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 and relate it to firm-level information on the U.S. automotive sector from 2006 to 2019. We find that firms persistently redirect innovation from conventional combustion technologies toward technologies that mitigate their emissions and electric vehicle technologies. However, we also uncover that firms—particularly those specialized in electric technologies—pursue strategies consistent with deterring competition: (anti-environmental) lobbying and strategic patenting. On aggregate, a 1% increase in the growth rate of the index has effects similar to a 50% increase in fuel price growth.

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

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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. However, the literature on directed technical change and the green transition has largely focused on tax policies.[1] In this paper, we shift the perspective, examining how firms respond to a greening of household preferences.

Our results reveal mixed effects of greener household preferences, which we quantify using a novel index on households' environmental willingness to act.[2] On the one hand, we observe a persistent reallocation of innovation efforts. Firms specialized in combustion engines increasingly innovate in *gray* technologies that reduce vehicle emissions, while EV-specialized firms expand innovation in electric and hybrid (*clean*) technologies. Both groups simultaneously scale back conventional combustion-engine (*dirty*) innovation. On the other hand, we find evidence indicative of competition-deterring firm strategies such as lobbying and strategic patenting,[3] especially among clean-technology firms. On aggregate, a 1% increase in the growth rate of our index on willingness to act is similar in size and dynamics to a 50% rise in fuel price growth.

As a first step towards these results, we construct an 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.[4] Before turning to firm responses, we demonstrate that our index mimics households' environmen-

[1] Examples of empirical contributions are Popp 2002; Martin et al. 2014; Aghion et al. 2016; Calel and Dechezleprêtre 2016; Bøler, Holtsmark, and Ulltveit-Moe 2025. Only in past years, a small literature on the effects of greener household preferences on the direction of research has emerged (Aghion et al. 2023; Keding and Ritterrath 2025).

[2] 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* interchangeably. We distinguish the concepts *environmental concerns* or *environmental attitudes* which rather express a state-of-mind that may occur without the intention to act.

[3] With *strategic* or *non-productive* patents we refer to patents that are aimed at avoiding heightened competition instead of productive use in new products (Baslandze 2021).

[4] 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).

tal attitudes derived in surveys and is a strong predictor of both green energy consumption and support for environmental policies.[5] A 1% increase in the index, six months prior to consumption, correlates with a 1.7% higher probability of consuming either solar energy or electric vehicles. The effect is comparable to an increase in monthly income by $100. Similarly, the probability of supporting environmental policies rises by 0.5%.

In the second part of the paper, we connect our measure of willingness to act with data on lobbying and innovation of 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% of U.S. greenhouse gas emissions (EPA 2023). Second, the industry produces heterogeneous goods with varying emission standards, which are easily identifiable by households.[6] Finally, the automotive industry is marked by significant lobbying expenditures and innovative activity enabling us to study complementarities between these two strategies.[7]

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% of environmental lobbying as pro- and 20% as anti-environmental. For innovation activity, we follow Aghion et al. 2016 and classify patents into clean, gray and technologies using their Cooperative Patent Classification (CPC).

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 geo-

[5]Here, we evaluate the index on a monthly frequency.

[6]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 (Moseman and Paltsev 2022). However, other externalities related to the production of electric vehicles still remain. What is important to our framework is that e-mobility is widely believed to be a low-emission alternative to combustion vehicles.

[7]We, thereby, circumvent problems to link firm-level information on lobbying and innovation faced by other recent empirical studies (Hultgren 2025).

graphic heterogeneity in firms' sales and production markets.[8] Second, we control for changes in environmental regulation at the federal level by including time fixed effects.[9] 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 hand-collected information on state-time specific environmental regulation.

Our results show that, on average, firms direct their knowledge stock[10] away from dirty towards gray technologies. The adjustment is persistent over a five-year horizon. Conversely, an immediate rise in electric and hybrid (*clean*) technologies is only short-lived and compensated in the medium run. Innovation responses are accompanied by an increase in expenditures on anti-environmental lobbying in the short and in pro-environmental lobbying in the long run.

We clarify the underlying factors behind these aggregate effects by examining how firm responses depend on the composition of their knowledge stock. To this end, we decompose the sample into firms with a high share of combustion-engine-related knowledge and those with a low share. In line with the theory on path dependence, we uncover that the non-response in clean innovation in the long run masks a persistent increase in clean knowledge stock growth by firms specialized in this technology. Conversely, the rise in gray innovation is driven by firms characterized by a high share of combustion-engine-related technologies, and all firms lower their innovation activity on dirty technologies persistently.

In addition to the productive adjustment in innovation, the results reveal firm behavior congruent with competition-deterring strategies. Firms characterized with a high share of knowledge on clean technologies more strongly complement the adjustment in innovation with anti-environmental lobbying in the short and pro-environmental lobbying in the long run. A closer look at the composition of firms within each group reveals that, on average, clean-knowledge firms hold higher market and revenue shares of the combustion-engine segment. Both features intensify firm exposure to the negative effects of a reduction in demand for combustion engines, and anti-environmental lobbying qualifies as a means to protect revenues.[11]

Furthermore, we provide evidence that parts of the aggregate rise in clean knowledge soon after the greening of household preferences consists in low-quality patents and partly reflects an adjustment in the timing to file patents earlier than usual. This finding is consistent with the

[8] Given the separation of consumption and production, we exclude the possibility that our results are confounded by wildfires affecting the supply of cars.

