construction of the treatment variable yet shifted in time to the base period $t - h$.[39] The instrument is given as a weighted average of changes in states' exposure to wildfires:

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

Model Specification. We measure outcome variables as the change over two years of the logarithmic transformation of the variable: $\Delta y_{it} = \log y_{it} - \log y_{it-8}$.[40] The main regressor of interest is the change in the standardized environmental attitudes index, ΔENV_{it}^{GT}, which we instrument with the weighted change in wildfires, Z_{it}. In sum, we estimate the following model by 2 stage least squares (2SLS):

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

Where 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 attitudes, conditional on a set of controls X_{it}.[41]

4.2 Identification and Inference

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

39. That is, predetermined shares capture the difference in the periods from $t - 16$ to $t - 8$. It is important to use predetermined sales since firms may strategically change their exposure to markets in response to our shocks. By using lagged exposure, we make sure to capture variation that comes only from the shocks thereby mitigating reverse causality arising from contemporaneous shares.

40. Thus, in the baseline specification of our model, outcome variables are measured in the same time period as our index of the willingness to act.

41. This interpretation holds true because changes are measured relative to a base period $t - 8$ which are unaffected by our shocks. Time indices refer to end-of period values.

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), holds under endogenous exposure shares with quasi-random shock assignment. Our study belongs to the latter category. This is natural in our setting because the shares are the equilibrium outcome of firms' strategic decisions. However, the change in attitudes triggered by wildfires can be considered as quasi-random conditional on controls. The relevant assumptions are (i) quasi-random shock assignment, (ii) many uncorrelated shocks, and (iii) relevance of the instrument.

Before we turn to discuss each assumption, we introduce a helpful transformation of our model. In the context of a shift-share design 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 which in our case corresponds to the state level, IV regression weighted by the average exposure of firms to a given state l: $s_{lt} = \frac{1}{N}\sum_i s_{ilt}$ (the average is taken over firms). The shock-level representation of equation (4) is defined as:

$$\widetilde{y}_{lt} = \beta \cdot \Delta\widetilde{ENV}_{lt}^{GT} + \widetilde{X}_{lt}'\gamma + \widetilde{\varepsilon}_{lt}. \tag{5}$$

Where $\widetilde{v}_{lt} = \frac{\sum_i s_{ilt-h} v_{it}}{\sum_i s_{ilt-h}}$ is the exposure-weighted average of variable v_{it}. This transformation has a few interesting properties: First, 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, while the interpretation remains the same. Second, this equivalent regression can be estimated with 2SLS, plugging in directly the shocks $\Delta\widetilde{FIRE}_{lt}$ as the instrument. Now, we are equipped to discuss the assumptions.

Quasi-random shock assignment. This condition requires that $\mathbf{E}[\Delta FIRE_{lt}|\bar{\varepsilon}_{lt}, \widetilde{X}_{lt} s_{t-h}] = \widetilde{X}_{lt}' \cdot \mu$. This implies that shocks are quasi-randomly assigned conditional on shock-level unobservable $\bar{\varepsilon}$, state average lagged exposure s_{t-h}, and shock-level observables $\widetilde{X}_{lt}$. 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 implying 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 weights s_{lt-h}, the average firm exposure to state l. Our effective sample size is large (above 700) and our largest importance weight s_{lt} is below 1%.[42]

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 6 in the Appendix visualizes the first-stage revealing a strong positive correlation between exposure to wildfires and green consumer preferences. 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), which in turn shape the wish to consume clean goods. 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.

4.3 Treatment Correlation and Robust Standard Errors

Our wildfire shocks, $\Delta FIRE_l$, generate dependencies in the instrument Z_i and in the residuals for automotive groups with similar exposures s_{il}. Consequently, the residuals are correlated across groups that share comparable exposures. As demonstrated by Adao, 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.[43] Moreover, this setting allows to account for the dependence of the errors by 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.[44]

42. 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 (Borusyak, Hull, and Jaravel 2022). We report the related statistics in Table 9 in Appendix A.

43. 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).

44. 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.

5 Results

This section details our results. First, we discuss the instantaneous effects of greener household preferences. Second, we take a dynamic perspective discussing local projection results.

5.1 Static baseline results

Our main results are shown in Table 5. The first two panels report results for our aggregate variables of innovation lobbying activity.[45] The following four panels decompose changes in innovation activity into changes in the stock of clean, dirty, gray and non-classified patents in a firm, respectively measured as the knowledge stock detailed in Section 3. 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. The last three panels focus on lobbying activities specifically targeting environmental issues. The first panel analyses firm response to green preferences on the overall environmental lobbying and the following two panels seek to decompose environmental lobbying based on political objectives, that is into anti-environmental and pro-environmental lobbying.[46]

Table 5 separates into the OLS estimates, in columns 1 to 4, and our preferred IV estimates, in columns 5 to 8. The first column applies a bare-bone specification that includes no further covariates. The OLS estimates suggest a positive correlation between the change in consumers' environmental interest and the change in both (anti-) environmental lobbying and clean patenting. Gray patenting and pro-environmental lobbying seem to decrease seem to decrease in response to greener consumer preferences.

The following four columns repeat the same specifications instrumenting the change in household preferences by wildfire exposure. The IV approach mitigates results about reverse causality: firm strategies may affect household preferences, for example, through advertisements. Furthermore, this strategy also takes care of confounding factors that affect both household preferences and firm strategies, such as environmental policy measures. Column (5) depicts the results of the IV estimation. While we do not observe an effect on total lobbying activity, lobbying on environmental topics increases and pro-

45. 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. Details on how lobbying expenditures are aggregated between issues can be found in **??** in the appendix.

46. Anti- and pro-environmental lobbying measures are based on the relationship of the lobbyists to the Republican and Democratic Party as explained in Section 3.

environmental lobbying decreases as a consequence of environmental concerns. This suggests a reallocation of the lobbying activity within topics and a redirection of the activity towards Republican legislators. Also, while we confirm the increase in firm clean patenting after a contemporaneous increase in green preferences, we additionally find an increase in dirty patenting of about half the magnitude. Both gray and non-classified patenting respond to decrease as environmental interest rises.[47]

Wildfire exposure per se is most likely correlated with state-level policies and firm strategies other than through household preferences threatening the exclusion restriction of our empirical strategy. We therefore control for potentially correlated variables. In column (6), we augment the model with a set of demographic controls, such as population, the share of urban population and income per capita. In column (7), we add controls for transportation habits and policies. In particular, we control for the share of the population commuting by personal car and state-level investments in transportation infrastructures. We also control for the state-level price of fuel and whether the state adopted California's light and heavy-duty vehicle regulations under Section 177 of the Clean Air Act. Finally, we control for the score for Republicans in the last presidential elections in column 8 to account for differences in policies on the state-time dimension that are not captured by the fixed effects. These specifications further address the concern that firms might respond to political changes and not household preferences. In all three specifications, the controls leave the results of similar magnitude and significance.

The results are economically meaningful. A one percent increase in environmental concerns implies a rise in the growth rate of environmental lobbying expenditures by 5.1 percent. Our results also imply that a one percent increase in the willingness to act spurs the the growth rate of green innovation on average by 4.5 percent and the growth rate of dirty innovation by 1.6 percent.[48]

The previous analysis leaves the impression that greener household preferences contribute to a green transition by spurring clean innovation. However, the positive effect on both dirty innovation and the reallocation of environmental lobbying towards anti-environmental lobbying suggest that firms also cope with the shock in the short-term

47. These results are in line with Aghion et al. 2023 who find that exposure to greener attitudes fosters clean innovation.

48. Note that our measure of innovation only capture the intensive margin. The rise of the total patent stock being higher that the rise of both clean and dirty innovation reflects the fact that firms started innovating on clean innovation, result on the extensive margin that is not captured in the third panel.

