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Opinions expressed in this paper are those of the author(s) and do not necessarily reflect views of the institute.

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# Environmentally-Responsible Households: Irresponsible Corporate Lobbying\*

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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 on the U.S. automotive sector from 2006 to 2019, we find ambiguous results. On average, firms innovate more in electric, hydrogen, and hybrid (*clean*) technologies and reduce combustion engine-related (*dirty*) innovation over time. However, firms also increase anti-environmental lobbying expenditures. We show that firms with a dirtier product portfolio tend to lobby more against stricter environmental regulation but also reduce R&D investment in dirty technologies to a greater extent. Firms' reactions to greener household preferences are stronger and more persistent than responses to higher fuel prices. Moreover, greener preferences have the additional effect of lowering innovation in dirty technologies. We interpret these results as evidence that shifts in household preferences are highly effective in promoting a market-based green transition. However, they also imply more anti-environmental lobbying, thereby complicating environmental policymaking.

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

Keywords: Green Household Preferences, Directed Technical Change, Environmental Lobbying

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# 1 Introduction

Environmental considerations shape household behavior. This has implications for firms whether through shifts in demand toward cleaner products or increased voter support for environmental regulation.<sup>1</sup> However, the literature on the transition to green economies has largely focused on tax policies.<sup>2</sup> In this paper, we shift the perspective to households, examining their effectiveness in accelerating the green transition.

Our results reveal mixed effects of greener household preferences. On the one hand, we observe a shift in innovation away from combustion engine technologies toward cleaner alternatives. The decline in innovation on the former, which we do not observe after a rise in fuel prices, makes greener household preferences particularly effective. On the other hand, however, firms spend more on lobbying against environmental regulation to cushion a greening of household preferences. We show that it is firms with a higher share of carbon-intensive products that opt for anti-environmental lobbying, thereby slowing a green transition. The rise in electric, hybrid, and hydrogen innovation, in turn, can be broken down into a shift in the timing of patenting by firms specialized in these clean technologies—with no material change in long-run growth rates—and a more substantial, long-run increase in clean innovation by firms with a mixed product portfolio.

In the first part of the paper, we construct a novel index of environmental willingness to act based on Google Trends search data. Unlike commonly used survey data, the high frequency and geographic granularity of our measure allow us to exploit exogenous variation in households' willingness to act driven by natural disasters at the state-quarter level.<sup>3</sup> Before turning to firm responses, we demonstrate that our index is a strong predictor of both green energy consumption and support for environmental policies. A one percent increase in our index, six months prior to consumption, correlates with a 1.7 percent higher probability of consuming either solar energy or electric vehicles. Similarly, the probability of supporting environmental

<sup>1.</sup> 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, a terminology emerged to refer to the phenomenon of an intrinsic willingness to avoid negative externalities through consumption: Bartling, Weber, and Yao 2015 and 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 which express a state-of-mind that may occur without the intention to act.

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

<sup>3.</sup> 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 Figure 1).

policies rises by 0.5 percent.

In the second part of the paper, we connect our measure of willingness to act with data on lobbying and innovation by U.S. automotive firms from 2006 to 2019. We focus on the automotive industry for several reasons. First, on-road transportation is a key contributor to greenhouse gas emissions. In 2021, for instance, the sector accounted for 23.5 percent of U.S. greenhouse gas emissions (United States Environmental Protection Agency (EPA) 2023). Second, the industry produces heterogeneous goods with varying emission standards, which are easily identifiable by households.<sup>4</sup> Finally, the automotive industry is marked by significant lobbying expenditures and innovative activity enabling us to study the trade-off between these two strategies.

In more detail, we differentiate environmental lobbying into anti- and pro-environmental using the political leaning of hired lobbyists as pioneered by Kwon, Lowry, and Verardo 2023. The idea is that a firm would rather hire a lobbyist with connections to democratic legislators if the firm wants to lobby in favor of environmental regulation and vice versa. To this end, we link firm lobbying expenditures with hired lobbyists on a report basis from raw lobbying reports from the U.S. Senate Lobbying Disclosure. We follow Kwon, Lowry, and Verardo 2023 and use lobbyists' campaign contributions to elicit their political leaning. We extend their approach by incorporating information on lobbyists' past work relationships with legislators. In sum, we classify 38 percent of environmental lobbying as pro- and 20 percent as anti-environmental.

Equipped with this dataset, 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 greener household preferences on lobbying and innovation due to, first, high geographic heterogeneity in firms' sales and production markets. Given this separation of consumption and production, we exclude the possibility that our results are confounded by wildfires affecting the supply of cars. Second, we control for a rise in environmental regulation at the federal level by including time-fixed effects.<sup>5</sup> 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, demographics, and state-specific environmental regulation.

Our results show that the average firm responds immediately to a one percent rise in the

<sup>4.</sup> Questions have been raised about the environmental benefits of electric vehicles. An MIT analysis confirms their emission advantage, even when accounting for the carbon-intensive production process (MIT Climate Portal 2022). However, other externalities related to the production of electric vehicles still remain.

<sup>5.</sup> Note that our analysis focuses on federal lobbying activity—as opposed to state-level lobbying—which impacts environmental policymaking at the federal level which is common to all firms.

index of willingness to act with a five percent increase in knowledge<sup>6</sup> growth in electric, hydrogen, and hybrid (*clean*) technologies. The short-term increase, however, is offset in the long run, with long-term growth rates remaining statistically unchanged from those without greener household preferences. Conversely, long-run growth rates of knowledge on combustion engines (*dirty*) start to decline three years after the shock and remain lower for the following two years. The shift in innovation is accompanied by an increase in lobbying expenditures against environmental regulation in the short and medium run. In contrast, pro-environmental lobbying expenditures decline sharply and remain low over a five-year horizon.

We clarify the underlying factors behind these aggregate effects by examining how firm responses depend on the *dirtiness* of their product sales and knowledge portfolios. In the first step, we exclude Tesla from our analysis, as it is unique in that both its products and the knowledge it generates are entirely clean. All other firms, in contrast, are characterized by mixed strategies. Excluding Tesla reverses the response in clean innovation: The clean knowledge stock of the average mixed-strategy firm begins to grow faster only after nearly four years. We interpret this result as Tesla accelerating the patenting of new, albeit immature, innovations as household preferences become greener—a strategy potentially optimal in anticipation of intensifying competition to patent clean technologies. In the long run, these early-filed patents are lacking resulting in an unusually low quarterly growth in clean knowledge.

In the second step of analyzing firm heterogeneity, we decompose the sample of mixedstrategy firms based on the share of revenues derived from combustion vehicles. We find that firms more reliant on selling such products respond less by increasing clean innovation. Instead, those firms react by innovating less in dirty technologies. The lack of a productive shift toward clean innovation is offset by a stronger rise in lobbying expenditures against environmental regulation. In doing so, firms that are more adversely affected by the shift in demand toward cleaner cars can protect their remaining revenues.

Finally, by comparing firm responses to greener household preferences with those to higher fuel prices,<sup>7</sup> we provide evidence that shifts in household preferences are highly effective in redirecting resources toward cleaner technologies: The effects are an order of magnitude larger and more persistent than those resulting from higher fuel prices. Furthermore, greener preferences have the additional effect of lowering R&D investment in dirty technologies. However, greener preferences come with the side effect that intensified anti-environmental lobbying agravates stringent environmental policymaking—a response that is negligible as a reaction to higher fuel prices.

<sup>6.</sup> *Knowledge* refers to the stock of patents, which we use as a proxy for R&D investment and innovation activity of firms.

<sup>7.</sup> We follow Aghion, Dechezleprêtre, Hemous, et al. 2016 and use firm exposure to changes in fuel prices outside the U.S.

We contribute to several strands of the economics literature. Firstly, we add to Literature the literature on endogenous growth. This literature 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 on trade shocks to investigate firm responses to increased competition (Bombardini 2008; Bloom, Draca, and Reenen 2016; 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 as new firms enter the market. Based on the intuition that other avenues exist to escape 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 confirm the findings of the literature in the framework of a demand shock: Firms closer to the frontier of clean innovation choose to innovate more, while firms further away increase their clean innovation activity less and turn to lobby against environmental regulation instead. Furthermore, we find that as demand shifts toward cleaner alternatives, incumbent firms with a strong innovation advantage anticipate rising competition in their clean market segments and file the clean innovations in their pipeline earlier than usual.

Second, while the literature cited above focuses on innovation and productivity in a Schumpeterian setting, we differentiate the direction of innovation. We show that firms closer at the innovation frontier for clean technologies are more likely to respond by raising their clean knowledge stock. In contrast, firms with a dirtier product portfolio recompose their knowledge stock by reducing investment into dirty R&D. Aghion et al. 2023 is similar to our paper in that they focus on the composition of innovation. 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 dirty product sales: The possibility to lobby against environmental regulation allows especially financially distressed firms to abstain from a green transition.

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).<sup>8</sup> Adverse environ-

<sup>8.</sup> A remarkable study shedding light on the impact of lobbying on the gap between voter preferences and political decisions is Giger and Klüver 2016—an aspect that remains understudied in the literature.

mental lobbying is particularly effective because (i) the strength of lobbying is multiplied when targeted at maintaining the status quo (McKay 2012), (ii) dirty firms tend to organize more than clean firms resulting in a higher impact on policies (Kim, Urpelainen, and Yang 2016), and (iii) environmental organizations lobby less than what would be considered rational (Gullberg 2008). Grey 2018 suggests that polluting firms may use pro-environmental lobbying to protect cleaner market segments, thereby raising the value of newly developed clean technologies. Our results point in the direction that pro-environmental lobbying is not used in response to a demand shock despite more clean innovation. Two recent papers empirically analyze pro- and anti-environmental lobbying on the firm level: Kwon, Lowry, and Verardo 2023 and Leippold, Sautner, and Yu 2024. Especially the former is related in that it also focuses on the interaction of lobbying with innovation. A distinctive feature of our work is that we look at how firms leverage lobbying and innovation in response to greener household preferences. Taking all these papers together, we add by showing that green household preferences intensify the use of anti-environmental lobbying with—according to the literature—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 household behavioral changes as a driver of the green transition, an issue that is gaining attention on the political agenda.<sup>9</sup> We compare the effects of greener household 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 of innovation. On the downside, however, firms respond with more anti-environmental lobbying complicating sound environmental policymaking.

Fourthly, the paper bridges the gap between the behavioral economics literature on climate change and the literature on firm strategies. Recent years have seen a surge in studies on social responsibility and the willingness to act against climate change. This literature derives house-hold preferences and attitudes from experiments or surveys (Bartling, Weber, and Yao 2015; Falk et al. 2021; Dechezleprêtre et al. 2023).<sup>10</sup> Recently, Kaufmann, Andre, and Kőszegi 2024 investigate market failures arising from socially responsible consumers and conduct a survey

<sup>9.</sup> 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).