[9] Our analysis focuses on federal lobbying activity—as opposed to state-level lobbying—which impacts environmental policymaking at the federal level common to all firms.

[10] *Knowledge stock* refers to a firm's stock of patents, which we use as a proxy for innovation.

[11] Akcigit, Baslandze, and Lotti 2023 show that firms with bigger market shares tend to leverage political connectedness more as the stakes from competition are higher.

hypothesis that firms use clean patents as a non-productive strategy to limit competition. The patterns are especially pronounced for clean-knowledge firms which hold a three times higher EV-market share than firms with a technological advantage in combustion vehicles. Intuitively, as demand for clean vehicles increases, market leaders have an incentive to protect this market segment from heightened competition.[12]

Finally, we compare firm responses to greener household preferences with those to higher fuel prices.[13] A 1% increase in the growth rate of our index of willingness to act qualitatively and quantitatively resembles a 50% increase in the growth rate of fuel prices. Our findings, hence, underline the political relevance of and the possibilities arising from greener household preferences. While households can effectively foster a reallocation of innovative efforts toward cleaner types of technology, the subsequent rise in anti-environmental lobbying[14] and other competition-deterring strategies may complicate a green transition.

Literature. We contribute to several strands of the economics literature. Firstly, we add to the literature on endogenous growth through competition. 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 (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 is from the innovation frontier, the more it prefers to leverage political influence tools to deal with heightened competition.

Further confirming the intuition of lobbying and innovation being substitutes, an important contribution by Akcigit, Baslandze, and Lotti 2023 scrutinizes the role of market domi-

[12] Argente et al. 2025 scrutinize this firm behavior in the market for consumer-packaged goods.

[13] We follow Aghion et al. 2016 and use firm exposure to changes in fuel prices in different countries.

[14] In light of the literature studying the effects of anti-environmental lobbying, we conclude that this shift in lobbying expenditures entails adverse and prolonged negative effects on the environment, even though anti-environmental lobbying remains unchanged in the long run. Studies on firm capacities to modify environmental regulations through political influence tools attest high social costs and individual gains from anti-environmental lobbying (Kang 2016; Meng and Rode 2019). 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. Adverse environmental 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).

nance: 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. In a similar vein, Argente et al. 2025 show that market power also motivates the use of strategic patenting—another strategy to deter competition.

We confirm the intuitions of the literature in the framework of a preference shock. First, firms respond to greener preferences with the type of knowledge where they have an advantage to do so: Clean-knowledge firms push for more innovation on electric and hybrid vehicles, while firms specialized in combustion engines innovate more in technologies that lower emissions of fuel vehicles. Second, clean-knowledge firms—who in our setting happen to hold dominant market shares in both EV and combustion vehicles—combine productive innovation with lobbying and non-productive patenting.

Secondly, this paper connects to a recent literature studying complementarities between environmental lobbying[15] and clean innovation. In a theory paper, Grey 2018 suggests that polluting firms use pro-environmental lobbying to protect cleaner market segments when investing in clean R&D, thereby raising the value of newly developed clean technologies. Our results are in line with this theory: Pro-environmental lobbying expenditures rise steadily after more clean and gray patents have been filed in response to greener preferences. 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. Notably the former is related in that it focuses on the interaction of lobbying with innovation. The authors provide evidence that clean innovation and anti-environmental lobbying complement each other as long- and short-run strategies, respectively. Our findings reinforce the notion of clean innovation and anti-environmental lobbying being used in tandem, here, in response to a greening of household preferences. Another highly related paper is Hultgren 2025 who empirically investigates how firms jointly leverage innovation and lobbying in response to regulatory uncertainty shocks. Next to focusing on a preference shock, we complement Hultgren 2025 by differentiating the direction of innovation and lobbying.

Thirdly, we add to the literature investigating the role of household preferences on firm innovation and competition. Jovanovic and Rob 1987 propose a demand-pull theory to explain firm responses to household preferences. Firms form expectations about future demands. Competing about future revenues, they direct research efforts to the type of goods they expect to be in high demand tomorrow. On the empirical side, a mounting literature analyzes demand-led

[15]We detail papers on the effects of environmental lobbying in Footnote 14.

explanations of competition and innovation such as the distribution of income (Jaravel 2019), brand preferences (Bronnenberg, Dubé, and Gentzkow 2012), aging (Bornstein 2025; Angelini and Brès 2024), and green preferences (Aghion et al. 2023; Keding and Ritterrath 2025). We contribute in two respects: first, by comparing innovation and lobbying responses. Putting both in parallel helps understand alternative firm strategies which curtail competition. Second, we propose a novel measure of household preferences.