Table 5: Regression Estimates: Effect of Greener Household Preferences on Firms Outcome

	OLS				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Aggregates								
Δ_8 *Innovation (Patent Stock)*								
$\Delta_8 ENV^{GT}$	4.06***	3.47***	3.28***	2.71*	7.51***	7.41***	6.13***	6.12***
	(1.40)	(1.07)	(1.19)	(1.45)	(0.60)	(0.51)	(0.47)	(0.48)
$\Delta_8 ln(lobby)$ (*Total*)								
$\Delta_8 ENV^{GT}$	3.74**	1.52	4.46**	2.55	-0.27	-1.94*	0.02	-0.38
	(1.75)	(2.06)	(1.77)	(2.13)	(1.06)	(1.13)	(0.92)	(1.08)
Decomposition Innovation								
Δ_8 ln(*Clean Patents Capital*)								
$\Delta_8 ENV^{GT}$	3.70***	3.52***	3.44***	3.04***	4.54***	4.50***	3.67***	3.54**
	(1.05)	(1.30)	(1.10)	(1.05)	(1.07)	(1.29)	(1.34)	(1.36)
Δ_8 ln(*Dirty Patent Capital*)								
$\Delta_8 ENV^{GT}$	1.38	1.23	1.12	0.44	2.35***	2.46***	1.66***	1.63***
	(0.98)	(0.85)	(0.86)	(1.07)	(0.75)	(0.70)	(0.50)	(0.48)
Δ_8 ln(*Gray Patent Capital*)								
$\Delta_8 ENV^{GT}$	-4.60***	-4.64***	-4.85***	-4.41***	-7.68***	-7.94***	-8.23***	-8.23***
	(1.29)	(1.31)	(1.53)	(1.31)	(0.74)	(0.76)	(0.90)	(0.91)
Δ_8 ln(*Non Classified Patent Capital*)								
$\Delta_8 ENV^{GT}$	-0.64	-0.40	0.32	-0.14	-2.83***	-2.66***	-1.46**	-1.53**
	(0.51)	(0.61)	(0.71)	(0.65)	(0.65)	(0.48)	(0.63)	(0.61)
Δ_8 ***Decomposition Lobbying***								
Δ_8 *Environmental lobbying*								
$\Delta_8 ENV^{GT}$	12.76***	12.14***	12.58***	11.68***	6.79***	5.92***	5.45***	5.11**
	(2.14)	(2.27)	(2.47)	(2.36)	(0.74)	(1.31)	(1.93)	(2.09)
Δ_8 *Anti-env lobbying*								
$\Delta_8 ENV^{GT}$	3.76***	3.74***	3.82***	4.11***	0.90**	0.66	0.25	0.07
	(0.95)	(1.03)	(1.17)	(0.99)	(0.44)	(0.51)	(0.67)	(0.69)
Δ_8 *Pro-env lobbying*								
$\Delta_8 ENV^{GT}$	-3.72**	-4.76**	-2.98**	-5.22***	-4.27***	-5.13***	-2.32**	-2.41**
	(1.42)	(1.87)	(1.38)	(1.70)	(0.81)	(0.84)	(1.15)	(1.19)
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)	1970	1970	1970	1970	1970	1970	1970	1970
Montiel-Pflueger first-Stage F					218	207	114	114

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 green preferences index that is constructed in section 3. 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 3 section.

by trying to offer more competitive fuel cars. It seems therefore imperative to assess the effectiveness of intrinsic changes in household behavior considering a longer horizon which we will do in the next section.

5.2 Dynamics

Figure 5 depicts dynamic responses of the total knowledge stock and lobbying in Panel (A), the responses of knowledge stocks by sort of technology (Panel (C)), and anti- and pro-environmental lobbying in Panel (E).[49] We find a strong and significant increase in overall patenting behavior of firms which only decays after roughly 12 quarters and a less clear but equally sizable reduction in total lobbying expenditures. As household preferences become greener, firms find it profitable to spur innovation.

Panel (C) is informative on the type of innovation driving the increase. Innovation on clean vehicle types explains the rise in innovation activity: The growth rate of clean knowledge accelerates by roughly 5 percent until 10 quarters after the change in environmental preferences before it returns to its counterfactual long-run growth rate. For dirty innovation the response differs: in contrast to the short-lived instantaneous increase in dirty innovation, there is no response until 12 quarters after the shock. Only the long run growth rate of dirty innovation reduces by roughly 5 percent, albeit persistent so until 5 years after the shock. Somewhat surprisingly, innovation on technologies that make combustion engines less polluting declines over the full horizon considered.

This pattern suggests that greener household preferences direct R&D investment towards clean vehicles away from research on other environmentally-friendly technologies. This finding underlines the power of greener consumer preferences to initiate a transition towards new technologies away from making old and polluting ones less polluting.

When looking at the composition of lobbying expenditures, the effect of greener household preferences becomes more ambiguous (Panel (E)). We find a strong and persistent decline of pro-environmental lobbying expenditures with more than 15 percent declines in the long-run growth rates. Anti-environmental lobbying expenditures, especially in the short run, increase. In sum, the share of anti-environmental lobbying increases having adverse and prolonged negative effects on the environment.

Taking together, our results point to firms using a combination of clean innova-

49. Results are growth rates relative to the base period for different horizons.

tion and lobbying to cope with greener household preferences. Relatively more anti-environmental lobbying helps maintain the status quo guarding revenues from established, polluting products. The greening of the composition of knowledge stocks, in turn, suggests a long-run strategy dealing with a change in household preferences.

5.3 Discussion

In this section, we want to gauge the effectiveness of greener household preferences a bit better by comparing our results to the effect of fuel prices.

The right-hand side of Figure 5 depicts the dynamic responses to an increase in fuel taxes of the same variables as discussed above. We exploit on arguably exogenous changes in fuel taxes from abroad. Variation in exposure comes from heterogeneous predetermined revenue shares of firms.[50]

Our results are largely in line with Aghion, Dechezleprêtre, Hemous, et al. 2016: Clean innovation rises from the short to medium run upon a 1 percent increase in fuel prices, while dirty innovation reduces mildly in the medium run. In the long run, there is no significant difference in growth rates to a counterfactual situation without fuel price increase.[51].

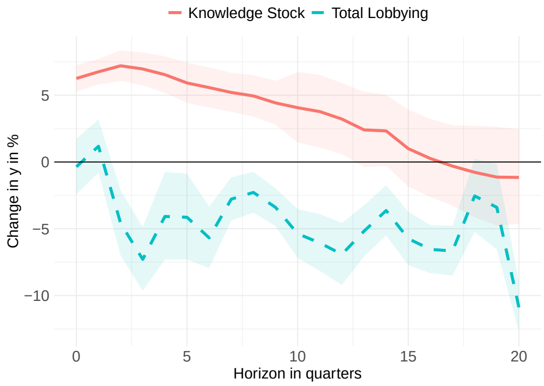
Three differences to greener consumer preferences stand out: First, the response in clean innovation is more slowly and less pronounced (at most a rise of below 0.4 percent as opposed to roughly 5 percent). Second, dirty innovation remains unchanged in the long run in response to higher fuel prices, while greener household preferences seem to have a persistent negative effect on dirty innovation. Thirdly, research on gray technologies remains unchanged in contrast to the effect of a greening in household preferences where gray innovation declines substantially and persistently.

The response in lobbying is qualitatively similar, Panel (F), to greener household preferences but less strong. What stands out is the rise in pri-environmental lobbying in the long run. This rise may be driven by firms having invested in cleaner technologies previously. Lobbying now for environmental regulation tailored to these technologies emerges as an instrument to protect clean markets from competitors. A similar surge in pro-envrionemntal lobbying is also visible in response to greener household preferences; yet, it is not strong enough to become positive.

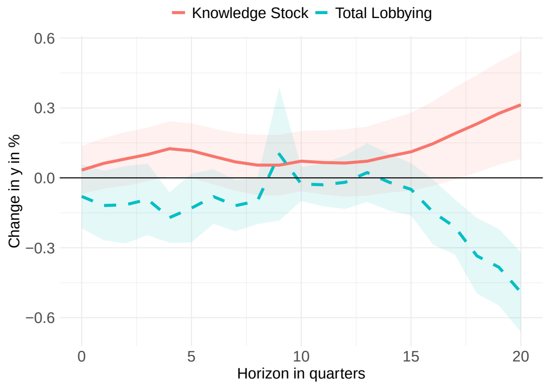
50. This analysis is closely related to Aghion, Dechezleprêtre, Hemous, et al. 2016, however, we use shares predetermined to each period and not the whole period of analysis. We opt for this approach in order to maintain Tesla in our sample which did not yet exist before our period of analysis.

51. There is no significant change in gray innovation activity

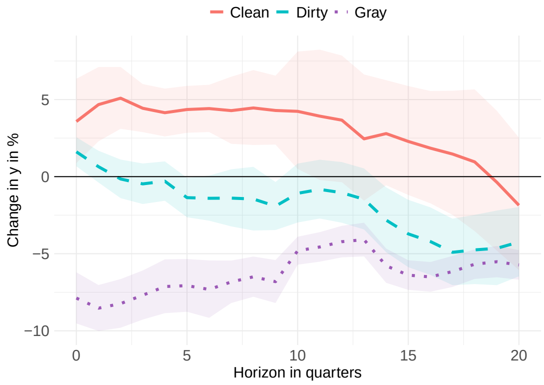
FIGURE 5: Effect of Fuel Prices



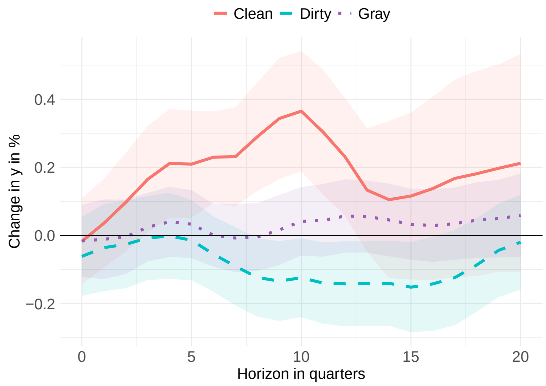
(A) Total Knowledge Stock and Lobbying: Greener Preferences