<sup>10.</sup> 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 study experiments to increase it. Similarly, Dechezleprêtre et al. 2023 focus on support for mitigation policies.

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 a time-series measure. Our findings make an important contribution to this literature by uncovering mechanisms that call into question the unqualified benefit of households' willingness to act, as it also fuels anti-environmental lobbying. Finally, by relating our index to firm responses we pave the way for macroeconomic analyses of greener household preferences.

**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

We start in Subsection 2.1 by constructing a measure of willingness to act on the state-quarter level from Google Trends data. We evaluate the index against survey data on consumption, attitudes, and environmental policy support in Subsection 2.2.

#### 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 a 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.<sup>11</sup> We download time series of the relative search intensity of each individual term for each state and harmonize the data as laid out in Appendix D. This provides us with three distinct time series for each state, one for each search term.

Index	Mean	SD	Min	Max
Willingness to Act	100.00	17.60	21.36	171.10
Environmental Interest	100.00	27.23	-22.51	236.08
Mixed	100.00	20.54	42.50	193.01

TABLE 1: Summary Statistics of the Indices

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

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

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 interest which includes keywords generally related with climate change and the environment but abstracting 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 *General Environmental Interest 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 interest 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.





*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 environmental pollution. The keywords are *Solar Energy, Recycling,* and *Electric Car.* 

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 with the stark decline in environmental awareness presented in Aghion et al. 2023. In our sample, we observe that the decrease started around 2008, one candidate explanation is 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 intensity for keywords as a measure of greener household preferences entails caveats. First, an online search does not convey the intention of the search, while survey data does. A second potential caveat is the representativeness of our measure. While access to the internet is widespread and Google is the most popular search engine in the U.S.<sup>12</sup> the types of households using it could be limited and self-selected.<sup>13</sup>

To assess the performance of our measure, we explore its relation with survey data on attitudes, with direct measures of environmentally-friendly changes in consumption behavior, and with support for environmental policies. If our index indeed captures a notion of willingness to act, we expect to observe positive correlations with all three comparisons. This is what we find from the analyses laid out in more detail below.

**Correlation with Survey-based Attitudes.** To investigate the proximity of our index to survey data on the state level, we turn to the Gallup survey<sup>14</sup> which 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<sup>15</sup>. 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

<sup>12.</sup> Official statistics on search engine use are difficult to find. According to Statista 2024, the average market share of Google from 2015 to 2019, that is, the period of our analysis for which data on search engine use are available. amounts to 86%. State-level information on the use of Google is even scarcer. WebFX 2012 provides some information for 2012, according to which the lowest state-level market share that Google obtained was as high as 70% in Delaware.

<sup>13.</sup> Despite this high popularity of Google, it is most likely the case that only certain types of households use search engines and thus Google. This would bias our results in both directions. For example, if it is especially *doers* who search the web, our estimates may be upward biased. Conversely, our measures would be downward biased if a web search mutes the willingness to act.

<sup>14.</sup> The Gallup survey measures public opinions and attitudes for the U.S. in representative samples. In our analysis, we use the Gallup Poll Social Series conducted in March 2023 on environmental topics (Gallup 2023).

<sup>15.</sup> 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.

of participants that answer "A great deal" to construct a survey-based index following the same steps as for our index based on Google Trends data.

Figure 2 contrasts for highly populated states<sup>16</sup>—California, New York, and Texas—our indices of willingness to act, environmental interest, and the mixed index to the index derived from the Gallup survey. 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 Gallupbased index mimics our indices for willingness to act and the mixed version, while it seems less closely related to the broader measure of general environmental interest. 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.

Finally, we depict the federal-level data from the Gallup, which is designed as a representative sample, 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.

**Correlation with Environmentally-friendly Consumption.** While the previous analysis is suggestive of our index being closely related to—or even predicted by—concerns about the environment, this section focuses on whether our measure predicts environ-mentally-friendly behavior. In the following, we will narrow the analysis to the index of willingness to act.

We first evaluate our index using data on new vehicle registration provided by S&P Global which we describe in more detail in section 3. 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 one 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 percent relative to the weighted average over states of 3.4 percent.

Having looked at state-level correlations, we now turn to the household level. To this end, we draw from the Consumption Expenditure Survey (CEX) provided by the U.S. Bureau of Labor Statistics 2024 (BLS). The degree of granularity provided by this dataset allows us to account for other household characteristics and to compare their relevance. We focus on the joint 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

<sup>16.</sup> Since the Gallup is not representative on state level, we focus on the most populated states only.

FIGURE 2: Comparison of Indices built from Survey Data on Attitudes and from Google Trends Data by State



- Google Trends: General Environmental Interest
- Google Trends: Mixed

*Notes:* This figure shows different indices built with Google Trends data 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". For the construction of the other indices see Subsection 2.1. 10



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 one percent 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. The coefficient is significant at the one percent level as indicated by the three asterisks, \*\*\*.

for all model specifications. The first model in column (1) is a plain vanilla OLS regression. When adding fixed effects for state and time in column (2), the correlation remains significant but its size reduces by more than 50 percent. 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<sup>17</sup> (in 1,000\$U.S. per month), raises the effect of our index slightly, column (6).

In our preferred specification with all controls, column (6), a one percent increase in 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 1.7 percent of the observed sample share of 2.4 percent. The effect size is comparable in magnitude to a 100\$U.S. increase in monthly per-capita income which is associated with a 0.03 percentage point increase in the

<sup>17.</sup> The modified OECD equivalence scale is applied.

probability to consume electric cars or solar energy. Finally, the correlation is similar in magnitude to the results based on registration data discussed above, confirming a robust relation of our index and green consumption.

	(1)	(2)	(3)	(4)	(5)	(6)
		Probabili	ty to spend	on Solar ene	rgy or EV	
$\log(Index_{-6Months})$	0.0858 *** ( 0.0031 )	0.0357 ***	0.0358 *** ( 0.0134 )	0.0357 *** ( 0.0134 )	0.035 *** ( 0.0134 )	0.0393 *** ( 0.0134 )
Age	(00001)	(0.0101)	2e-04 ***	2e-04 ***	3e-04 ***	3e-04 ***
Rural Area			(0)	-0.0055 ***	-0.0034 ***	(0) 2e-04
Education				(9e-04)	( 0.001 ) 0.0094 ***	( 0.001 ) 0.004 ***
Income in 1k\$US					(6e-04)	( 6e-04 ) 0.003 *** ( 1e-04 )
FE: year-month		X	X	X	X	X
N:	178,262	178,262	178,262	178,262	178,262	,777,590

TABLE 2: Green Energy Consumption and Index of Willingness to Act

*Notes:* Significance codes: \*\*\*: 1%, \*\*: 5%, \*: 10%

The table shows regression coefficients of a linear regression of the share of CEX households consuming either solar energy or electric vehicle charging within the sample periods from 2017 to 2023 (this is, where the conusmption items of interest are included in the CEX) on the index of willingness to act measured 6 months prior to consumption. Except for the first column, fixed effects for time and state are included in the regression.

**Correlation with Environmental Policy Support.** 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 U.S. citizens around election dates.<sup>18</sup> 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".<sup>19</sup> The final time series contains 3 years: 2008 (ANES 2008), 2012 (ANES 2012), and 2016 (ANES 2016). Given the variation in the exact month when a survey is conducted, the time series contains nine

<sup>18.</sup> The ANES is a long-standing date source on voting behavior, public opinion, and political participation collected since 1948 and designed to be representative of the U.S. electorate. For more information consult https://electionstudies.org/.

<sup>19.</sup> 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.

FIGURE 4: Coefficients on Index of Willingness to Act prior to 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 (from the ANES) on different lags of our index of environmental willingness to act by the red triangles. The violet circles show equivalent correlations with environmentally-friendly energy consumption (from the CEX). Vertical lines indicate 10 percent confidence intervals. The horizontal axis shows the lags relative to the consumption measure. The x-axis indicates the time structure: At zero, the index is measured at the time of the survey. The negative values indicate the number of months by which the index precedes the time of consumption or the statement on the opinion.

distinct month-year combinations.<sup>20</sup>

We run linear prediction model of the probability to support a higher environmental budget share using our index of willingness to act with varying lags as regressors, one lag per regression. The results given in percent relative to the average share of households supporting an increase in the environmental budget<sup>21</sup> are shown by the red triangles in Figure 4 separately for each considered lag of the the index. Clearly, a higher index predicts a higher share of environmental policy support. Thus, greener household preferences may affect firm strategies through a political channel.

The blue circles in the same figure show the coefficients of a similar regression using our measure of environmentally-friendly energy consumption from the CEX discussed above.<sup>22</sup> In-

<sup>20.</sup> 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.

<sup>21.</sup> The average share of supporters in our constructed time series is 48.90 percent where sample weights are applied.

<sup>22.</sup> These are the results of the model underlying results in column (6) in Table 2 for the lags indicated on the x-axis of Figure 4. The effects are expressed in percent of the average probability to consume green

terestingly, the size of the effects 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 on attitudes, to green energy consumption, and to support of environmental protection jointly suggest that our measure of environmental willingness to act is an appropriate proxy for the greening of household preferences that foster behavioral change be it voting or consumption. Previous work also highlights the usefulness of Google Trends to predict near-term economic indicators (Choi and Varian 2012; Stephens-Davidowitz and Varian 2014; Wu and Brynjolfsson 2015; D'Amuri and Marcucci 2017). Vosen and Schmidt 2011 show in the context of private consumption that Google Trends outperforms survey-based indicators in forecasts.

### **3** Other Data and Summary Statistics

We next detail the remaining data sources for our main analysis.

**Vehicle Sales: S&P Global.** The data on new vehicle registrations is sourced from S&P Global covering the years 2006 through 2019.<sup>23</sup>This comprehensive dataset provides quarterly registration details for each U.S. 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.<sup>24</sup> Using this dataset, we can determine the market share of each firm<sup>25</sup> at the state level which we use to assess firm exposure to household preferences.

**Fires: FIRMS.** In the main analysis, we use exogenous shocks to household preferences through wildfires. Data on fires comes from the Fire Information for Resource Management System (FIRMS) of the U.S. NASA. In particular, the data divides the U.S. into cells of one square kilometer and documents several times a day whether there is a fire in a cell.<sup>26</sup> We apply the following procedure to obtain a map of all fires in the U.S. over time. First, we collapse this highly disaggregated data at the week level, considering that there was a fire in a cell if a fire was declared in the cell at least once during that week. Second, we determine clusters of fires using

energy (2.36 percent). All coefficients are positive and significant at the 10 percent level.

<sup>23.</sup> For more information on the dataset see https://www.spglobal.com/mobility/en/products/ automotive-market-data-analysis.html.