In so doing, fourthly, the paper bridges the gap between the behavioral economics literature on climate change and the literature on firm strategies in the green transition. Recent years have seen a surge in studies on social responsibility and the willingness to act against climate change. This literature derives household preferences and attitudes from experiments or surveys (Bartling, Weber, and Yao 2015; Falk et al. 2021; Dechezleprêtre et al. 2025; Kaufmann, Andre, and Kőszegi 2024).[16] We extend this literature by developing a time-series measure of households' willingness to act that enables relating firms and households in a panel setting. Our findings make an important contribution by uncovering mechanisms that call into question an unqualified benefit of households' willingness to act due to competition-avoiding firm strategies.

Finally, the paper complements a fast-evolving literature on the transition to green economies that generally focuses on climate change mitigation policies (model-based contributions are, for instance, Golosov et al. 2014; Fried 2018; Barrage 2020; examples of empirical work are Popp 2002; Martin et al. 2014; Aghion et al. 2016; Calel and Dechezleprêtre 2016; Bøler, Holtsmark, and Ulltveit-Moe 2025). The novelty of our paper is the departure from a focus on tax policies by investigating household behavioral changes as a driver of the green transition; an issue that is gaining attention in the political debate.[17] We show that greener household preferences have similar effects than higher fuel prices.

Outline. The remainder of the paper is structured as follows. We present the index of willingness to act in Section 2. Section 3 outlines the 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, before Section 7 concludes.

[16] 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. 2025 focus on support for mitigation policies. Kaufmann, Andre, and Kőszegi 2024 investigate market failures arising from socially responsible consumers.

[17] 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 2025).

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 green energy consumption and environmental policy support in Subsection 2.2.

2.1 Constructing an index of environmental willingness to act

To construct an index of willingness to act, 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 for, or to make an investment to consume cleaner goods. To this end, we consider the keywords *Electric Car*, *Recycling*, and *Solar Energy*. We download time series of the relative search intensity of each individual term for each state and harmonize the data as laid out in Online Appendix A. This provides us with three distinct time series for each state, one for each search term.

We follow Baker, Bloom, and Davis 2016 to summarize the information into one index per state, 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 $\frac{100}{mean_{state}}$.[18]

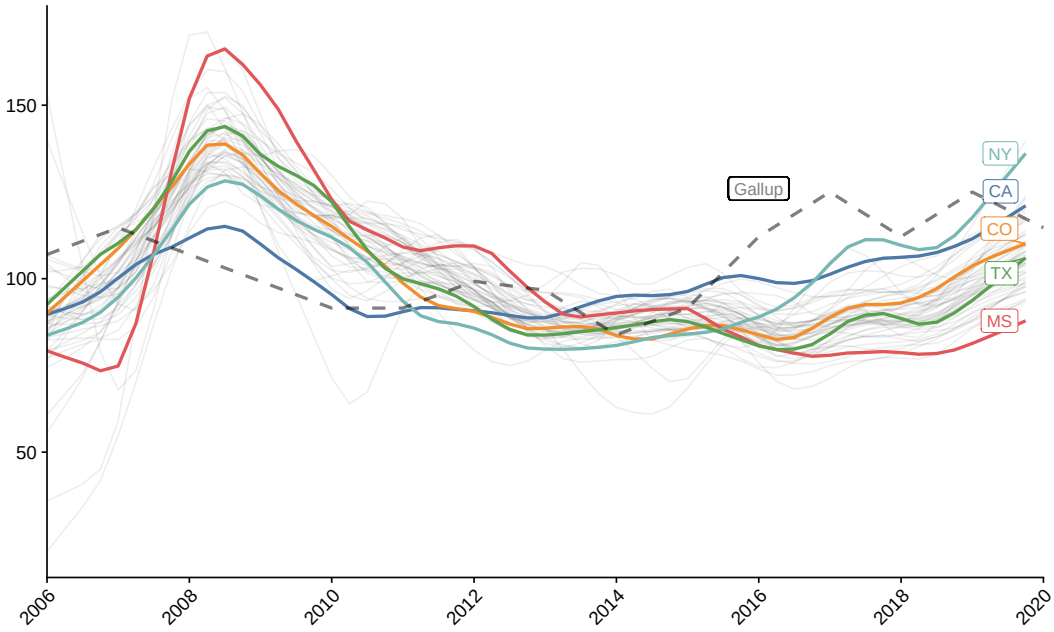
Figure 1 presents the index. A positive trend over the first years is followed by a noticeable U-shape. In our sample, we observe that the decrease started around 2008. One candidate explanation is the drop in the salience of climate issues as a consequence of the financial crisis.[19] The subsequent resurgence in willingness to act across states begins around 2015—coinciding with the adoption of the Paris Agreement in December 2015—and continues through the end of our sample period in 2019. Importantly for the empirical exercise, there is significant variation at the state level and over time.

The gray-dashed graph in Figure 1 depicts a federal-level index built from Gallup data (Gallup 2023) on the share of survey participants that is highly worried about climate change. The graph closely mimics and foreshadows the state-level indices on willingness to act. See Subsection D.2 for further details and a discussion.