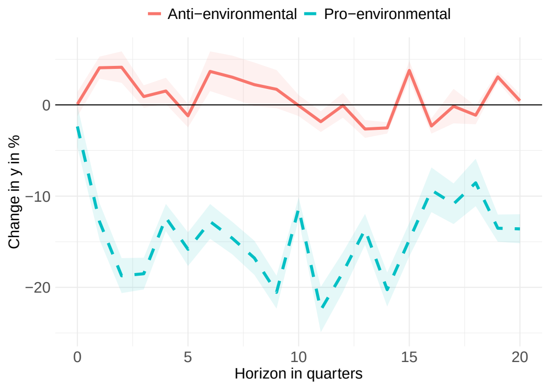
(B) Knowledge Stock and Lobbying: Fuel Prices



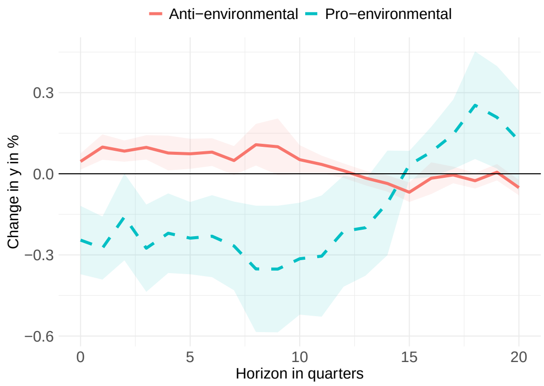
(C) Knowledge Stocks: Greener Preferences



(D) Knowledge Stocks: Fuel Prices



(E) Env. Lobbying: Greener Preferences



(F) Env. Lobbying: Fuel Prices

Note: Graphs show impulse responses of key variables to a one percent increase in our index of green household preferences or fuel prices according to the specification $\Delta y_{i,t+h} = \lambda_t^h + \alpha_i^h + \beta_{i,t}^h \Delta ENV_{i,t}^{GT} + \gamma^h X_{i,t} + \epsilon_{i,t+h}$, for quarters h=0, ..., 20 after the shock. Shaded areas are 90% error bands, and standard errors are clustered at the state level.

6 Robustness

In this section we present our robustness analyses: Results when using an alternative empirical strategy based on observed sales in subsection 6.1, alternative instruments in subsection 6.2, and results with different measures of innovation in **??**.

6.1 Alternative Measures of Demand

Our main analysis aims at estimating the effect of a change in social responsibility on lobbying and innovation outcomes. As demand is not measurable, we proxy it by environmental interest.[52] 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: [53]

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

With N_{ct} the number of clean vehicles sold in a cell c at time t.[54]

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

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

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

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

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 5.

Table 6: Effect of Environmental Preferences of Firms Outcome - Alternative Strategy

	Aggregates		Decomposition Innovation				Decomposition of Lobbying		
	Knowledge Stock (1)	Total Lobbying (2)	Clean Know. Stock (3)	Dirty Know. Stock (4)	Grey Know. Stock (5)	Non-classified Know. Stock (6)	Environmental Lobbying (7)	Pro Env. Lobbying (8)	Anti Env Lobbying (9)
$\Delta_8 Demand^{clean}$	2.03***	-0.12	1.17**	0.54***	-2.72***	-0.51**	1.69**	-0.80*	0.02
	(0.25)	(0.35)	(0.52)	(0.16)	(0.41)	(0.22)	(0.80)	(0.42)	(0.23)
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)	1970	1970	1970	1970	1970	1970	1970	1970	

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.

6.2 Alternative Instruments

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 from the National Oceanic and Atmospheric Administration (NOAA) Monthly U.S. Climate Divisional Database as instruments. More precisely, we use the log average temperature, the log maximum average temperature and 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.[55]

Table 7: Effect of Green Consumer Preferences on Firms Outcome - Alternative Instrument

	Patent Stock	Total Lobbying	Clean Stock Stock	Dirty Stock	Grey Stock Stock	Non Classified Stock	Env. Lobbying	Pro Env. Lobbying	Anti Env Lobbying
$\Delta_8 ENV^{GT}$	2.03***	-0.12	1.17**	0.54***	-2.72***	-0.51**	1.69**	-0.80*	0.02
	(0.25)	(0.35)	(0.52)	(0.16)	(0.41)	(0.22)	(0.80)	(0.42)	(0.23)
FE: year-quarter	X	X	X	X	X	X	X	X	X
Lagged Firm Controls	X	X	X	X	X	X	X	X	X
Lagged Demographic Controls	X	X	X	X	X	X	X	X	X
Lagged Transportation Controls	X	X	X	X	X	X	X	X	X
Lagged Political Controls	X	X	X	X	X	X	X	X	X
First-Stage F									
N (states - periods)	1970	1970	1970	1970	1970	1970	1970	1970	1970

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 green preferences index that is constructed in section 3 and is instrumented by different measure of extreme temperatures and extreme precipitations as described in the text.

Our results are qualitatively very similar to the estimated coefficients of our benchmark regression reported in Table 5. In particular, we confirm that environmental interest spurs clean innovation and increases dirty innovation with a less pronounced effect. We report a positive effect on environmental lobbying and a negative effect on pro-environmental lobbying expenditures, similarly to the one reported in the dynamic results presented in Figure 5. We also confirm the decrease in gray innovation and non-classified innovation.

Our estimates remain economically meaningful, yet, the estimated coefficient on clean innovation falls from 3.5 to 1.2, the coefficient on dirty innovation decreases from 1.6 to 0.5, and , the estimated coefficient on environmental lobbying declines from 5.1 to 1.7.

7 Conclusion

Climate change and environmental pollution raise household solicitude about the environment and demand shifts to greener goods. How do firms react to greener household preferences? The literature points to the innovation of cleaner technologies as a response (Aghion et al. 2023). While we confirm this result, we also show that there exists another margin of adjustment: anti-environmental lobbying.

55. More details on the data can be found in subsection 6.2 in the Appendix.

More precisely, we examine firm responses in the automotive industry to exogenous changes in consumers' social responsibility in the U.S. from 2006 to 2019. To this end, we construct a novel index capturing households' environmental willingness to act based on Google Trends data. This measure allows us to study firm responses to changing household behavior in a panel setting.

Our results suggest that greener consumer preferences are extremely effective in inducing a technological green transition; yet, they entail a rise in anti-environmental lobbying thereby aggravating environmental regulation. The possibility to protect profits through lobbying against stricter environmental regulation makes greener household preferences—contrary to intuition—slow down a green transition.

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Appendix

A Additional Summary Statistics

Table 8: 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 9: 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

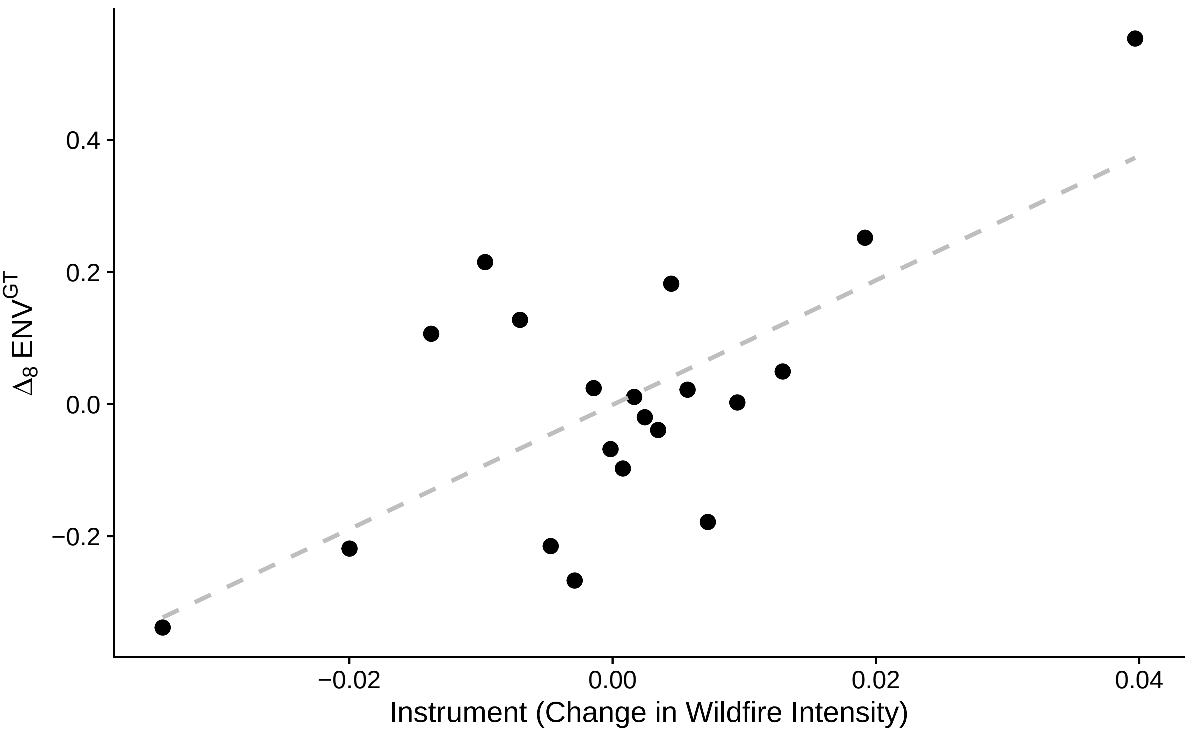
Panel B: Shares Summary Statistics

	Mean	Max
$1/HHI$	743.68	743.68
s_{lt} (pct)	0.05	0.50
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).