<sup>24.</sup> It is generally forbidden to register a vehicle in another state than the state of residency in the U.S. Exceptions exists for citizen that are living in multiple states, or working in another state.

<sup>25.</sup> We use the term *firm* to refer to vehicle groups, that is, global automotive producers commonly comprising several makes.

<sup>26.</sup> We focus on *presumed vegetation fire* and drop the other types of fires to focus on natural disasters.

the *dbscan* algorithm provided by Ester et al. 1996.<sup>27</sup> Third, we draw a convex polygon around each cluster to determine the area of the fire. Finally, we compute a fire exposure variable for each state *l* by summing over all the fires *f* that are within a distance of 500km to a state:

$$Fire \ Exposure_{lt} = \sum_{f \in F_{500lt}} \text{intensity}_{it} \times \frac{\text{surface}_{ft}}{\text{distance}_{flt}^4},$$
  
where  $F_{500lt} = \{f \in F | \text{distance}_{flt} < 500km\},$ 

where the *intensity* is proxied by the fire radiative power (in Megawatts) and *surface* refers to the size of the fire. The set *F* contains all the fires in our dataset. We finally divide our measure by the distance between the fire and the state to the power of four to ensure that close populations are exponentially affected.<sup>28</sup>

**Lobbying:** LobbyView and U.S. Senate Lobbying Disclosure Act Reports. Following the Lobbying Disclosure Act of 1995, all lobbyists ought to register their lobbying activity with the U.S. Senate Office of Public Records. In particular, they need to declare their client, the amount spent on lobbying, the topics lobbied, and the entity targeted by the lobbying activity. Although this information is publicly available at the Senate Office of Public Records, we use the clean version *LobbyView* provided by Kim 2018. Based on this data, we derive information on the topic firms lobby and form an *Environmental Lobbying* category that includes all expenditures targeting the issues: Environmental/Superfund, Energy/Nuclear, Clean Air & Water (Quality), and Fuel/Gas/Oil.

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 lobby for more environmental regulation. We exploit information on lobbyist-firm linkages on a report basis from raw lobbying reports provided by the U.S. Senate Lobbying Disclosure.

More precisely, to determine whether a lobbyist is republican or democrat, we first use information on campaign contributions by lobbyists. In particular, following Kwon, Lowry, and Verardo 2023, we consider that a lobbyist is democrat (republican) if more than 75 percent of the lobbyist's lifelong campaign contributions target democrat (republican) legislators. Second, we complement this definition using the past relationships of lobbyists with legislators. To that end, we use the data constructed by Garza, Liu, and Ruehle 2023, available on the LobbyView website, listing all legislators lobbyists have indicated previously working for. A lobbyist is then

<sup>27.</sup> We focus on clusters to exclude fires that are very small. To be precise, we choose to compose clusters of at least 5 points at a maximum normalized distance of 0.25.

<sup>28.</sup> The distance is computed between the fire's and the state's center of gravity.

additionally defined as democrat (republican) if the lobbyist previously worked for a democrat (republican) legislator.<sup>29</sup>

Finally, *pro-environmental lobbying* includes all lobbying activities on environmental issues for which democrat lobbyists are hired. Symmetrically, *anti-environmental lobbying* is the activity relying on republican lobbyists to target environmental issues. In our dataset, we categorize around 38 percent of environmental lobbying as pro-environ-mental lobbying, 20 percent as anti-environmental lobbying, and the remaining 42 percent as non-classified environmental lobbying activity.

**Innovation: Patentsview.** We measure innovation activity through granted patents at the U.S. Patent and Trademark Office (USPTO). Patents are dated by their quarter-year of application to more precisely represent the time of their invention. We match patents with firms in our sample using the assignee disambiguation method of PatentsView and manual inspection.<sup>30</sup> 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 refer to technologies rendering fuel engines less polluting, and dirty patents indicate all other innovations on fuel engines.<sup>31</sup>

Finally, following Hall 2005 and Bloom, Draca, and Reenen 2016, we compute a measure of knowledge stock, *K*<sub>*ist*</sub>, according to the recursive identity:

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

Where  $R_{ist}$  represents the number of new patents<sup>32</sup> from firm *i* in technology *s*, with  $s \in \{\text{clean, gray, dirty}\}$ , at time *t*. The variable  $\delta$  stands in for the quarterly depreciation of knowledge.<sup>33</sup> We use  $K_{ist}$  in our main analysis to measure changes in innovation activity. Using a

<sup>29.</sup> When a lobbyist worked for both a republican and a democratic legislator, we consider the legislator politically unaffiliated. Similarly, we do not assign an affiliation to lobbyists for whom the campaign contribution definition and the past employment definition are conflicting.

<sup>30.</sup> For more details consult: https://patentsview.org/disambiguation.

<sup>31.</sup> The classification of patents into these three categories by their CPC code can be found in Appendix D.

<sup>32.</sup> The literature commonly uses quality adjusted measures of patents, for example by employing stock market information (e.g. Kogan et al. 2017), or citation weights. The concern is that the number of patent applications may not reflect actual investment in R&D as high- and low-quality patents are treated equivalently when only using the number. Nevertheless, we take the number of patents as our baseline measure of knowledge as it does not entail any additional information on the green transition. For example, the response to greener household preferences in clean innovation may be partly driven by more citations which arise as the economy becomes greener in the future. 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 citation weights in subsection 6.3. Our main results remain unchanged. However, these two latter measures, as expected, inflate firm responses to greener household preferences.

<sup>33.</sup> Following the literature on depreciation of R&D (Li and Hall 2020), we set  $\delta = 0.2$  for the annual frequency.

stock instead of a flow variable is less prone to arbitrary results arising from the choice of lags in the regression.<sup>34</sup>

**State-level controls.** We control for a series of state characteristics through which changes in wildfires may affect firm strategies other than via household willingness to act. In particular, we control for local transportation habits (through the percentage of the population commuting by personal car, by public transportation, or by bike, and the percentage of the population working remotely) and local investments in the energy transition of transports (number of alternative fueling stations). This data comes from the Bureau of Transportation Statistics.<sup>35</sup> We combine this information with a dummy for whether a state adopted California's light and heavy-duty vehicle regulations under Section 177 of the Clean Air Act building on hand-collected data from online investigations.<sup>36</sup> We also control for demographic information such as the employment rate and the share of young persons in the population (from the Bureau of Economic Analysis).<sup>37</sup> We control for major political preferences by using the share of votes for Republicans in the past presidential election which we derive from data from the MIT Election Data and Science Lab.<sup>38</sup> Finally, we include state-quarter dummies (such as California-summer) to control for seasonality in the response of firms that coincides with changes in wildfires.

#### 3.1 Summary Statistics

Having specified all main data sources of interest, we now briefly discuss our sample.

**Innovation and Lobbying.** Our dataset is composed of 17 firms, which are the main groups of the automotive sector offering private cars.<sup>39</sup> We focus on groups, which are aggregates of makes because we observe that both lobbying and innovation are most often set at the group level.<sup>40</sup> Table 3 reports the distributions of our main outcome variables and Table 4 firm char-

<sup>34.</sup> Using knowledge stocks prevents zero entries in the data. Like this we avoid working with a logarithmic transformation of ln(1 + x) which would bias our results (Chen and Roth 2023).

<sup>35.</sup> The data on transportation habits can be found at https://www.bts.gov/ browse-statistical-products-and-data/state-transportation-statistics/commute-mode and number of alternative fueling stations data on the at https://www.bts.gov/ the browse-statistical-products-and-data/state-transportation-statistics/alternative-fuel-stations.

<sup>36.</sup> The sources of the state-level information is available upon request.

<sup>37.</sup> For more information on the dataset see https://www.icip.iastate.edu/tables/population/urban-pct-states and https://apps.bea.gov/regional/docs/DataAvailability.cfm.

<sup>38.</sup> For more information on the dataset see https://electionlab.mit.edu/data.

<sup>39.</sup> We remove from the sample groups with less than 30,000 registered cars over the whole period and truck-only companies.

<sup>40.</sup> 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.

acteristics.

	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 <sub>clean</sub>	71.06	233.75	0.00	0.76	19.58	495.42	2097.71
<i>K<sub>dirty</sub></i>	95.47	195.58	0.00	5.30	75.15	570.82	1373.91
Kgray	12.62	33.11	0.00	0.15	8.33	67.70	257.89

TABLE 3: Summary Statistics of Outcome Variables

*Notes:* The table summarizes the main outcomes in our analysis as quarterly averages over firms. The first row depicts the average lobbying targeted to environmental topics in thousands of dollars. The second row shows total lobbying expenditures in thousands of dollars. The last three rows refer to the knowledge stocks for clean, dirty, and gray technologies. See section 3 for a description of the dataset.

We document that dirty technologies represent 48 percent of granted patent applications in our period of analysis, clean technologies around 41 percent, and gray technologies account for only 7 percent. Figure 10 in the Appendix depicts the evolution of the different types of patenting since 1976. There is an exponential increase in the number of patents since the late 1990's which was mainly driven by clean patent applications. The number of clean patents rose by a factor of five during the period.<sup>41</sup> The number of dirty patents also increased over the period yet less rapidly so. Gray and non-classified patents are the least important and grew only mildly.<sup>42</sup>

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 clean technologies (Table 4). However, all firms—with the exception of Tesla—innovate in all types of technologies. When studying the heterogeneity in response to households' environmental will-ingness to act we, therefore, do not compare *clean* to *dirty* firms but use a continuous scale of *dirtiness*.

Out of the 17 firms in our sample, 15 firms lobby, and lobbying expenditures are substantial.<sup>43</sup> The average quarterly expenditure is US\$683,000 with a maximal expenditure of more than US\$6,3 million.<sup>44</sup> Splitting lobbying expenditures according to targeted topics at the firm level, we observe that on average 13 percent of lobbying expenditures are directed toward en-

<sup>41.</sup> In our dataset, we only observe patent applications that were accepted by the USPTO. The application process takes a few years, so that applications after 2018 have not been accepted in our dataset. This explains the sharp decrease in patenting we observe in the last quarter.

<sup>42.</sup> These trends are congruent with trends presented in Aghion, Dechezleprêtre, Hémous, et al. 2016 and Aghion et al. 2023.

<sup>43.</sup> The two groups that do not lobby are Suzuki and Isuzu.

<sup>44.</sup> 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.

Group	Clean Patents	Dirty Patents	Gray 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	0.00	0.00	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

#### TABLE 4: Summary Statistics by Firm (Quarterly, 2006-2019)

*Notes:* The table summarizes patenting activity, lobbying, and market share for the firms in our sample. The 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.

vironmental 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 percent of total expenditure) and Tesla (30 percent of total expenditures). In comparison, both General Motors and Ford allocate 18 percent of their individual lobbying to environmental issues.