[18] We discuss alternative yet related indices in Subsection D.1. Subsection 6.3 elaborates on results using a broader index, including keywords more generally associated with environmental interest.

[19] This pattern aligns with the stark decline in environmental awareness presented in Aghion et al. 2023.

FIGURE 1: Index of environmental willingness to act



Notes: This figure shows the index 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 terms are *Solar Energy*, *Recycling*, and *Electric Car*. The dashed graph depicts an index constructed from Gallup data (Gallup 2023) on the share of survey participants that is highly concerned about climate change. For further details on the latter see Subsection D.2.

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 concern is the representativeness of our measure. Access to the internet is widespread and Google is the most popular search engine in the U.S.[20] However, the types of households using it could be limited and self-selected.[21]

To assess the performance of our measure, we explore its relation with direct measures of environmentally-friendly changes in consumption and with support for environmental poli-

[20]Official statistics on search engine use are difficult to find. According to StatCounter 2025, the average market share of Google from 2015 to 2019 amounts to 86%. State-level information on the use of Google is even scarcer. The digital marketing agency 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.

[21]Despite this high popularity of Google, it is most likely the case that only certain types of households use search engines. This could 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. In Subsection 6.1 we use sales data to proxy household preferences for environmentally-friendly consumption. The results are very similar to the ones based on the index.

cies. If our index indeed captures a notion of willingness to act, we expect to observe positive correlations with both comparisons. This is what we find from the analyses laid out in more detail below. Comparisons to state-level information on survey-based attitudes and on electric vehicle registration are presented in Online Appendix D, further confirming the strength of our measure.

Correlation with environmentally-friendly consumption. To investigate whether our measure predicts environmentally-friendly behavior at the household level, we draw from the Consumption Expenditure Survey (CEX) provided by the U.S. Bureau of Labor Statistics 2024. The degree of granularity provided by this dataset allows us to account for household characteristics and to compare their relevance. We focus on the joint probability to either spend on electric vehicle charging, having solar panels, or both which we perceive as a measure of green energy consumption. The analysis is conducted on a monthly level.

Table 1 depicts the results of a linear probability model with varying controls. The index is strongly significant at the 1% level 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%. 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[22] (in k$ per month), raises the effect of the index slightly, Column (6).

In our preferred specification with all controls, Column (6), a 1% increase in the index is associated with a 0.04 percentage point increase in the probability of green energy consumption. This is a meaningful effect equivalent to 1.7% of the observed sample share of 2.4%. The effect size is comparable in magnitude to a $100 increase in monthly per-capita income which is associated with a 0.03 percentage point increase in the probability of green energy consumption. Finally, the strength of the correlation is equivalent to that of the results based on vehicle registration data discussed in Subsection D.3, corroborating the relation of the index and green consumption.

Correlation with environmental policy support. Having established that the index robustly predicts higher probabilities of environmentally-friendly consumption, we now examine its relationship with support for environmental protection. We use data from the American Na-

[22]The modified OECD equivalence scale is applied.

TABLE 1: Green energy consumption and index of willingness to act

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

Notes: Significance codes: ***: 1%, **: 5%, *: 10%
The table shows regression coefficients of a linear regression of the share of CEX households consuming either solar energy, electric vehicle charging, or both from 2017 to 2023 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. Regressions use monthly data.

tional Election Studies (ANES) which surveys political opinions of U.S. citizens around election dates.[23] We construct a repeated cross-section of the reoccurring question on whether a survey participant supports an increase of the federal budget share spent on environmental protection. Possible answers are "increase", "keep about the same", "decrease", or "don't know".[24] The final repeated cross-section 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 dataset contains nine distinct month-year combinations.[25]

We run linear prediction models 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 are shown by the red triangles in Figure 2 separately for each considered lag of the the index. Numbers reflect values in percent relative to the average share of households supporting an increase in the environmental budget.[26] Clearly, a higher index pre-

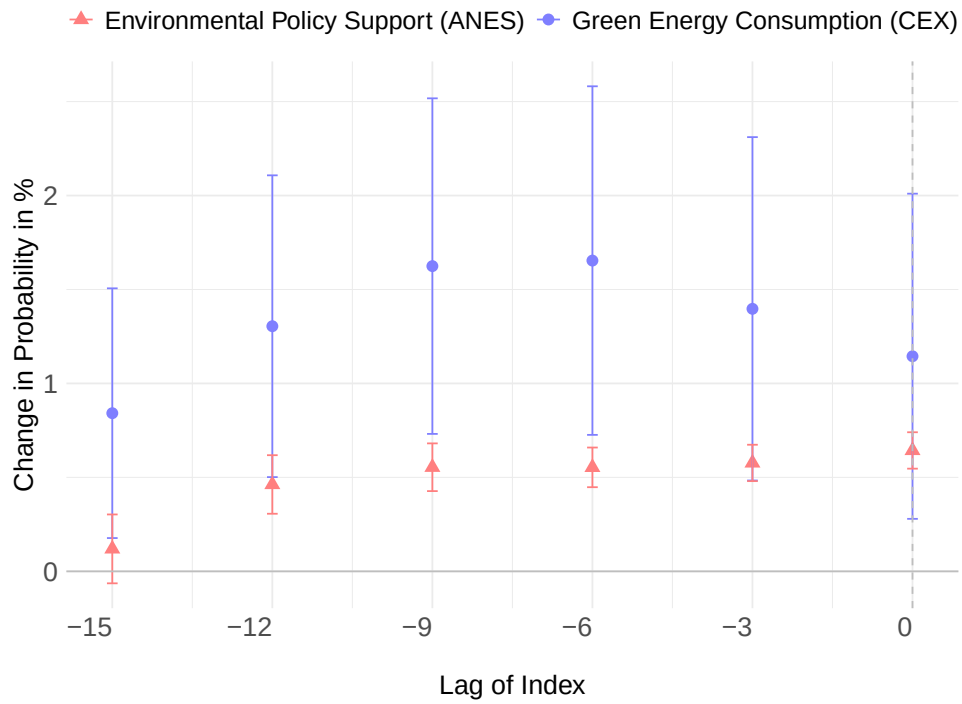
[23]The ANES is a long-standing data source on voting behavior, public opinion, and political participation collected since 1948 and designed to be representative of the U.S. electorate. For more information consult https://electionstudies.org/.