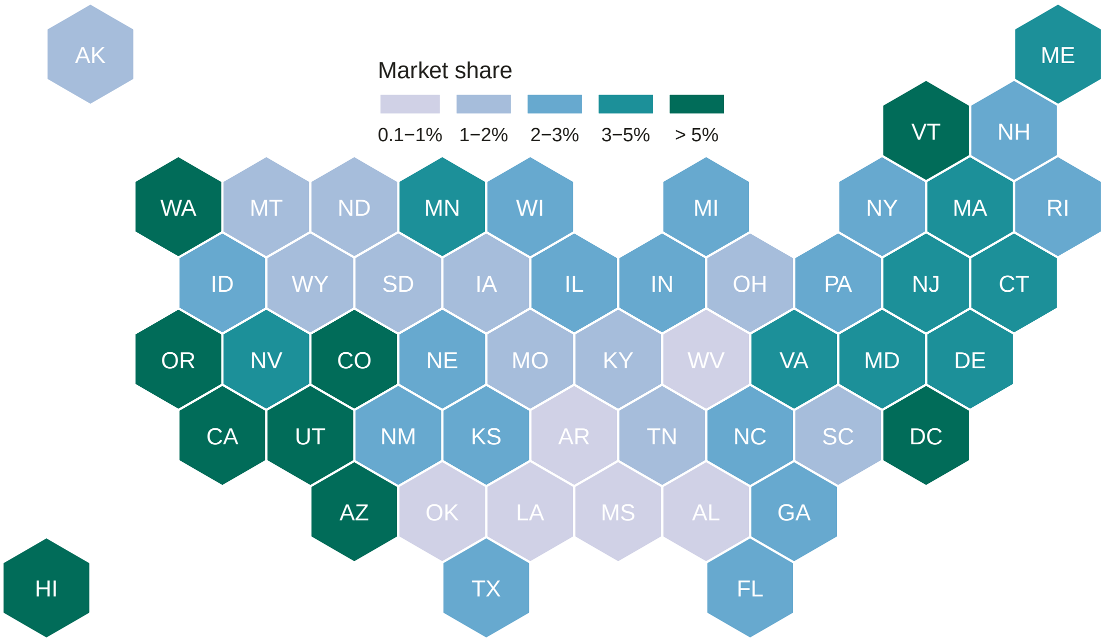
B Additional Figures

Figure 6: First-stage estimation, shift-share IV



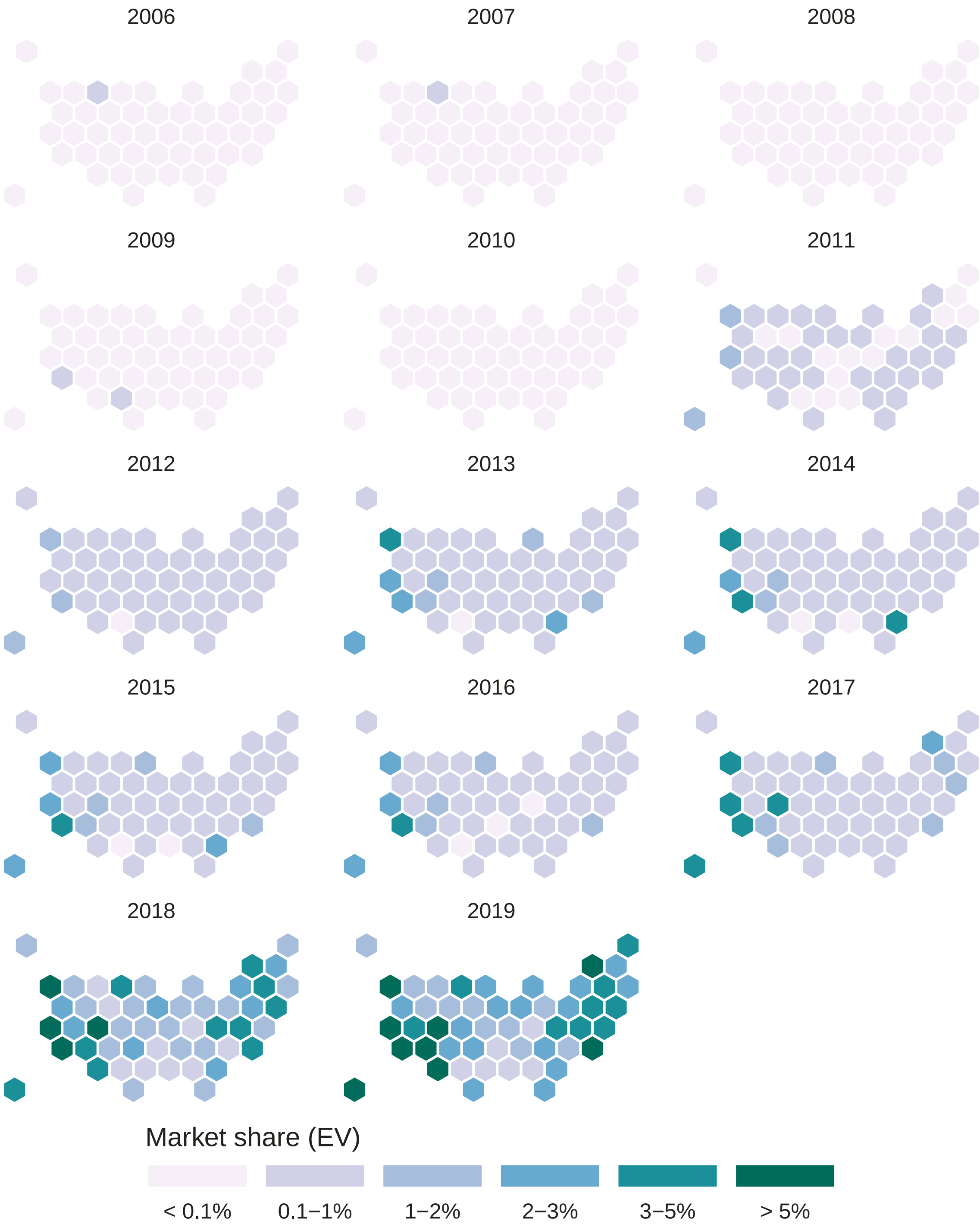
Notes: The figure plots the reduced-form relationship underlying our shift-share IV design. It plots the correlation between our instrument (in x-axis) and change in the environmental preferences index (in y-axis). Each point accounts for 5% of the data. The data is first residualized on a set of firm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