**Variation in shock exposure.** Figure 12 in the Appendix compares market shares across firms over the U.S. A more bluish (redish) color means that the area represents a more (less) important market for a given firm than for other firms. There is important heterogeneity between firms. Some are unexceptionably exposed to demand across the U.S. (Ford, Toyota, and Jeep, for instance), while others are particularly exposed to some regions only. To Tesla the West and Washington DC are of superior importance, while New England and the West Coast are highly important to BMW, and General Motors is sells a high share of its products in the Midwest and the South. These variations in the importance of specific states for firm revenues are at the heart of our empirical strategy. In the next step, we discuss another crucial source of variation: changes in wildifres across states and time.

**Exposure to wildfires.** As a final crucial aspect of our data, Figure 13 pictures states' exposure to wildfires through time. The index is centered with respect to a yearly linear trend

and state-quarter fixed effects. 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 households' willingness to act on firm behavior. We elaborate on the construction of our instrument and model specifications (Subsection 4.1), the assumptions underlying the identification of the effect of greener preferences (Subsection 4.2), and comment on the robustness of standard errors (Subsection 4.3).

#### 4.1 Research Design

We seek to estimate the effect of a change in households' willingness to act on firms. The ideal experiment would, all else equal, change random firms' exposure to households' environmental willingness to act. However, such willingness is an endogenous object. To approximate the ideal experiment, we only consider changes in household preferences 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 household preferences and predetermined firm exposure shares to local markets. The analysis is conducted at the firm-quarter level.

**Firm Treatment.** We embed our index of household willingness to act,  $ENV_{lt}$ , which is measured at the state level (see Section 2) as main regressor in the analysis. To connect it to firm-level data, we weigh the index in state *l* with the share of firm *i*'s sales in that state. These shares are a proxy for firm exposure to local markets. We specify our model in changes over a two year horizon (eight quarters).<sup>45</sup> The main regressor of firm exposure to household willingness to act is defined as:

$$\Delta_{8,s_t}^{\log} ENV_{it} := \sum_{l}^{L} s_{ilt} \left( \log(ENV_{lt}) - \log(ENV_{lt-8}) \right). \tag{1}$$

Where  $s_{ilt} := \frac{S_{ilt}}{S_{it}}$  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 the same period. Shares sum to one over states for a given time and firm.<sup>46</sup>

**Instrument.** Regressing firm behavior on our index of willingness to act by ordinary least squares would suffer from, first, reverse causality, for example because firm innovation behav-

<sup>45.</sup> Time indices refer to end-of period values.

<sup>46.</sup> 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 willingness to act require uncorrelatedness to the error term for the validity of our methodology.

ior may affect household preferences through the supply of cleaner goods. Second, omitted variables may coincide with changes in preferences and move firm behavior, e.g., 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 wildfires over a period of 8 quarters:

Fire 
$$Shock_{lt} := \log(Fire \ Exposure_{lt}) - \log(Fire \ Exposure_{lt-8}).$$
 (2)

Based on these state-level shocks, we construct our instrument for firm exposure to household willingness to act. 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 - 8.<sup>47</sup> The instrument follows as the weighted average of the shocks:

$$Z_{it} := \sum_{l}^{L} s_{ilt-8} Fire \ Shock_{lt}.$$
(3)

**Model Specification.** We measure outcome variables as gross growth rates over two years,  $\frac{y_{ii}}{y_{it-8}}$ , and apply a logarithmic transformation.<sup>48</sup> We instrument the main regressor,  $\Delta_{8,s_t}^{log} ENV_{it}$ , with the weighted wildfire shocks,  $Z_{it}$ . In short, we estimate the following model by 2 stage least squares (2SLS):

$$\log(y_{it}) - \log(y_{it-8}) = \lambda_t + \alpha_i + \beta \Delta_{8,s_t}^{\log} ENV_{it} + \gamma X_{it} + \varepsilon_{it}.$$
(4)

Where  $\lambda_t$  is a time fixed effect,  $\alpha_i$  is a firm fixed effect, and  $X_{it}$  indicates a set of controls. The coefficient of interest is  $\beta$  which captures the elasticity of the outcome variable to a change in the index of willingness to act, conditional on controls,  $X_{it}$ .

**Local Projections and Interpretation of Coefficients.** Most of our results derive from local projections in the form of

$$\log(y_{it+h}) - \log(y_{it-8}) = \lambda_t^h + \alpha_i^h + \beta^h \Delta_{8,s_t}^{\log} ENV_{it} + \gamma^h X_{it} + \varepsilon_{it+h}, \quad h = 0, ..., H.$$
(5)

We thus measure the effect of a rise in our index on the long-run gross growth rate between period t - 8 and t + h:  $\frac{y_{it+h}}{y_{it-8}}$ .

<sup>47.</sup> More concretely, 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.

<sup>48.</sup> Thus, in the baseline specification of our model, outcome variables are measured in the same time period as our index of willingness to act.

**Tranformation of coefficients** The coefficients we back out with our model specification can be transformed to give the percentage change in the outcome variable relative to the expected growth rate without a change in household preferences, dEnv = 0, as follows:

$$\frac{\frac{y_{t+h}}{y_{t-8}} - \left(\frac{y_{t+h}}{y_{t-8}}\right)_{dEnv=0}}{\left(\frac{y_{t+h}}{y_{t-8}}\right)_{dEnv=0}} = (1.01^{\beta^h} - 1).$$

It can be shown that whenever  $(1.01^{\beta^h} - 1) < (1.01^{\beta^{h-1}} - 1)$ , the quarterly growth rate between period h - 1 and h deviates negatively from its expected value absent a shock to household preferences, and vice versa. This relation holds under some assumptions on the size of the estimated effects which our results satisfy.<sup>49</sup> The proof can be found in Appendix E.2.

#### 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 Goldsmith-Pinkham, Sorkin, and Swift (2020), is the standard case where past exposure shares are thought to be exogenous. The second source, studied in 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 household preferences triggered by wildfires can be considered as quasi-random conditional on controls as long as the following assumptions are satisfied: (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 firm-level IV regression can be represented as an equivalent shock-level IV regression—which in our case corresponds to the state level—weighted by the average exposure of all firms to a given state  $l: s_{lt} := \frac{1}{N} \sum_{i} s_{ilt}$ . The shock-level representation of equation (4) is defined as:

$$\widetilde{\log(y)}_{lt} - \widetilde{\log(y)}_{lt-8} = \beta \cdot \Delta_{8,s_t}^{\widetilde{\log}ENV} V_{lt} + \widetilde{X}'_{lt}\gamma + \widetilde{\varepsilon}_{lt}.$$
(6)

Where  $\tilde{v}_{lt} := \frac{\sum_{i} s_{ilt-h} v_{it}}{\sum_{i} s_{ilt-h}}$  is the exposure-weighted average of variable  $v_{it}$ .<sup>50</sup> This transformation has two interesting properties: First, the regression will recover the same coefficient  $\hat{\beta}$  as the

<sup>49.</sup> The assumption is that a negative effect on the growth rate is smaller than 100 percent.

<sup>50.</sup> For more details on the equivalence of the shock-level regression see Borusyak, Hull, and Jaravel

firm-level regression in equation (4) because the shock-level regression is merely a change in the summation order and the interpretation remains the same. Second, this equivalent regression can be estimated with 2SLS, plugging in directly the shocks *Fire Shock*<sub>*lt*</sub> as the instrument.

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

To test the exogeneity of the shocks, we implement falsification tests in the form of shock balance tests following Borusyak, Hull, and Jaravel 2022 on the state and the firm level. The idea is to falsify that shocks predict predetermined variables. If the shocks are as-good-as-randomly assigned to firms and states within periods, we expect them to not predict these predetermined variables. At the state level, we scrutinizefor the exogeneity of the shocks with respect to vehicle registrations, registrations of electric vehicles, and various state-level controls. At the firm level, we use lobbying activity and innovation measured by the log-transformed value of the knowledge stock and the number of patents<sup>51</sup> by technology type.

The results are presented in Table 5. At the state level, we find that states with a higher number of electric vehicle charging stations are systematically more exposed to wildfires. We also find a negative relationship significant at the 10 percent level between the share of republican voters and the exposure of a state to wildfires, and a positive relationship with state-level greenhouse gas regulation and gasoline prices. Since we control for these variables in our analysis, the assumption of quasi-random shock assignment is not violated by these results. At the firm level, there is indeed no statistically significant correlation between wildfires and tested variables, consistent with the quasi-randomness assumption. The only exception is environmental lobbying which is significant at the 10 percent level.

**Many Uncorrelated Shocks.** This condition states that shocks should not be concentrated in few observations. This assumption implies that average firm exposure converges to zero as the number of observations increases. The effective number of leveraged shocks can be estimated by the inverse of the Herfindhal index, HHI, of the average firm exposure to states,  $s_{lt-h}$ . Our effective sample size is large (above 700) and our largest importance weight,  $s_{lt-h}$ , is below one percent. This suggests that given the small number of units (17 firms) and treatment groups (50

<sup>2022.</sup> 

<sup>51.</sup> Here we use the transformation of the number of patents as in Aghion et al. 2023: log(1 + #patents).

#### TABLE 5: Shock Balance Tests

Balance variable	Coef.	SE
# Registrations	-0.000	(0.000)
# Clean registrations	-0.000	(0.000)
Share of republican votes	-0.494*	(0.267)
Share pop. commuting by personal car	-0.000	(0.003)
Share pop. commuting by public transportation	-0.000	(0.003)
Share pop. commuting by bicycle	0.029	(0.063)
Share pop. working remotely	0.002	(0.046)
# New EV charging stations	0.001***	(0.000)
Share of active pop.	-0.000	(0.000)
Share of young pop.	2.248	(3.598)
Share of urban pop.	-0.000	(0.002)
Income per capita	0.000	(0.000)
Gasoline price	0.007*	(0.004)
Diesel price	0.003	(0.003)
Regulation pollutant	0.058	(0.046)
Regulation ghg	0.245*	(0.130)
Regulation zeroev	0.044	(0.044)
# of state-period: 1970		

#### Panel A: State-Level Balance

Panel B: Firm-Level Balance		
Balance variable	Coef.	SE
Log total lobbying expenditures	0.001	(0.010)
Log environmental lobbying expenditures	-0.038*	(0.020)
Log pro-environmental lobbying expenditures	-0.007	(0.024)
Log anti-environmental lobbying expenditures	0.006	(0.024)
Total patent stock	0.004	(0.013)
Clean patent stock	-0.004	(0.011)
Dirty patent stock	0.001	(0.009)
Grey patent stock	0.020	(0.014)
Non-classified patent stock	0.000	(0.000)
Log (1+# clean patents)	-0.003	(0.009)
Log (1+# dirty patents)	-0.005	(0.009)
Log (1+# gray patents)	-0.000	(0.011)
Log (1+# clean patents) - log (1+# dirty patents)	0.001	(0.008)
# of firm-period: 924		

*Notes:* Significance codes: \*\*\*: 1%, \*\*: 5%, \*: 10%

states), the shocks are not too clustered and the frequency of observation is sufficient to reach consistency (Borusyak, Hull, and Jaravel 2022).<sup>52</sup>

<sup>52.</sup> We report the related statistics in Table 10 in Appendix A.