[24]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.

[25]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.

[26]The average share of supporters in our constructed time series is 48.90% where sample weights are

FIGURE 2: Coefficients on index of willingness to act prior to green energy consumption and environmental policy support at monthly frequency



Notes: This figure shows regression coefficients of the share of participants supporting an increase in the budget share on environmental protection (ANES) on different lags of the index of environmental willingness to act by the red triangles. The violet circles show equivalent correlations with environmentally-friendly energy consumption (CEX). Vertical lines indicate 10% confidence intervals. The horizontal axis shows the lags of the index relative to the respective survey. At zero, for instance, the index is measured at the time of the survey.

dicts a higher share of environmental policy support. An increase of 1% in the index 9 months prior to the survey, for instance, predicts a roughly 0.5% higher probability that a household supports an increase of the environmental budget share.

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.[27] Interestingly, the size of the effects suggests that our index is more important a predictor of green energy consumption (the blue circles), indicating that the demand channel is more relevant when relating firm decisions and the index on willingness to act.

Overall, the comparisons to green energy consumption, support for environmental protection, and survey data on attitudes (Subsection D.3) indicate that our measure of environmental willingness to act captures a greening of household preferences, which drive behavioral

applied.

[27] These are the results of the model underlying Column (6) in Table 1 for the lagged index as indicated on the x-axis of Figure 2. The effects are expressed in percent of the average probability to consume green energy (2.4%). All coefficients are positive and significant at the 10% level.

changes in voting and 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 the 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.[28] The 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.[29] Using this dataset, we can determine the market share of each firm[30] at the state level which we use to assess firm exposure to household preferences. From this dataset we also derive the lagged U.S.-wide market share for firms that is included as a control in the regressions.

Fires: NASA FIRMS. As basis for the instrument, we use exogenous shocks to household preferences through wildfires. Data on fires comes from the Fire Information for Resource Management System (FIRMS) of the 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.[31] We apply the following procedure to obtain a map of all fires in the U.S. over time. First, we collapse the 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 the *dbscan* algorithm provided by Ester et al. 1996.[32] Third, we draw a convex polygon around each cluster to determine the area of the fire. Finally, the fire exposure of a particular state l is computed in two steps: One, we sum over all the fires f that are within

[28] For more information on the dataset see https://www.spglobal.com/mobility/en/products/automotive-market-data-analysis.html.

[29] 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.

[30] We use the term *firm* to refer to vehicle groups, that is, global automotive producers commonly comprising several makes.

[31] We focus on *presumed vegetation fire* and drop the other types of fires to focus on natural disasters.

[32] We focus on clusters to exclude fires that are very small. Therefore, we choose to compose clusters of at least five points at a maximum normalized distance of 0.25.

a distance of 1000km to a state a function of fire-state characteristics:

$$Fire_{lt} = \sum_{f} intensity_{ft} \times \frac{surface_{ft}}{distance_{flt}^{4}} \times \mathbf{1}\left(distance_{flt} < 1000km\right),$$

where the variable *intensity* is proxied by the radiative power of the fire (in Megawatts) and *surface* refers to the size of the fire. We divide our measure by the distance between the fire and the state to the power of 4 to capture that close populations are exponentially affected, but we also allow for populations further away from the fire to be affected, for instance, via the media.[33] Two, to get the final fire exposure of a state, we condense the fire information to a dummy that takes on the value 1 if a state's $Fire_{lt}$ measure exceeds the median in the panel:

$$Fire\ Exposure_{lt} = \mathbf{1}(Fire_{lt} > Median(Fire_{lt})).$$

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. Based on this dataset, we derive information on the topics firms lobby on. As expenditures on environmental topics we consider all expenditures targeting the issues: Environmental/Superfund, Energy/Nuclear, Clean Air & Water (Quality), and Fuel/Gas/Oil.[34]

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 focusing on environmental topics.