FIGURE 7: Market Share of Electric Vehicles in 2019



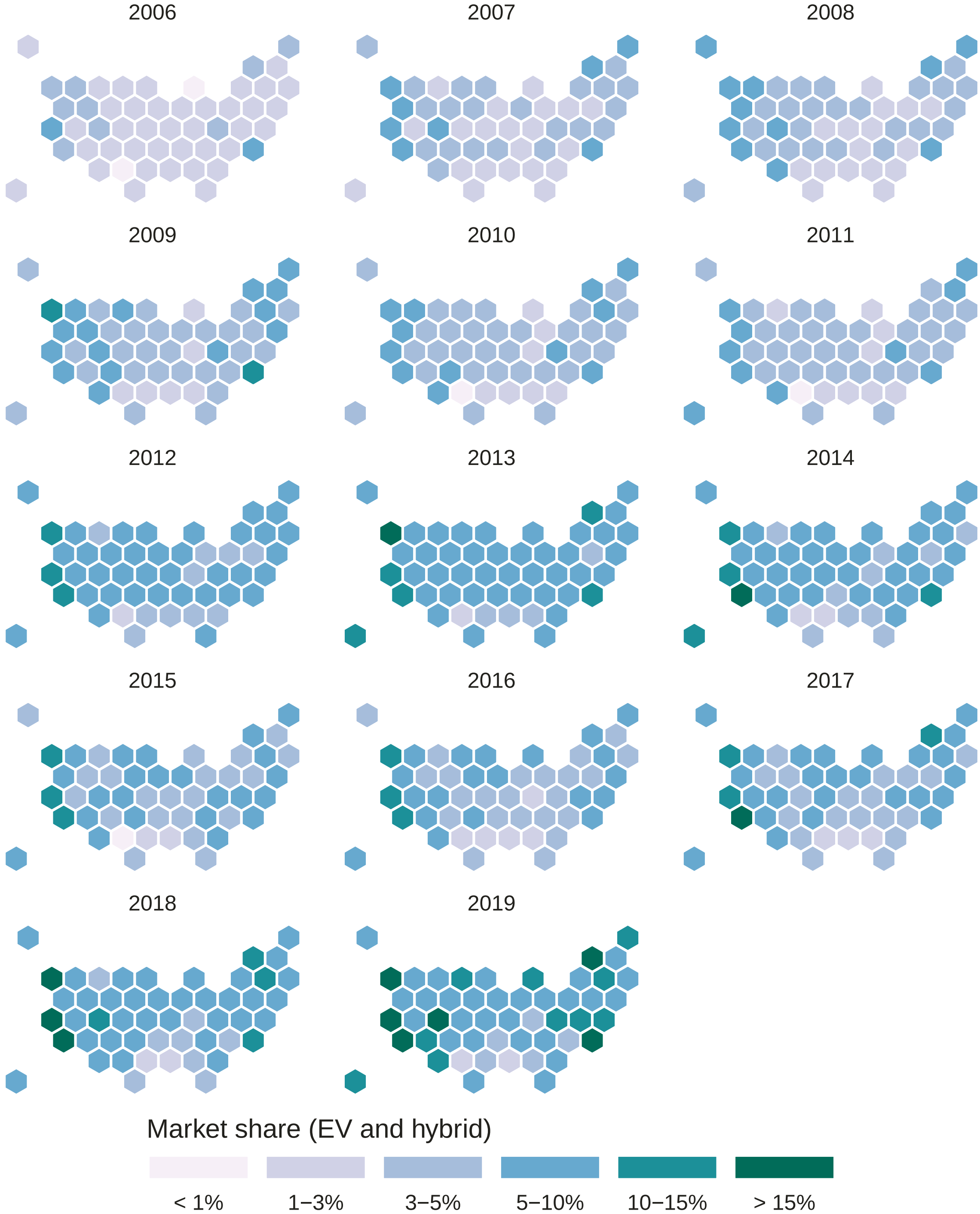
Notes: The figure shows the market share of electric vehicles in each U.S. states for vehicle registrations in 2019. The market shares are computed as the fraction of clean passenger cars registered over total passenger cars registrations in the state.
Source: S&P Global, authors' calculation.

Figure 8: Market Share of Electric Vehicles



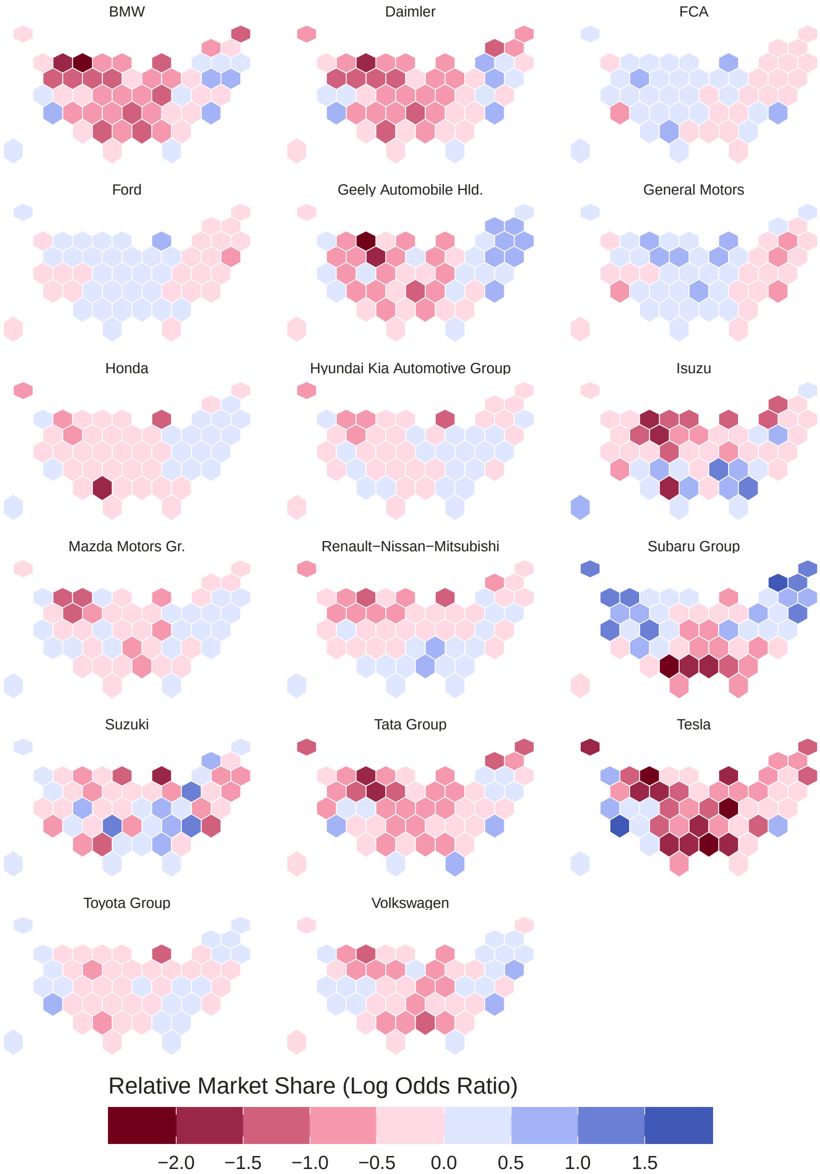
Notes: The figures show the market shares of electric vehicles in each U.S. states between 2006 and 2019. The market shares are computed as the fraction of clean cars registered over total passenger cars registrations in the state.
Source: S&P Global, authors' calculation.

FIGURE 9: Market Share of Low Emission Vehicles



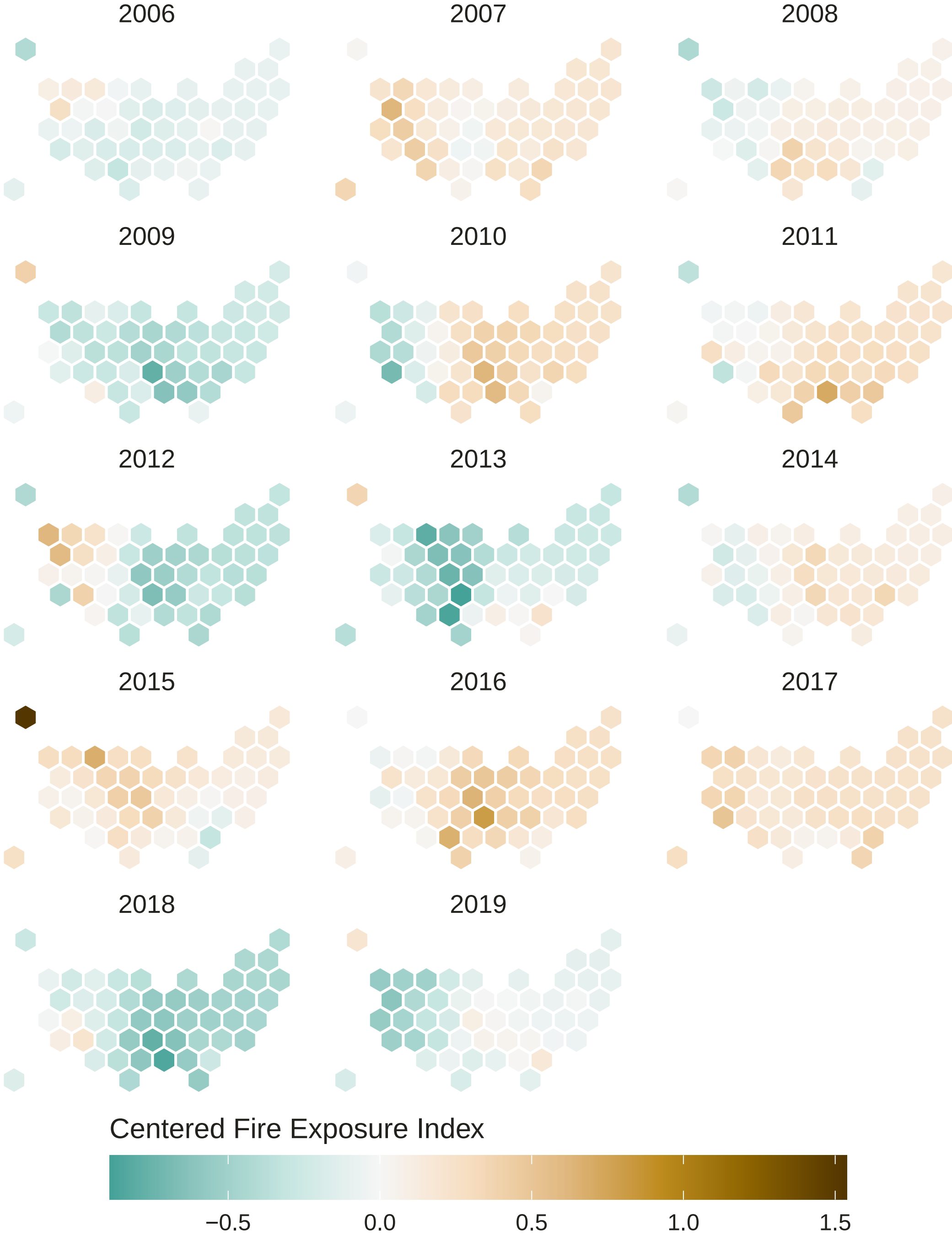
Notes: The figures show the market shares of low emissions vehicles in each U.S. states between 2006 and 2019. The market shares are computed as the fraction of clean cars registered over total passenger cars registrations in the state.
Source: S&P Global, authors' calculation.