**Relevance Condition.** The relevance condition requires that the instrument has power, that is  $\mathbf{E}[\Delta_{8,s_t}^{\log} ENV_{it} \cdot Z_{it}|X_{it}] \neq 0$ . We check this by computing the Montiel-Pflueger first-stage Fstatistic which we report in our tables of results. We find a strong positive correlation between exposure to wildfires and green household 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). Appendix C provides an overview of the literature on the relationship between natural disasters and environmental interest as well as state-level evidence in our sample.

#### 4.3 Treatment Correlation and Robust Standard Errors

Our wildfire shocks, *Fire Shock*<sub>1</sub>, generate dependencies in the instrument,  $Z_i$ , and in the residuals of firms with similar exposures,  $s_{il}$ . Consequently, the residuals are correlated across firms that face 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 shift-share IV regression. However, running the exposure-weighted shock-level IV regression of Equation 6 yields valid standard errors (Borusyak, Hull, and Jaravel 2022).<sup>53</sup> Moreover, this setting allows to account for the dependence of the errors by clustering standard errors at the shock level. In all regressions, we run estimations using this equivalent exposure-weighted shock-level transformation and cluster the standard errors at the state level.<sup>54</sup>

# 5 Results

We are now equipped to discuss our results. First, we analyze the instantaneous effects of greener household preferences in Subsection 5.1. Second, in Subsection 5.2, we take a dynamic perspective by discussing local projection results. Third, we scrutinize potential explanations for the average effects by looking at firm heterogeneity in Subsection 5.3. To close this section, we assess the magnitudes of our results by comparing them to the effect of fuel prices in Subsection 5.4.

<sup>53.</sup> 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.

<sup>54.</sup> 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.

#### 5.1 Static baseline results

Our main results are shown in Table 6. The first two panels report results for aggregate variables: innovation and lobbying activity, measured by the knowledge stock and lobbying expenditures, respectively.<sup>55</sup> The following four panels decompose changes in innovation activity into clean, dirty, gray and non-classified knowledge. The last three panels focus on lobbying activities specifically targeting environmental issues: environmental lobbying on aggregate, antienvironmental, and pro-environmental lobbying.<sup>56</sup> 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. Column (1) applies a bare-bone specification that includes no further covariates. These estimates suggest a positive correlation between household environmental willingness to act and both (anti-) environmental lobbying and clean knowledge. Gray patenting and pro-environmental lobbying decrease in response to greener household preferences. There is no significant effect on dirty innovation.

The next column, column (2), instruments the change in household preferences by wildfire exposure. The IV approach mitigates concerns 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. Indeed, using an instrumental variable approach changes estimates. For instance, while the OLS regression suggested a positive effect of greener household preferences on total lobbying, the effect vanishes in the IV specification (column (2)). Conversely, the effect of greener household preferences on dirty knowledge becomes significant.

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 (3), we augment the model with a set of demographic controls, such as population, the urban population share, and income per capita. In column (4), we add controls for transportation habits and environmental policies. In particular, we control for the share of the population commuting by personal car and state-level investments in transportation infrastructures. Transportation could be affected by the likelihood of wildfires and clearly determines the demand for cars. Transportation controls also include 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. With the lat-

<sup>55.</sup> We focus on the intensive margin of lobbying. Lobbying activity has inherent fixed costs rendering it extremely persistent. We, thus, do not have enough variation in the extensive margin to measure the impact of greener household preferences.

<sup>56.</sup> 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.

ter two controls we aim at mitigating concerns that our results are confounded by systematic variations in environmental regulation similar to firm exposure to wildfires. Finally, we control for the score of Republicans in the last presidential elections in column (5) 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.<sup>57</sup>

The results in our preferred specification with the full set of controls, column (5), are economically meaningful.<sup>58</sup> A one percent increase in our index of willingness to act on average implies, for instance, (i) a reduction in the growth rate of pro-environmental lobbying expenditures by 2.5 percent, (ii) a rise in the growth rate of clean innovation by 3 percent, and (iii) a rise of the growth rate of dirty innovation by 1.8 percent.

While we do not observe an effect on total lobbying activity, lobbying on environmental topics increases and pro-environmental lobbying decreases as a consequence of greener household preferences. This suggests a reallocation of lobbying activity within topics and a redirection towards anti-environmental lobbying. As expected, firm clean patenting increases after a contemporaneous greening of preferences. However, somewhat unexpectedly, we find an increase in dirty innovation of about half the magnitude. Both gray and non-classified innovation decrease as environmental willingness to act rises.

Taken together these results suggest that greener household preferences have an ambiguous effect on a greening of the economy: On the one hand, they contribute to a green transition by directing innovation away from gray to clean innovation. On the other hand, firms also increase dirty innovation and reallocate environmental lobbying towards anti-environmental lobbying. Firms cope with greener household preferences by offering more competitive combustion vehicles and by protecting revenues from dirty products. Both strategies hamper a green transition.

#### 5.2 Dynamics

The previous conclusions derive from a potentially misleading short-run perspective. What matters for a green transition is how greener household preferences operate over time. It is, thus, imperative to widen our perspective to a longer horizon, which we will do in this section.

<sup>57.</sup> The only exception is anti-environmental lobbying expenditures where the estimate becomes insignificant (column (2) to (5)). One explanation may be that both changes in wildfires and changes in our index are positively correlated with the share of the population commuting by car. Firms seem to lobby more against additional environmental regulation as a higher fraction of the population commutes by private car. When not controlling for transportation habits, we would, thus, count differential firm behavior that stems from transportation habits instead of a greening of preferences.

<sup>58.</sup> In Appendix E.1, we elaborate on the transformations we apply to our coefficients to interpret them as elasticities.

	OLS		Г	V	
	(1)	(2)	(3)	(4)	(5)
Aggregates					
Total Knowledge Stock					
$\Delta^{\log}_{8s} ENV$	4.06***	7.51***	7.41***	6.13***	6.12***
0,51	(1.40)	(0.60)	(0.51)	(0.47)	(0.48)
Total Lobbying					
$\Delta^{\log}_{8,s_t} ENV$	3.74**	-0.27	-1.94*	0.02	-0.38
	(1.75)	(1.06)	(1.13)	(0.92)	(1.08)
Decomposition Knowledge Stock					
Clean Knowledge Stock					
$\Delta^{\log}_{8,s_t} ENV$	3.70***	4.54***	4.50***	3.67***	3.54**
	(1.05)	(1.07)	(1.29)	(1.34)	(1.36)
Dirty Knowledge Stock					
$\Delta^{\log}_{8,s_t} ENV$	1.38	2.35***	2.46***	1.66***	1.63***
· · ·	(0.98)	(0.75)	(0.70)	(0.50)	(0.48)
Gray Knowledge Stock					
$\Delta^{\log}_{8cl}ENV$	-4.60***	-7.68***	-7.94***	-8.23***	-8.23***
0,31	(1.29)	(0.74)	(0.76)	(0.90)	(0.91)
Non-Classified Knowledge Stock					
$\Delta^{\log}_{8si}ENV$	-0.64	-2.83***	-2.66***	-1.46**	-1.53**
0,01	(0.51)	(0.65)	(0.48)	(0.63)	(0.61)
Decomposition Lobbying					
Environmental Lobbying					
$\Delta^{\log}_{8si}ENV$	12.76***	6.79***	5.92***	5.45***	5.11**
	(2.14)	(0.74)	(1.31)	(1.93)	(2.09)
Anti-Environmental Lobbying					
$\Delta^{\log}_{8.st}ENV$	3.76***	0.90**	0.66	0.25	0.07
0,01	(0.95)	(0.44)	(0.51)	(0.67)	(0.69)
Pro-Environmental Lobbying					
$\Delta^{\log}_{8,s_t} ENV$	-3.72**	-4.27***	-5.13***	-2.32**	-2.41**
-7.1	(1.42)	(0.81)	(0.84)	(1.15)	(1.19)
FE: year-quarter	X	x	x	x	x
FE: state-quarter	Х	Х	Х	Х	Х
Firm Irend	Х	X	X	X	X
Lagged Firm Controls	Х	Х	X	X	X
Lagged Demographic Controls			X	X	X
Lagged Transportation Controls			Х	Х	X
Lagged Folitical Controls	1070	1070	1070	1070	A 1070
Montiel-Pflueger first-stage F	1970	218	207	114	1970

#### TABLE 6: Effect of Greener Household Preferences on Firms

Significance codes: \*\*\*: 1%, \*\*: 5%, \*: 10%

*Notes:* Column (1) depicts OLS, and columns (2) to (5) are shift-share IV results. Standard errors clustered at the state level are in parentheses. All changes are in two years differences (eqight quarters).  $\Delta_{8,s_t}^{\log} ENV$  represents the eight quarters difference in the index of environmental will-ingness to act that is constructed in section 3. In columns (2) to (5), it is instrumented by the change in wildfire exposure computed using satellite data from NASA's FIRMS dataset. Each column is the result of a different regression. Each row reports the results for a different outcome variable. The unit of analysis are firms, i.e., U.S. automotive groups. Outcomes are extensively described in Section 3.

Figure 5 depicts dynamic responses of key variables.<sup>59</sup> We find a strong and significant increase in overall patenting behavior of firms which only decays after roughly twelve quarters (three years) and a less clear but equally sizable reduction in total lobbying expenditures (Figure 5a). As household preferences become greener, firms find it profitable to spur innovation.

Figure 5b sheds light 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 five percent immediately after the shock. It remains higher for roughly ten quarters after the change in household preferences, before it returns to its counterfactual long-run growth rate. The reduction means that the short-run growth rate between two adjacent quarters deviates negatively from its counterfactual when household willingness to act is kept constant. We conclude that the immediate increase in clean innovation growth is merely a reallocation of clean patenting from the future to the present. In the long run, a reduction in clean knowledge growth compensates for the initial increase and a substantial long-lasting effect of greener household preferences fails to materialize.<sup>60</sup>

For dirty innovation the picture drawn by the long-run perspective also differs markedly from the instantaneous effect observed in the previous section. The initial rise vanishes already after one quarter. Followed by no change in long-run growth rates until 3 years after the shock. Only then do long-run growth rates of dirty innovation reduce by roughly 5 percent, albeit persistent so until 5 years after the shock. We record that greener household preferences are effective in persistently redirecting innovation away from polluting products.<sup>61</sup>

Somewhat surprisingly, innovation on gray technologies that make combustion engines less polluting declines massively immediately after the shock and only recovers so slowly so that over the full horizon considered, i.e. up to five years after the shock, long-run growth rates remain depressed as household preferences become greener. Taken together, these patterns suggest that, on aggregate, greener household preferences direct R&D investment towards clean vehicles away from research on other environmentally-friendly technologies.