To determine whether a lobbyist is Republican or Democrat, we first use information on campaign contributions by lobbyists.[35] In particular, following Kwon, Lowry, and Verardo 2023, we consider that a lobbyist is Democrat (Republican) if more than 75% of the lobbyist's lifelong campaign contributions target Democrat (Republican) legislators. Second, we comple-

[33]The distance is computed between the fire's and the state's center of gravity.

[34]We define a report as related to the environment if at least one of the reported topic is in the former list. The records that have at least one environmental issue correspond to around 60% of overall expenditures.

[35]The data is available at https://www.lobbyview.org/data-download/. For more information on the data see Kim 2018 and Garza, Liu, and Ruehle 2023.

ment 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 additionally defined as Democrat (Republican) if the lobbyist previously worked for a Democrat (Republican) legislator.[36]

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 targeting environmental issues. In our dataset, we categorize around 38% of environmental lobbying as pro-environmental lobbying, 20% as anti-environmental lobbying. A remaining 42% are not classified.

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 invention. We match patents with firms in our sample using the assignee disambiguation method of PatentsView and manual inspection.[37] Following Aghion et al. 2016 we categorize patents using their Cooperative Patent Classification (CPC) into *clean*, *dirty*, and *gray* technologies. Clean patents correspond to innovation on electric and hybrid engines, gray patents refer to technologies rendering fuel engines less polluting, and dirty patents indicate all other innovations on fuel engines.[38]

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

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

Where R_{ist} represents the number of new patents from firm i in technology s, with $s \in \{clean, gray, dirty\}$, at time t.[39] The parameter δ stands in for the quarterly depreciation of

[36] 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.

[37] For more details consult https://patentsview.org/disambiguation.

[38] The classification of patents into these three categories by their CPC code can be found in Online Appendix A.

[39] 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. Despite these concerns, we take the number of patents as our baseline measure of knowledge as it does neither entail market expectations on the green transition nor is it subject to self-citation which may implicitly weight big firms more in the estimations. We present a robustness exercise weighting patent applications with an estimation of their private economic value from Kogan et al. 2017 updated until 2020 and with citation weights in Subsection 6.4.

knowledge.[40] We use K_{ist} in our main analysis to measure changes in innovation activity. Using a stock instead of a flow variable is less prone to arbitrary results arising from the choice of lags in the regression.[41]

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.[42] 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. In particular, we control for the adoption of different components of the Act: regulation on pollutants, regulation on greenhouse gas, and regulation on zero-emission vehicles.[43] To further include changes in taxation and pecuniary consumer incentives, we control for the end-use price of gasoline and diesel. We also account for demographic information such as the employment rate and the share of young persons in the population (from the Census), the share of the rural population (from the Decennial Census), and income per capita (from the Bureau of Economic Analysis).[44] We condition on 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.[45] 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. We further motivate the choice of controls when discussing our results in Subsection 5.1.

[40] Following the literature on depreciation of R&D (Li and Hall 2020), we set the depreciation rate to 0.2 for the annual frequency.

[41] Using knowledge stocks prevents zero entries in the data. We then avoid working with a logarithmic transformation of $ln(1 + x)$ which would bias our results (Chen and Roth 2023).

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

[43] Sources are available upon request.

[44] 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.

[45] For more information see https://electionlab.mit.edu/data.

3.1 Summary Statistics

Having specified all main data sources, we 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.[46] 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.[47] Table 2 reports firm characteristics of the main outcome variables.[48] There is high heterogeneity in the mix of technologies patented by firms, with firms such as Mazda or Isuzu innovating mainly in dirty technologies, and others focusing on clean technologies (Table 2). However, all firms—with the exception of Tesla—innovate in all types of technologies.

TABLE 2: Summary statistics by firm on quarterly level, 2006-2019

Group	Clean patents	Dirty patents	Gray patents	Total lobbying (k$)	Pro-env. lobbying (k$)	Anti-env. lobbying (k$)	Market share (avg,%)
BMW	106.55	52.92	16.60	117.67	7.27	27.16	2.32
Daimler	99.95	115.48	19.25	377.90	1.87	26.80	2.09
Ford	575.30	910.44	95.54	1869.56	1026.52	106.99	15.03
Geely Automobile Hld.	42.68	48.38	9.40	289.02	4.40	92.60	0.52
General Motors	764.59	563.85	138.91	2988.84	713.34	568.43	19.61
Honda	594.52	543.27	55.78	736.56	363.78	39.43	9.82
Isuzu	2.94	63.50	16.43	0.00	0.00	0.00	0.03
Mazda Motors Gr.	15.55	107.92	14.66	32.28	0.00	0.00	1.85
Renault-Nissan-Mitsubishi	507.79	463.26	77.60	1152.61	0.00	150.00	8.46
STELLANTIS	58.42	34.47	6.05	1372.67	270.85	89.41	11.61
Subaru Gr.	19.71	7.23	1.68	2.14	0.00	0.00	2.45
Suzuki	35.26	59.77	1.99	0.00	0.00	0.00	0.23
Tata Gr.	38.87	14.04	4.66	109.65	0.00	31.82	0.45
Tesla	55.53	0.00	0.00	186.54	92.27	17.67	0.10
Toyota Group	1370.03	860.10	192.09	1564.18	231.72	2.29	15.00
Volkswagen	190.78	105.54	42.87	360.82	39.26	0.60	3.34

Notes: The table summarizes patenting activity, lobbying expenditures, and market shares for the firms in our sample. The first three columns are the average number of patent applications per quarter by patent category. Lobbying is the average lobbying expenditures per quarter. The last column reports the quarterly average market share of the firm relative to all sales in the quarter by all firms. The column may not sum to one.