FIGURE 10: Relative Market Shares (log Odds-Ratio)



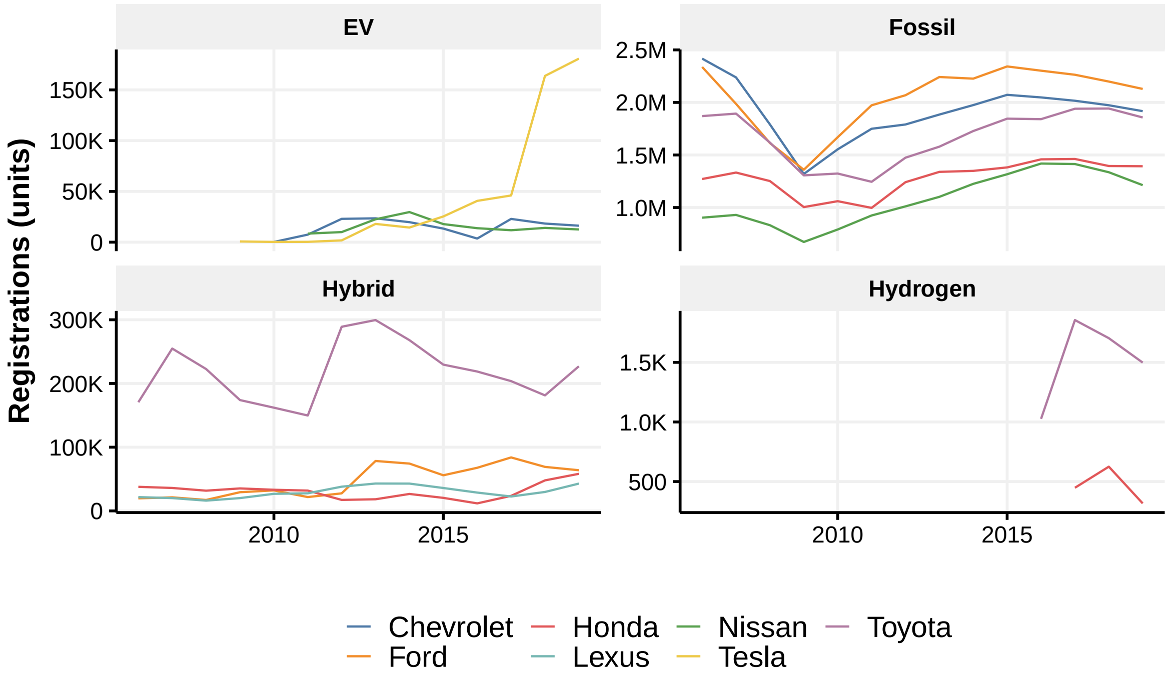
Notes: The figures show the relative market share of each make, compared to the other makes. We define $p_{il} = P(l|i)$ the proportion of vehicles registered in state l for a make i, and $p_{0l} = P(l|\neg i)$ the proportion of vehicles not made by i registered in state l. Then the log odds-ratio is $r_{li} = log\left(\frac{p_{il}/(1-p_{il})}{p_{0l}/(1-p_{0l})}\right)$. 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 11: Centered Fire Exposure Index (yearly average)



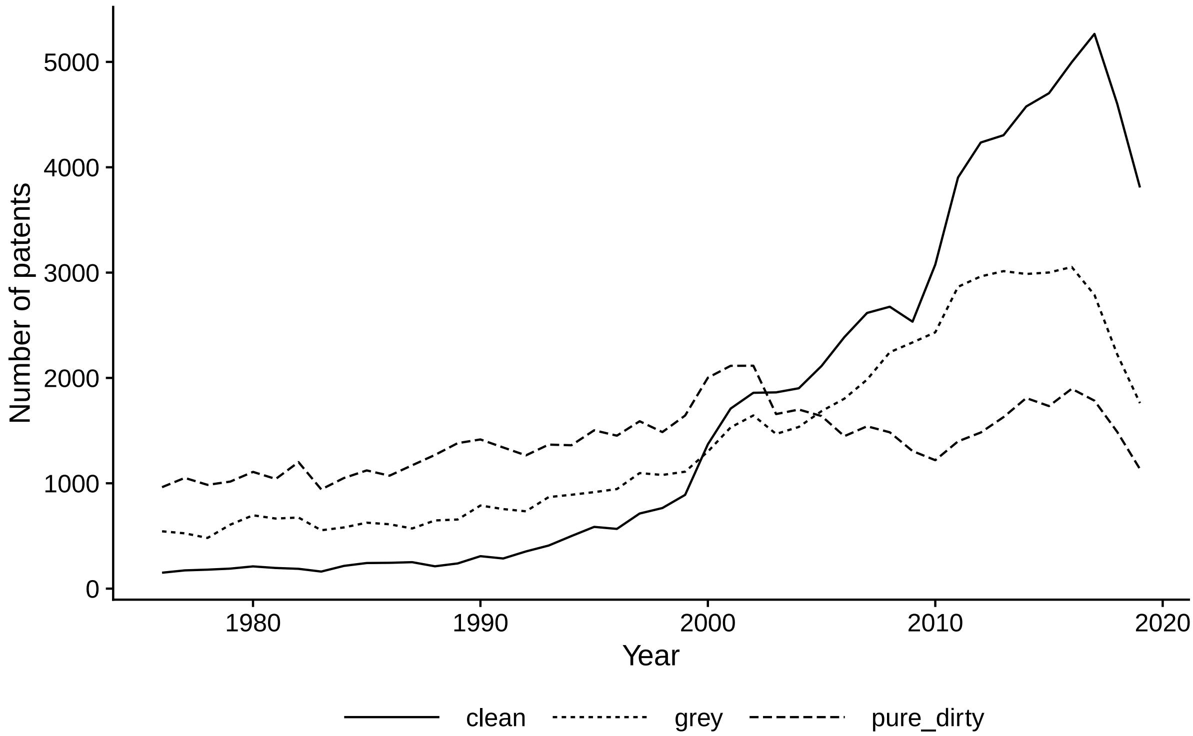
Notes: The figures show the centered wildfire measure. The measure is centered with respect to a yearly linear trend and state × quarter fixed effects. We report annual average for each state. Brown shade indicates over-exposure. Blue shades indicates under-exposure.
Source: NASA's FIRMS, authors' calculation.

Figure 12: 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 13: 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