When looking at the composition of lobbying expenditures, the effect of greener household preferences becomes more ambiguous (Figure 5c). We find a strong and persistent drop of proenvironmental lobbying expenditures exceeding more than 15 percent. The reduction is not compensated and growth rates remain diminished over the full horizon we study. Conversely, anti-environmental lobbying expenditures, especially in the short run, increase. After ten quar-

<sup>59.</sup> Results are effects on long-run growth rates relative to the base period t - 8. That is, we measure the change in long-run growth rates at different horizons  $h : \frac{y_{t+h}}{y_{t-8}}$ . In the figures, the sign of the slope between two periods can be interpreted as the sign of the differential effect on the growth rate between these two periods:  $\frac{y_{t+h}}{y_{t+j}}$ , where 0 < j < h. We refer to the growth rate between two adjacent periods as *short-run* or quarterly growth rates.

<sup>60.</sup> We will see in the heterogeneity analysis (Subsection 5.3), that Tesla is driving this average effect. 61. Unfortunately, our data does not admit studying a longer horizon.







*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  $\log(y_{it+h}) - \log(y_{it-8}) = \lambda_t^h + \alpha_i^h + \beta^h \Delta_{8,s_t}^{\log} ENV_{it} + \gamma^h X_{it} + \epsilon_{it+h}$ , for quarters h=0, ..., 20 after the shock. Shaded areas are 95% error bands with standard errors clustered at the state level.

ters, the effect decays and long-run growth rates seem largely unaffected by greener household preferences. In sum, the share of anti-environmental lobbying increases over the full horizon. In light of the literature studying the effects of anti- and pro-environmental lobbying we conclude that this shift in lobbying expenditures entails adverse and prolonged negative effects on the environment, even though anti-environmental lobbying is unchanged in the long run.

All in all, our results point to firms using a combination of clean innovation 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 to deal with a change in household preferences. However, the heterogeneity analysis which follows suggests that it is different firms choosing to lobby or to adjust the direction of innovation.

#### 5.3 Discussion: Firm Heterogeneity

In this section, we explore some mechanisms behind our results by distinguishing between the *dirtiness* of firms. We first show that Tesla drives the front-loaded response of clean innovation, while other firms with a mixed product and knowledge portfolio increase their clean innovation in the long-run. We then examine the role of firm reliance on sales of combustion vehicles. The dirtier the firm the more important anti-environmental lobbying and the reduction in dirty innovation. The shift from gray to clean innovation, in contrast, is muted.

A Special Case: Excluding Tesla from the sample. While the automotive industry mainly consists of mixed firms which derive an important part of their revenues from selling combustion vehicles, Tesla is an extreme exception by solely generating revenues from selling clean cars and by engaging only in R&D on clean technologies.<sup>62</sup> Excluding Tesla from the analysis uncovers the pivotal role of Tesla when it comes to innovation and clean innovation in particular. While in our baseline results the growth rate of both variables rise in the short run and revert to their no-shock value after ten to 15 quarters (the blue-solid graphs in Figure 6), the same growth rates only increase in the long-run when Tesla is excluded from the sample (the red-dashed graphs in Figure 6).

This observation suggests that, as expected, innovation activity of the average mixed-strategy firm responds with a lag (here by slightly less than four years) to changing household preferences. Tesla, in contrast, leverages its competitive advantage to patent more clean technologies immediately after the shock. Results support the interpretation that the firm prepones filing clean patents in expectation of increased clean competition: Clean knowledge stock growth in

<sup>62.</sup> In 2015, for instance, the share of clean sales amounts to below 20 percent for all other firms.

the short run is higher than expected without a greening of preferences, whereas, after three years, clean knowledge growth rates are below their status quo absent a greening of preferences.<sup>63</sup> In addition to a bigger clean knowledge stock on which Tesla can build, the firm's revenues are also less negatively affected by a shift in preferences towards cleaner products. If anything, the firm should profit from greener household preferences.



FIGURE 6: Effect of Greener Household Preferences in Sample with and without Tesla

*Note:* This figure reports the impulse responses of total knowledge stock and clean knowledge stock following an increase in our index of willingness to act environmentally friendly according to the following specification:  $\log(y_{it+h}) - \log(y_{t-8}) = \lambda_t^h + \alpha_i^h + \beta^h \Delta_{8,s_t}^{\log} ENV_{it} + \gamma^h X_{it} + \varepsilon_{it+h}$ , for quarters h=0, ..., 20 after the shock. Shaded areas are 95% error bands, where standard errors are clustered at the state level.

The Importance of Dirty Product Sales. The case of Tesla points to the importance of firm heterogeneity. We, therefore, want to dig a bit deeper into heterogeneous firm responses focusing on the share of revenues coming from dirty products. This measure allows to capture how exposed a firm is to a reduction in demand for cars with combustion engine. We hypothesize that dirtier firms have an increased incentive to prevent stricter environmental regulations in response to a shift in demand toward clean products for three reasons. First, those firms are affected more adversely by the shift in demand. Second, these firms need to catch-up with cleaner firms to eventually survive a green transition of the economy. Third, dirtier firms are hit more by stricter environmental regulation.

We run the following regression:

$$\log(y_{it+h}) - \log(y_{it-8}) = \lambda_t^h + \alpha_i^h + \beta^h \Delta_{8,s_t}^{\log} ENV_{it} + \delta^h Dirty\_Share_{it-8} + \gamma^h \Delta_{8,s_t}^{\log} ENV_{it} \times Dirty\_Share_{it-8} + \zeta^h X_{it} + \varepsilon_{it}^h$$
(7)

<sup>63.</sup> The increased magnitude in the sample without Tesla may be explained by a smaller average level of clean innovation.

for different horizons h = 0, ..., 20. The variable *Dirty\_Share* represents the share of revenues from dirty products in the total revenues of the firm before the shock<sup>64</sup> ranging from 0 to 1.<sup>65</sup> We instrument the interaction term by the interaction of the share of dirty sales over the total revenues of the firm, *Dirty\_Share*<sub>it</sub>, and the weighted average of changes in fire exposure, *Z*<sub>it</sub>.

Figure 7 depicts the coefficient on the interaction term in model (7) transformed to reflect the additional effect of a one percent increase in the index of willingness to act on the outcome variable in percent at two distinct values of our measure of dirtiness: the average and the maximum value of the share of dirty sales.<sup>66</sup> We restrict ourselves to the sample without Tesla to more precisely capture decisions of firms that have a choice between clean and dirty R&D.

In essence, the results suggest that dirtier firms respond less with a reallocation of innovation activity to greener household preferences.<sup>67</sup> The rise in clean innovation is largely muted throughout the horizons considered (Figure 7b), and gray innovation reduces less (Figure 7d). Thus, instead of a radical shift to cleaner technologies, dirtier firms opt for a soft response by making their in principle dirty products a bit cleaner. In addition, the dirtier a firm, the less it relies on innovation to cope with greener household preferences (Figure 7a), and dirty firms put some of their dirty patenting on hold (Figure 7c). As compared to a fictive firm without any dirty sales, the average dirty firm reduces its dirty knowledge stock roughly 25% more in the medium term. This finding underscores the sizable effect of greener household preferences on innovation of dirty technologies

The reduction in dirty innovation is accompanied with a rise in anti-environmental lobbying expenditures (Figure 7f) in the medium run. This increase is rationale in view of dirtier firms relying more on dirty revenues so that anti-environmental lobbying is more profitable per se.

Taken together, dirtier firms rely more on anti-environmental lobbying and less so on innovation. This could be explained by financial difficulties arising from a shift in household preferences, or by path dependency of innovation. Cleaner firms, conversely, opt for a stronger shift towards clean technologies and rely less on anti-environmental lobbying. This suggests that anti-environmental lobbying does not operate as a strategy to finance a green transition on

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

<sup>64.</sup> We follow Kwon, Lowry, and Verardo 2023 and define the dirtiness of a firm as the firm's share of revenues coming from dirty products. The rationale to use revenues shares from dirty products rather than the share of dirty technologies is that firms extracting revenues from polluting products might innovate green to protect themselves against potential environmental regulation and to gain a first-mover advantage to deter competition. However, if firms' current cash flows derive more from brown-type operations, these firms could decide not to supply cleaner products despite the availability of clean technologies. In this scenario, clean innovation corresponds to a long-term insurance rather than to a transition in production.

<sup>66.</sup> Consult subsection E.1 for more details.

<sup>67.</sup> The results of the heterogeneity analysis are only mildly precise, yet large in magnitudes. The discussion which follows should therefore be understood against the background of statistical uncertainty. Nevertheless, the large magnitudes of the effects keep us from concluding that firm heterogeneity does not play a role.

#### FIGURE 7: Additional Effect of Greener Household Preferences at varying Degrees of Dirtiness in the Sample without Tesla



*Note:* Graphs show the additional effect on key variables to a one percent increase in our index of green household preferences at the firm average of the share of dirty sales, 0.66, and the maximum, 1. That is, graphs depict the coefficient  $\gamma$  of the specification  $\log(y_{it+h}) - \log(y_{it-8}) = \lambda_t^h + \alpha_i^h + \beta^h \Delta_{8,s_t}^{\log} ENV_{it} + \delta^h Dirty_Share_{it-8} + \gamma^h \Delta_{8,s_t}^{\log} ENV_{it} \times Dirty_Share_{it-8} + \zeta^h X_{it} + \varepsilon_{it}^h$ , for quarters h=0, ..., 20 after the shock. Shaded areas are 95% error bands, and standard errors are clustered at the state level. Coefficients are transformed to reflect a percentage change in the outcome variable. Standard errors are transformed using the delta method. Results correspond to our most restrictive specification with controls and fixed effects.

the firm level.

Above findings substantiate insights from recent empirical analyses which report a negative relationship between innovation and lobbying (Akcigit, Baslandze, and Lotti 2020; Bombardini, Cutinelli-Rendina, and Trebbi 2021). The intuition comes from the influential study of Aghion et al. 2005 which predicts that firms close to the technological frontier should innovate when facing high competitive pressures. When innovation over the frontier is too expensive, lobbying qualifies as a potential margin of adjustment. By distinguishing between types of innovation, we can contribute to this literature and show that the absence of dirty innovation constitutes a response in the direction of innovation.