Tesla is an outlier not only in terms of its knowledge stock but also in terms of its revenue

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

[47] 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.

[48] Table 7 in Online Appendix B reports summary statistics of the outcome variables. The average quarterly expenditure on lobbying is $905,000 with a maximal expenditure of more than $7.86 million. 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.

structure. Figure 13c in Online Appendix C compares firms and in particular Tesla in terms of clean sales and innovation. While on average firms' revenues depend on clean sales by less than 20% over the full sample period, it is the unique source of revenues for Tesla. Similarly, Tesla is the only firm without any knowledge on combustion engines. We expect these deviations to make Tesla special in how it reacts to a greening of household preferences. For instance, an increase in demand for electric vehicles will profit Tesla but might exert pressures on revenues for other firms. We therefore drop Tesla from the main analysis.[49]

Looking at aggregate innovation activity, we document that dirty technologies represent 48% of granted patent applications in our period of analysis, clean technologies around 41%, and gray technologies account for only 7%. Since the late 1990's, there has been an exponential increase in the number of patents which was mainly driven by clean patent applications. The number of clean patents rose by a factor of five during the period.[50] 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.[51] Figure 9 in Online Appendix B depicts the evolution of the different types of patenting since 1976.

Out of the 16 firms in our baseline sample, 14 firms lobby, and lobbying expenditures are substantial.[52] Most firms spend on both pro- and anti-environmental lobbying. Yet, up to six (five) firms do not engage in pro-environmental (anti-environmental) lobbying. We drop these firms only in the estimations using the respective variable as an outcome.[53] The largest firms in terms of market shares are also the largest spenders in lobbying, with General Motors spending around $3.0 million per quarter and Ford spending on average $1.9 million per quarter (Table 2). Interestingly, the biggest firms also spend more on pro-environmental lobbying in comparison to other firms and relative to their spending on anti-environmental lobbying.

Finally, to shed light on the link between firms' knowledge stocks and their market shares by vehicle type, Table 3 reports average values for firms with a high share of combustion-engine knowledge (*Above median*) and those with a low share (*Below median*).[54] Row (1) underlines that firms below the median combustion-engine knowledge share—henceforth clean-knowledge firms—on average hold a substantially higher market share in electric and hybrid

[49] In Online Appendix G, we compare the baseline results to the results in the sample with Tesla.

[50] 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.

[51] These trends are congruent with trends presented in Aghion et al. 2016 and Aghion et al. 2023.

[52] The two groups that do not lobby are Suzuki and Isuzu.

[53] Our goal is to improve the precision of estimates for other outcomes, though the sample of firms differs depending on the outcome variable.

[54] Firms are classified taking the full sample period from 2006 to 2019 into consideration. The sample split is equivalent to the one we explore in the heterogeneity analysis in Subsection 5.3.

vehicles. Their share is nearly three times that of firms with a comparably high share of knowledge on combustion-engine technologies.

Following the literature on competition-deterring corporate strategies, this correlation points to potential hindrances for greener household preferences to result into the production of greener goods. Akcigit, Baslandze, and Lotti 2023 document that market leaders tend to exploit political connections instead of improving their productivity. Argente et al. 2025 make a case for non-productive patenting as another strategy to deter competition used by market leaders. Taken together, while clean-knowledge firms may have the potential to innovate cleaner products, they may instead choose non-productive measures.

Furthermore, clean-knowledge firms (i) tend to hold a higher market share in all the market segments, including the combustion-engine one (Row (2) in Table 3), and (ii) combustion engines account for more than 98% of their sales on average (Row (3)).[55] Hence, a shrinking market for combustion engines may be especially costly for clean-knowledge firms, urging them to protect their conventional cash flows.

Table 3: Firm characteristics by sample

	Full sample	Below median	Above median
(1) Market share in electric and hybrid vehicles	0.05	0.08	0.03
(2) Market share in combustion-engine vehicles	0.07	0.08	0.06
(3) Share of clean sales	0.02	0.02	0.01

Notes: The table depicts sample averages over firm-specific averages over time (from 2006 to 2019). The *Below median* sample are firms with a relatively low share of combustion-engine-related technologies, i.e., firms owning a cleaner knowledge stock. The group named *Above median* comprises firms with a knowledge advantage on gray and dirty technologies.

Variation in shock exposure. Figure 11 in Online Appendix B 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 a few regions. For instance, New England and the West Coast are highly important to BMW, General Motors 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.