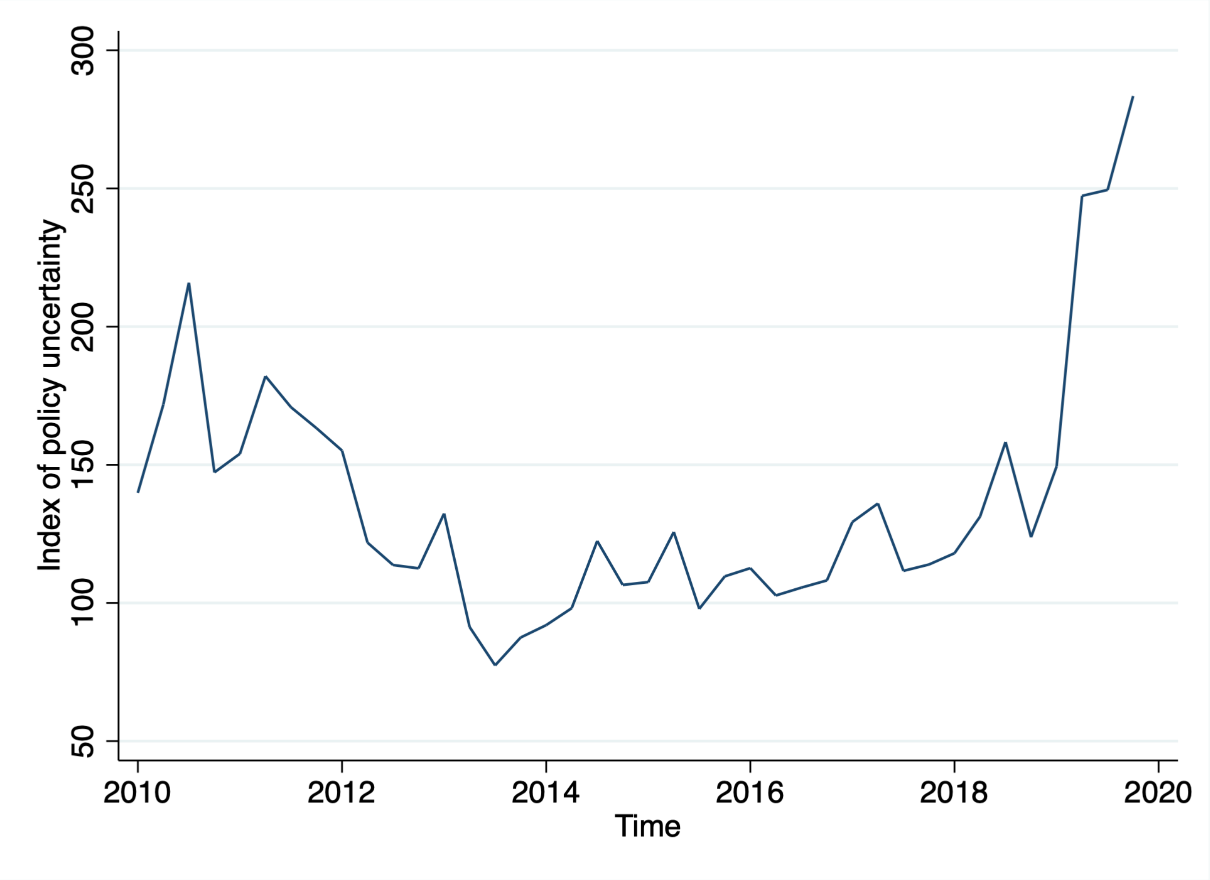


Figure 14: Economic policy uncertainty over time

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

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:

$$\tilde{ENV}_{l,t} = \alpha_{l,q} + \lambda_t + \sum_{k=0}^{10} \beta_k \tilde{W}_{l,t-k} + \epsilon_{l,t} \tag{6}$$

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.

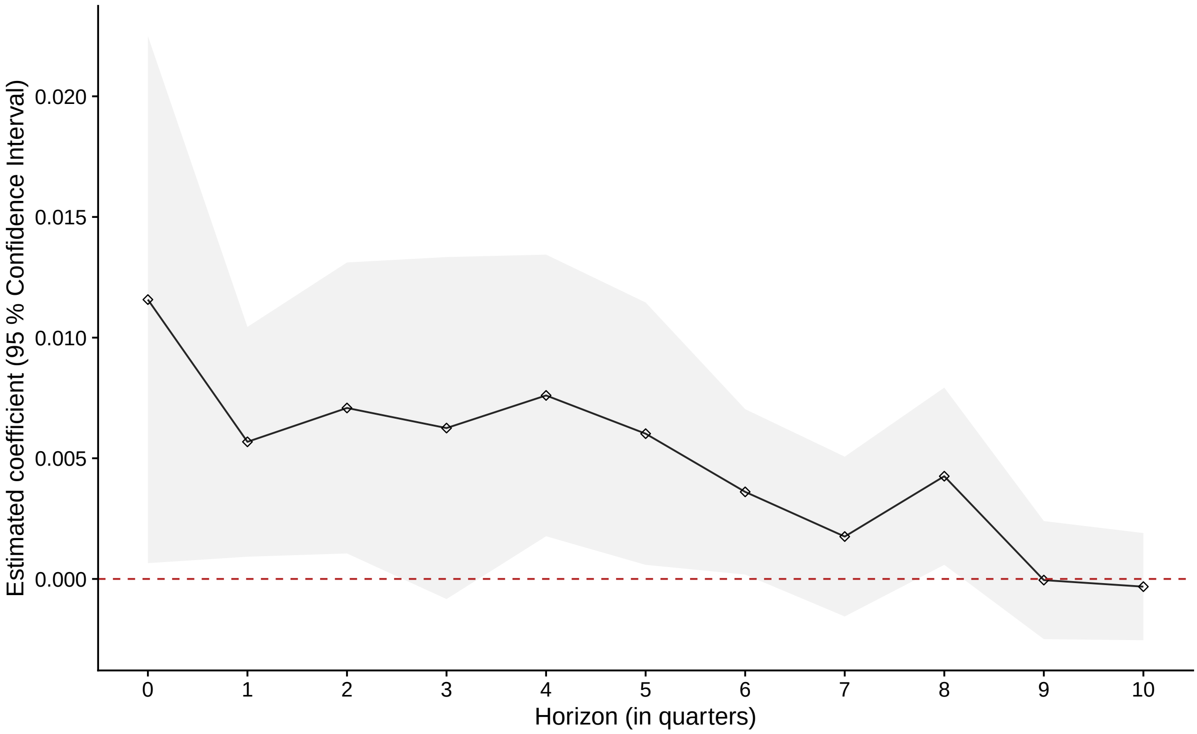


FIGURE 15: Dynamic relationship between wildfires and environmental interest by quarters

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 15 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 [56]. Figure **??** 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 16 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.

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

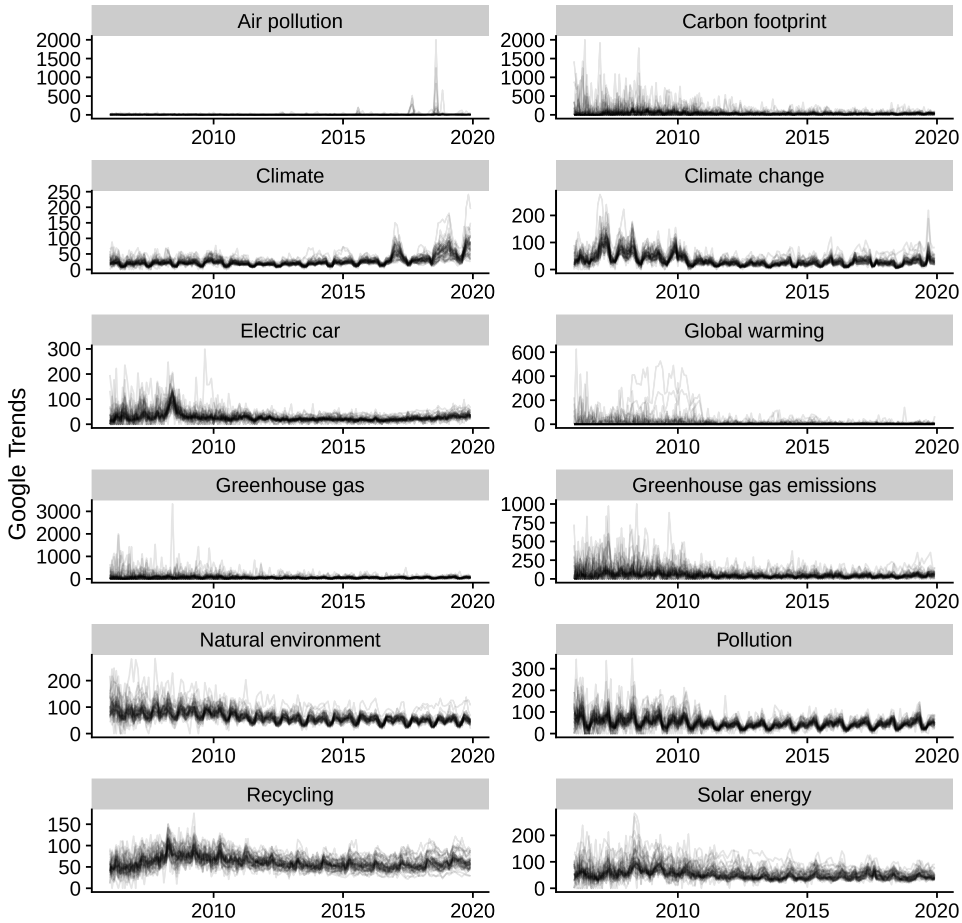


Figure 16: Google Trends series for keywords related to the environment

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" [57]. Figure 17 (and Figure 18) shows that the index is robust to the choice of the keywords.