#### 5.4 Discussion: Comparison to the Effect of Fuel Prices

Next, we want to gauge a bit better the effectiveness of greener household preferences by comparing our results to the effect of fuel prices.<sup>68</sup> To this end, we follow Aghion, Dechezleprêtre, Hemous, et al. 2016 and exploit changes in fuel prices outside the U.S. considered exogenous to our firm outcomes. Variation in exposure comes from heterogeneous predetermined revenue shares of firms.<sup>69</sup>

Figure 5 depicts the dynamic responses to an increase in fuel prices. Our results are largely in line with Aghion, Dechezleprêtre, Hemous, et al. 2016: Clean innovation growth increases constantly until 10 quarters upon a one percent increase in fuel prices (Figure 8b), while dirty innovation growth reduces mildly in the medium run. In the long run, there is no significant difference in growth rates of all knowledge types to a counterfactual situation without fuel price increase. Gray innovation activity remains unaffected by higher fuel prices.

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, Figure 8b). Given that the strong initial increase in clean innovation was driven by Tesla and rather a reallocation of clean patents over time than a substantial increase, these results point to such a strategy not being profitable in response to higher fuel prices. Second, the long-run growth rate of dirty innovation remains largely unchanged in response to higher fuel prices, while greener household preferences seem to have a persistent negative effect on dirty innovation driven by dirtier firms. Thirdly, research on gray technologies is also unaffected in contrast to the effect of household preferences where gray innovation declines substantially and persistently.

<sup>68.</sup> We use data on quarterly energy and fuel prices on country level from the IEA's "End-use energy prices and taxes for OECD countries" table.

<sup>69.</sup> In contrast to Aghion, Dechezleprêtre, Hemous, et al. 2016, 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.









(B) Knowledge Stocks: Fuel Prices





*Note:* Graphs show impulse responses of key variables to a one percent increase in fuel prices according to the specification  $\log(y_{it+h}) - \log(y_{it-8}) = \lambda_t^h + \alpha_i^h + \beta^h \Delta_{8,s_t}^{\log} ENV_{it} + \gamma^h X_{it} + \varepsilon_{it+h}$ , for quarters h=0, ..., 20 after the shock. Shaded areas are 95% error bands with standard errors clustered at the state level.

The response in lobbying is qualitatively similar to greener household preferences but less pronounced (Figure 8c). What stands out is the rise in pro-environmental lobbying in the long run. In line with the argument put forward by Grey 2018, this rise may be driven by firms having invested in cleaner technologies previously. Lobbying for environmental regulation tailored to these technologies emerges as an instrument to protect clean markets from competitors. A similar surge in pro-environmental lobbying is also visible in response to greener household preferences; yet, it is not strong enough to become positive.

In a nutshell, greener household preferences suggest to be extremely effective in directing innovation to cleaner alternatives by not only making cleaner firms innovate more clean technologies, but also by lowering the profitability of dirty innovation for dirtier firms. Second, the size of the effect of changing household preferences on clean innovation is about an order of magnitude higher than fuel prices. However, the more pronounced shift in lobbying away from pro- to anti-environmental in response to greener preferences aggravates a green transition.

### 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 Subsection 6.3.

#### 6.1 Alternative Measures of Demand

Our main analysis aims at estimating the effect of a greening in demand on lobbying and innovation, and we argue in the paper that demand is the main driver behind identified firm responses. However, as demand is not measurable,<sup>70</sup> we proxy it by environmental willingness to act which may also affect firms through alternative channels as, for instance, voter behavior. As a robustness exercise, we propose an alternative proxy of green demand based on observed vehicle registrations in this section.

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 households were willing to buy electric vehicles from the manufacturer if they could. To solve this issue, we can estimate demand using all sales made within the same market segment. We define a segment, henceforth called a *cell*, as a tuple of location and vehicle type.<sup>71</sup> The change in clean demand in this cell is then given by

<sup>70.</sup> Because we merely observe the realized equilibrium of supply and demand, and not the demand curve of consumers.

<sup>71.</sup> Examples of cells are (SUV, Ohio) or (Compact, Florida).

the change in the number of clean vehicles sold in this cell. The following exemplifies a change in demand in a cell:

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

with  $N_{ct}$  indicating the number of clean vehicles sold in a cell *c* at time *t*. We use a symmetric percent change which has the great advantage of limiting the risk of having a denominator equal to 0. 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:

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

We use this measure as an alternative to our index and leverage the exact same instrument. The estimated coefficients are presented in Table 7. The results are both qualitatively close to our main results presented in column (8) in Table 6. In particular, while the coefficients are smaller than in the baseline regression, the relative size of the effect of greener household preferences on the different firm-level variables is very similar.

	Aggre	gates		Decompositi	on Innovation		Decompos	ition of Lob	bying
	Knowledge Stock (1)	Total Lobbying (2)	Clean Know. Stock (3)	Dirty Know. Stock (4)	Gray 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*** (0.25)	-0.12 (0.35)	$1.17^{**}$ (0.52)	0.54*** (0.16)	-2.72*** (0.41)	-0.51** (0.22)	$1.69^{**}$ (0.80)	$-0.80^{*}$	0.02 (0.23)

1970

TABLE 7: Effect of Greener Household Preferences - Alternative Strategy

1970 Signif. codes: \*\*\*: 1%, \*\*: 5%, \*: 10%

1970

1970

N (states - periods)

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). log<sub>8</sub> Demand<sup>clean</sup> represents the 8 quarters difference in the the registration of electric cars in the market segments of the firm and is instrumented by exposure to wildfires as in the main specification.

1970

1970

1970

1970

1970

#### 6.2 **Alternative Instruments**

Table 8 reports results using extreme temperatures and droughts as alternative instruments. For our baseline instrument, we considered every state to be affected by all the wildfires in the U.S. within a radius of 500 km. We now assume that environmental willingness to act is only affected by extreme temperatures that take place in the state of consideration. The main advantage of the former strategy was to allow households to be influenced by large and distant wildfires, for instance through the 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 Vose et al. 2014. More precisely, we use the log average temperature, the log maximum average temperature and three variations of the Palmer Index for extreme precipitations: the Palmer "Z" index, the Palmer hydrological drought index, and the Palmer drought severity index. *The first stage F-statistics of 14 suggests that, while these instruments have less power than wildfires, the relevance condition is met.* 

	Aggregates		Decomposition Innovation				Decomposition of Lobbying		
	Patent	Total	Clean Stock	Dirty	Gray Stock	Non Classified	Env.	Pro Env.	Anti Env
	Stock	Lobbying	Stock	Stock	Stock	Stock	Lobbying	Lobbying	Lobbying
$\Delta_8 ENV$	14.93**	3.194	13.89*	14.32**	-1.400	-2.126	12.78***	-11.44***	9.185***
	(6.895)	(5.186)	(7.857)	(6.395)	(4.269)	(3.657)	(4.606)	(3.736)	(3.247)
N (states - periods)	1920	1920	1920	1920	1920	1920	1920	1920	1920

TABLE 8: Effect of Green Household Preferences - Alternative Instrument

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). log *ENV* 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 6. In particular, findings confirm that greener household preferences spur clean innovation and increase dirty innovation albeit the effect is of a similar magnitude. We report a positive effect on (anti-)environmental lobbying and a negative effect on pro-environmental lobbying expenditures, similarly to the one reported in the dynamic results presented in Figure 5. However, results don't display a decrease in gray innovation and non-classified innovation.

Estimates are economically more meaningful, yet, as the instrument has less power, we conjecture an upward bias. The reduced effectiveness could be due to the assumption that households which live close to the state where the natural disaster occurs are considered non-treated in this alternative analysis. When those households are in fact treated, our estimates would be biased downwards.

#### 6.3 Alternative Knowledge Stock Measures

One concern with using the number of patents as a measure of knowledge is that low-quality patents and high-quality ones are treated equally. However, patents and knowledge stocks

serve as a proxy for firms' R&D investment, and most likely high-quality patents reflect more innovative effort than low-quality ones. The literature, therefore, has reverted to citation weighted patents or leveraged stock market information Kogan et al. 2017.<sup>72</sup>

Our baseline results rely on the number of patents. This choice allows to focus our results solely on firm behavior on the micro level. Both, citation and stock-market weighted patents eventually contain information on realized or expected macroeconomic changes. For example, a clean patent may have assigned a higher citation weight than a dirty patent solely because the future trajectory of the economy is green, and innovation is, therefore, directed to clean patents. Similarly, weights based on the stock market comprise a notion of expectations of the evolution of the automotive market. In response to greener household preferences the stock market most likely assigns a higher weight to clean patents, not because they are of a higher quality but because they are more valuable in a green future.

Figure 9 contrasts the effect of a one percent increase in our index of willingness to act on different measures of knowledge stock: a stock-market measure based on Kogan et al. 2017, a citation-weighted measure, and our baseline measure of the number of patents. The first thing to note is that qualitatively our results are robust to the measure of the knowledge stock: Total and clean knowledge stocks rise in all specifications in the short to medium run, dirty innovation increases initially, and gray innovation declines persistently.

The stock-market measures for clean and total innovation stand out remarkably for two reasons. First, they are 3 times as large as the response of the citation weighted and our baseline measure. Second, the stock-market measure's response remains distinct from zero for the full horizon considered. We argue that this amplified effect is explained by greener household preferences also moving stock markets. This inflates the response of stock-market weighted clean patents. Especially in the long run, the rise in clean and total innovation suggests to be solely driven by stock market responses and not an adjusted innovation behavior of firms.

<sup>72.</sup> Another alternative is to focus on triadic patents (e.g. Aghion, Dechezleprêtre, Hemous, et al. 2016) which are patents that are filed at all three patent offices: at the Japanese Patent Office (JPO), the US Patent and Trademark Office (USPTO), and the European Patent Office (EPO). Given that filing a patent is costly, firms only opt for such a strategy if the innovation is of high quality. Our data from *patentsview*, however, only contains patents filed with the USPTO.



# FIGURE 9: Effect of Greener Household Preferences - Alternative Measures of Knowledge

*Notes:* This figure reports the impulse responses of innovation following an increase in the willingness to act index according to the specification  $\log y_{it+h} - \log y_{it-8} = \lambda_t^h + \alpha_i^h + \beta^h \Delta_{8,s_t}^{\log} ENV_{it} + \gamma^h X_{it} + \epsilon_{it+h}$ , for quarters h=0, ..., 20 after the shock. Shaded areas are 95% error bands with standard errors clustered at the state level.

# 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: antienvironmental lobbying.

More precisely, we examine firm responses in the automotive industry to exogenous changes in households' environmental preferences 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 preferences in a panel setting.

Our findings suggest that the average automotive firm shifts innovation away from dirty to cleaner technologies in response to greener household preferences. However, the rise in clean innovation is accompanied with an increase of anti-environmental lobbying. We further show that firm responses depend on the degree of *dirtiness*, measured as the share of dirty products in firm revenues. Firms that sell relatively more electric and hybrid cars focus on an adjustment of their innovation strategy towards clean technologies. In contrast, dirtier firms react by lowering innovation of dirty technologies and employ lobbying against environmental regulation to cope with a greening of household preferences.