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

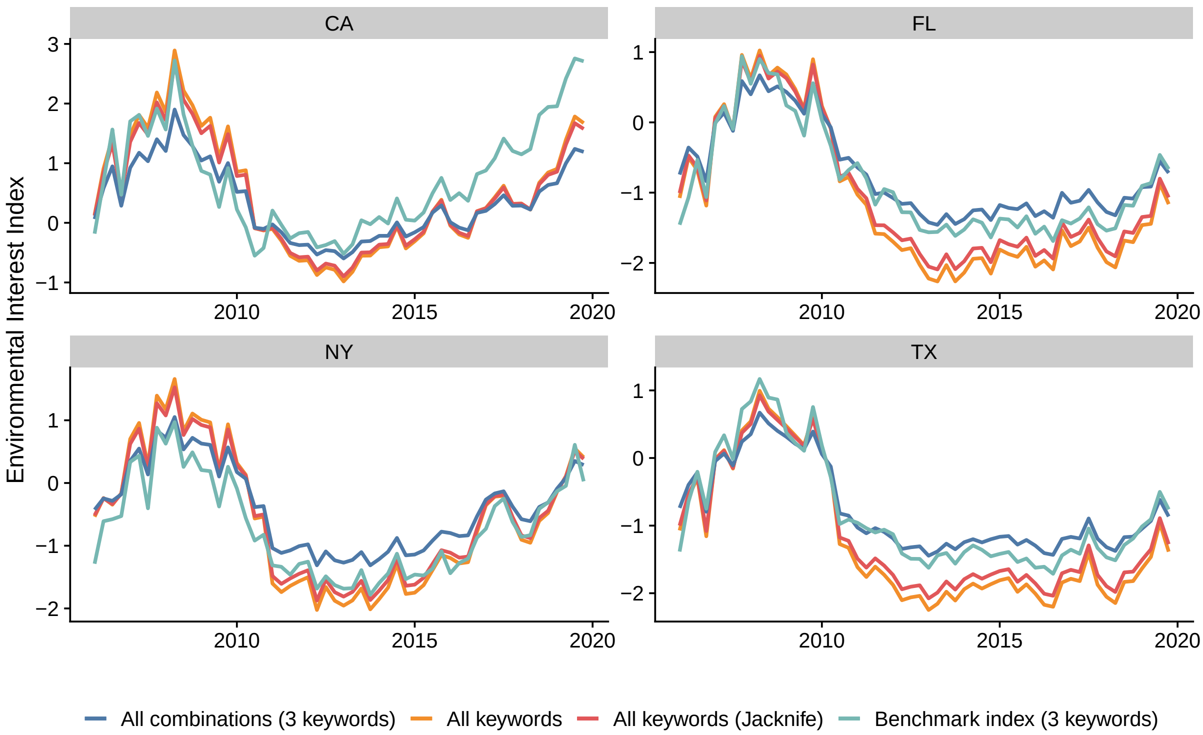


FIGURE 17: Environmental interest index, comparison of the benchmark to alternative computations

Notes: This figure shows our measure of environmental interest built with Google Trends series at the state level discussed in section 3 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.

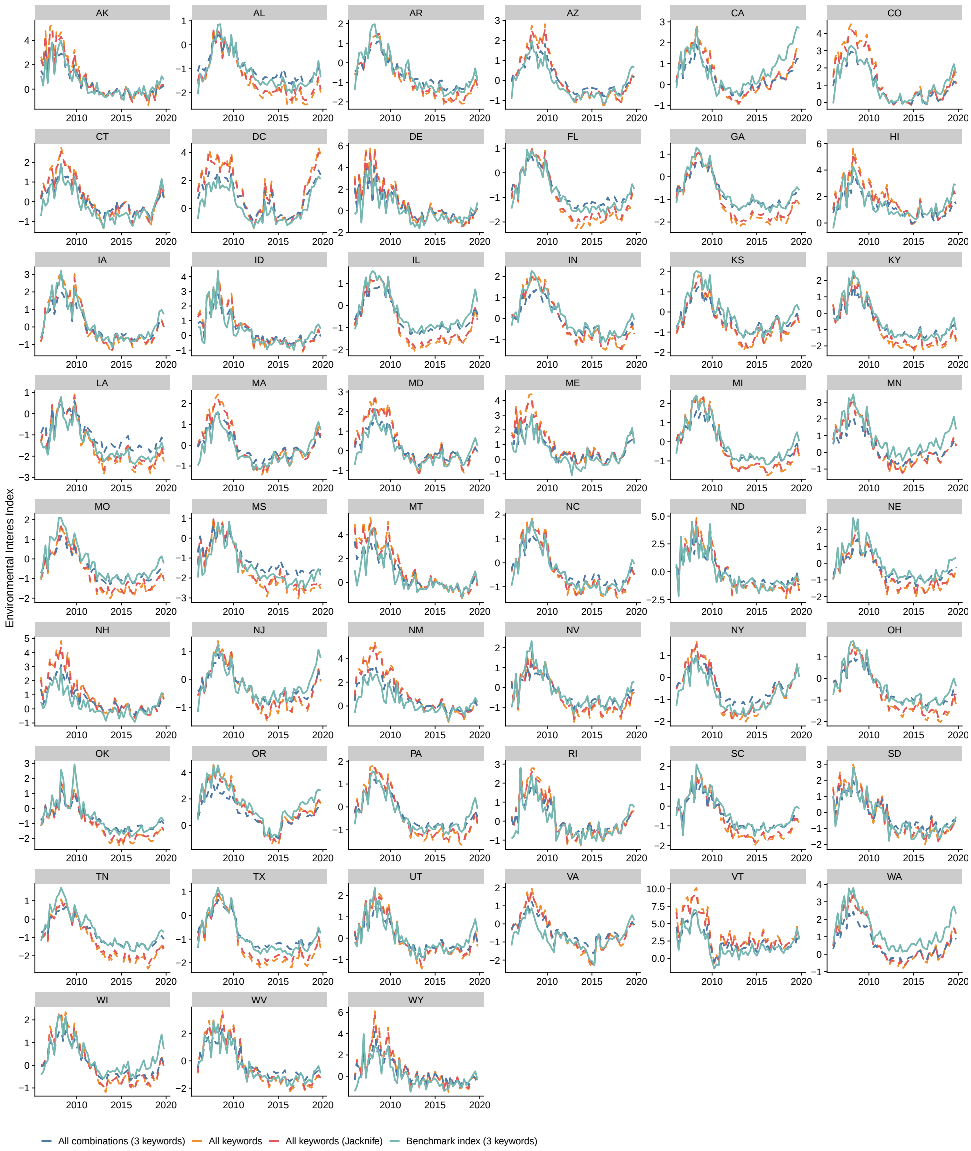


FIGURE 18: Environmental interest index, comparison of the benchmark to alternative computations

Notes: This figure shows our measure of environmental interest build with Google Trends series at the state level discussed in section 3 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.[58]

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.[59] 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 19 presents our index of green preferences and the proxy of environmental wilingess to act 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 10 presents a positive and significant correlation between the two indices.

58. 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?

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

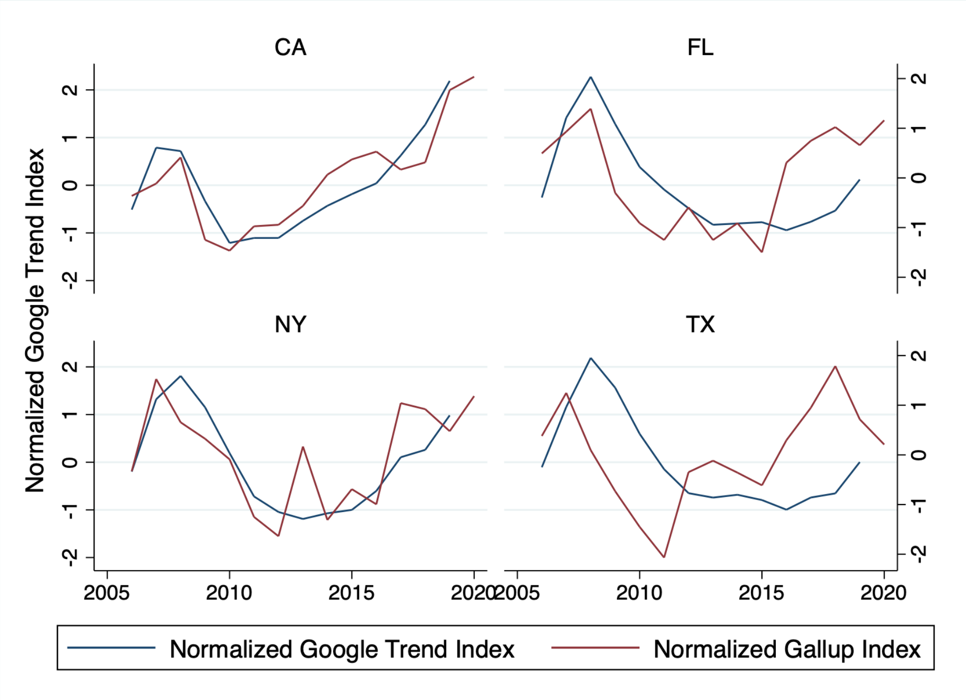


FIGURE 19: Google trends index of environmental interest and Gallup survey.

Notes: This presents our measure of environmental interest built from Google Trends series at the state level discussed in section 3 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 10: 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 3. The sample includes all the state-year observations present in the Gallup survey.

E.2 Patents classification

Table 11: 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.