We also differentiate our sample into mixed-strategy firms, that is, those with both clean and dirty products and knowledge, on the one hand, and specialized firms, i.e., those only selling clean products and innovating clean technologies, on the other hand. We find evidence that firms specialized in clean technologies choose to patent their half-baked clean technologies earlier than usual implying lower clean knowledge stock growth rates than absent a change in household preferences in the medium to long run. A strategy potentially important in anticipation of other firms innovating more clean technologies in the future. There is no sign, however, of a substantial long-run rise in clean patenting by specialized firms.

Finally, our results provide evidence that greener household preferences are extremely effective in inducing a technological green transition. In contrast to a fuel price increase, greener household preferences urge firms to lower innovation on both technologies on combustion engines and technologies that make combustion vehicles less polluting. Furthermore, the increase in clean innovation is more pronounced. Yet, a greening of household preferences entails a rise in anti-environmental lobbying, thereby, aggravating environmental regulation. Thus, the possibility for firms to protect profits through lobbying against stricter environmental regulation makes greener household preferences—contrary to intuition—adversely affect a green transition.

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# Appendix

# A Additional Summary Statistics

	Mean	SD	P25	P50	P75	Max
Total Lobbying	683.92	842.94	38.01	380.00	1040.01	6380.00
Topics						
– Énvironment	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
<ul> <li>Manufacturing</li> </ul>	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

TABLE 9: Firm lobbying expenditures by target (Quarterly)

*Notes:* The table summarizes the distribution of quarterly lobbying expenses for a list of targets in thousands of dollars. The first row reports total lobbying expenditures. On average, firms spend 684k\$ on lobbying each quarter.

#### TABLE 10: Shocks and Shares Summary Statistics

		Mean	S	D	P1	P99
Fire Shock <sub>lt</sub>		0.0000	0.000	02 -0.0	0009	0.0009
Fire Shock <sub>lt</sub> (	(w. period FE)	0.0000	0.000	02 -0.0	)009	0.0009
	Panel B: Shar	es Summ	ary Sta	tistics		
		Ν	lean	Max	•	
	1/HHI	74	13.68	743.68	-	
	$s_{lt}$ in percent		0.05	0.50		

Panel A: Shocks Summary Statistics

*Notes:* Panel A summarizes the distribution of the instrument (change in wildfire exposure) across states. All statistics are weighted by the average state exposure share  $s_{lt}$ . Panel B reports the *effective sample size* computed as the inverse of the Herfindahl index of the average state exposure share  $s_{lt}$ . 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 50 states (excluding DC).

50.00

50.00

Treatment Groups

# **B** Additional Figures



FIGURE 10: Number of Granted Patents by Type, 1976-2019

*Notes:* The figure illustrates the number of granted patents for *clean, dirty,gray* and *non-classified* technologies over time filed with the U.S. patent office. Dirty patents are defined as innovations related to internal combustion engines 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 11: 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 12: Relative Market Shares



*Notes*: The figures show the relative market share of each firm, compared to the other firms. 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 firm is over-represented in a state *l* and negative if it is under-represented in the state. Source: S&P Global, authors' calculation.



*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. Green shades indicates under-exposure. Source: NASA's FIRMS, authors' calculation.

### C 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 preferences but also by changes in supply. Second, some confounding factors could affect both household preferences and firm behavior. We use an instrument for household 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). The 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 willingness to act in our specific framework. To do so, we regress our index on our measure of wildfire exposure up to ten 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 variation in wildfires to identify the effect of wildfires on environmental preferences. The estimated linear relation is given by:

$$\widetilde{ENV}_{lt} = \alpha_{lq} + \lambda_t + \sum_{k=0}^{10} \beta_k \widetilde{FireShock}_{lt-k} + \epsilon_{lt}$$
(8)

Where  $X_{lt}$  denotes the variable X weighted by the population of state *l* at time *t*. The variable  $\alpha_{lq}$  and  $\lambda_t$  are state-quarter and time fixed effects respectively.



FIGURE 14: Dynamic relationship between wildfires and environmental willingness to act by quarters

*Notes:* The figure reports the dynamic effect of wildfires on the index of environmental willingness to act within U.S. states. The data is a panel of U.S. 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 ten 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.

Figure 14 shows the long lasting effect of wildfires on environmental interest. The estimated coefficients are positive and mostly significant for up to two years (eight quarters) after the wildfire. The effect is stronger at the time of the shock and then decreases linearly over time.

## **D** Data Construction

This section provides further information on Google Trends (Subsection D.1) and the classification of patents that we apply (Subsection D.2).

#### **D.1 Google Trends**

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 zero 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 zero indicates the lowest observed popularity.

We pull monthly data for the US states from January 2006 to December 2019. Figure 15 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.

The data is provided as the *share* of searches relative to all searches within a given month and area including the keyword.<sup>73</sup> 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 U.S. index is contained in each query. Note that this does not imply that values are normalized with the U.S. 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 U.S. 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 U.S. independent of the query composition.

<sup>73.</sup> 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 an automated browser.



FIGURE 15: 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 U.S. to allow the comparison of multiple geographical regions. Each subplot shows one line per state.

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  $\frac{share_{atk}}{\max_{i,t}\{share_{itk}\in q\}}$ , where  $q \in Q$  denotes the specific query. Dividing by the U.S. value of the same query yields:  $\frac{share_{atk}}{share_{US,tk}}$ . The share of searches directed to keyword k in state s at time t relative to the share of searches directed to 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.

# D.2 Patents classification

TABLE 11: Patent classification into clean, gray, and dirty by CPC code

CPC code	Label
Clean Patent	S
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 pro- vided 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 combus- tion 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. The classification follows Aghion, Dechezleprêtre, Hemous, et al. 2016.

# **E** Interpretation of Coefficients

#### E.1 Transformation of Coefficients

We transform coefficients to represent elasticities. Given our log-log specification of the model, coefficients are transformed as

$$\widehat{b} = 100 \times (1.01^b - 1).$$

We use the delta method to adjust standard errors:

$$\widehat{SE} = 100 \times 1.01^b \log(1.01) SE$$

Similarly, the additional effect of our index at values of the interacted variable different from zero is given by

$$\widehat{b}_{additional} = 100 \times (1.01^{b_3 \widehat{X}_2} - 1).$$

where  $\bar{X}_2$  is the value of  $X_2$  at which we evaluate the effect of environmental preferences. Transformed standard errors are again obtained by application of the delta method:

$$\widehat{SE} = 100 \times 1.01^{(b_3 \bar{X}_2)} \log(1.01) \bar{X}_2 SE.$$

#### E.2 Relating effects on long-run and quarterly growth rates

In our figures showing local projection results, we can interpret a negative slope between two adjacent horizons as a negative deviation of the quarterly growth rate from h - 1 to h. To show this, let

$$\tilde{\beta}^{h} = \frac{\frac{y_{t+h}}{y_{t-8}} - \left(\frac{y_{t+h}}{y_{t-8}}\right)_{dEnv=0}}{\left(\frac{y_{t+h}}{y_{t-8}}\right)_{dEnv=0}}$$

be the transformed coefficient of our local projection at horizon h.<sup>74</sup> Subtracting the transformed coefficients of horizon h - 1 from h, i.e., two adjacent horizons, yields:

$$\tilde{\beta}^h - \tilde{\beta}^{h-1} = \frac{\frac{y_{t+h}}{y_{t-8}}}{\left(\frac{y_{t+h}}{y_{t-8}}\right)_{dEnv=0}} - \frac{\frac{y_{t+h-1}}{y_{t-8}}}{\left(\frac{y_{t+h-1}}{y_{t-8}}\right)_{dEnv=0}}.$$

We want to show that if above expression is negative, then the quarterly growth rate between two adjacent periods deviates negatively from its counterfactual without change in the index of willingness to act. Formally, that means that  $\frac{\frac{y_{t+h}}{y_{t+h-1}} - \left(\frac{y_{t+h}}{y_{t+h-1}}\right)_{dEnv=0}}{\left(\frac{y_{t+h}}{y_{t+h-1}}\right)_{dEnv=0}} := \tilde{\beta}_{h-1}^{h} < 0.$ 

<sup>74.</sup> We abstract from multiplication by 100 as is done in the figures.

Noting that  $\frac{y_{t+h}}{y_{t-8}} = \frac{y_t}{y_{t-8}} \times ... \times \frac{y_{t+h}}{y_{t+h-1}}$ , factoring out common terms, and simplifying gives

$$\frac{\frac{y_{t+h-1}}{y_{t-8}}}{\left(\frac{y_{t+h}}{y_{t-8}}\right)_{dEnv=0}} \times \left(\frac{y_{t+h}}{y_{t+h-1}} - \left(\frac{y_{t+h}}{y_{t+h-1}}\right)_{dEnv=0}\right)$$

Multiplication with  $1 = \frac{\left(\frac{y_{t+h}}{y_{t+h-1}}\right)_{dEnv=0}}{\left(\frac{y_{t+h}}{y_{t+h-1}}\right)_{dEnv=0}}$  yields:

$$\frac{\frac{y_{t+h-1}}{y_{t-8}}}{\left(\frac{y_{t+h-1}}{y_{t-8}}\right)_{dEnv=0}} \times \underbrace{\frac{\frac{y_{t+h}}{y_{t+h-1}} - \left(\frac{y_{t+h}}{y_{t+h-1}}\right)_{dEnv=0}}{\left(\frac{y_{t+h}}{y_{t+h-1}}\right)_{dEnv=0}}_{=\tilde{\beta}_{h-1}^{h}} = \tilde{\beta}^{h} - \tilde{\beta}^{h-1}.$$

The first multiplier of above expression is positive if and only if  $\tilde{\beta}^{h-1} > -1$ . To see this note that

$$\frac{\frac{y_{t+h-1}}{y_{t-8}}}{\left(\frac{y_{t+h-1}}{y_{t-8}}\right)_{dEnv=0}} > 0 \Leftrightarrow \frac{\frac{y_{t+h-1}}{y_{t-8}} - \left(\frac{y_{t+h-1}}{y_{t-8}}\right)_{dEnv=0}}{\left(\frac{y_{t+h-1}}{y_{t-8}}\right)_{dEnv=0}} > -1.$$

A negative value of the first multiplier means a reduction of the considered long-run gross growth rate by more than 100%. We do not observe in our results so large effects. We, therefore, focus here on the case where the first multiplier is positive. It then follows from the above that

$$ilde{eta}^h - ilde{eta}^{h-1} > 0 \quad \Longleftrightarrow \quad ilde{eta}^h_{h-1} > 0.$$

Hence, a negative slope between two adjacent periods in our local projection graphs implies a negative differential effect of greener household preferences on the considered variable's quarterly gross growth rate.