[55] Figure 13 in Online Appendix C contrasts the distribution of the share of clean knowledge and the share of revenues from sales of electric vehicles illustrating an apparent discrepancy of an important clean knowledge share and a low importance of electric vehicles in firm revenues.

Exposure to wildfires. As a final crucial aspect of our data, Figure 12 pictures states' exposure to wildfires through time, $Fire\ Exposure_{lt}$. The variable 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. As our measure of fire exposure includes all the wildfires in a distance of 1,000 kilometers from the state, the number of state-quarter observations not exposed to wildfires is very reduced. In Section 4, we provide evidence that the distribution of shocks satisfies relevant conditions to identify the effect of greener household preferences on firms.

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 in Subsection 4.1, on the assumptions underlying the identification of the effect of greener preferences in Subsection 4.2, and on the robustness of standard errors in 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: local 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 the index of household willingness to act, ENV_{lt}, which is measured at the state-quarter 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 serve as a proxy for firm exposure to local markets through the demand side. We specify our model in changes over a two year horizon (8 quarters).[56] Time indices refer to end-of period values. The main regressor of firm exposure to household willingness to act is defined

[56] Specifying the model in differences deals with unit roots in the data.

as the firm-specific growth rate in the index:

$$\Delta^{log}_{8,s_t} ENV_{it} \coloneqq \sum_{l}^{L} s_{ilt} \left(\log(ENV_{lt}) - \log(ENV_{lt-8}) \right), \tag{1}$$

where $s_{ilt} \coloneqq \frac{\sum_{\tau=0}^{8} S_{ilt-\tau}}{\sum_{l} \sum_{\tau=0}^{8} S_{ilt-\tau}}$ is the share of total sales, $S_{ilt-\tau}$, of firm i in state l over the period $t-8$ to t relative to total sales of that firm over the same period. Shares sum to one over states for a given time and firm.[57]

Instrument. For reasons spelled out above, we only use the variation in the index that follows unexpected changes in wildfires—henceforth referred to as *shocks*. We measure shocks as changes in states' exposure to wildfires over a period of 8 quarters:

$$Fire\ Shock_{lt} \coloneqq Fire\ Exposure_{lt} - Fire\ Exposure_{lt-8}. \tag{2}$$

Based on such state-level shocks, we construct the instrument for firm exposure to household willingness to act. To this end, we rely on predetermined period shares from firm local sales lagged by 16 quarters, σ_{ilt-16}.[58] The instrument follows as the weighted average of the shocks:

$$Z_{it} \coloneqq \sum_{l}^{L} \sigma_{ilt-16} Fire\ Shock_{lt}. \tag{3}$$

Model specification. We instrument the main regressor, $\Delta^{log}_{8,s_t} ENV_{it}$, with the wildfire shocks, Z_{it}. Outcome variables enter as gross growth rates over two years in logs. In sum, we estimate the following model by 2 stage least squares (2SLS):

$$\log(y_{it}) - \log(y_{it-8}) = \beta \Delta^{log}_{8,s_t} ENV_{it} + \gamma X_{it} + \varepsilon_{it}, \tag{4}$$

where X_{it} indicates a set of controls including time and firm fixed effects.[59] The coefficient of interest is β which is a function of the elasticity of the outcome variable to a change in the growth rate of the index of willingness to act, conditional on controls, X_{it}.

[57] Note that these shares are not predetermined. This is possible because the instrument—which is based on predetermined shares—and not firm exposure to environmental willingness to act requires uncorrelatedness to the error term for the validity of our methodology. We consider the sum of sales over the two-year horizon to better capture firm exposure over this period.

[58] 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.

[59] Firm fixed effects in the difference specification of the model capture firm trends.

Local projections and interpretation of coefficients. Most of our results derive from local projections in the form of

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

We, thus, measure the effect of a rise in the growth rate of the index on the cumulative gross growth rate between period $t-8$ and $t+h$. We scale the outcome variables so that we measure effects on average annual growth rates over different horizons.

4.2 Identification and inference

The instrument is a combination of predetermined exposure shares and random 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 in period t: $\sigma_{lt} := \frac{1}{N}\sum_i \sigma_{ilt}$. The shock-level representation of Equation (4) is defined as:

$$\widetilde{\log\left(\frac{y_{lt}}{y_{lt-8}}\right)} = \beta \cdot \widetilde{\Delta^{log}_{8,s_t} ENV}_{lt} + \widetilde{X}'_{lt}\gamma + \widetilde{\varepsilon}_{lt}. \tag{6}$$

Where $\widetilde{v}_{lt} := \dfrac{\sum_i \sigma_{ilt-16} v_{it}}{\sum_i \sigma_{ilt-16}}$ is the exposure-weighted average of variable v_{it}. This transformation has an interesting property: The regression will recover the same coefficient $\hat{\beta}$ as the firm-level regression in Equation (4) because the shock-level regression is merely a change in the summation order and the interpretation remains the same.

Quasi-random shock assignment. The condition of quasi-random shock assignment requires that

$\mathbf{E}[Fire\ Shock_{lt}|\bar{\varepsilon}_{lt}, \widetilde{X}_{lt}, \sigma_{t-16}] = \widetilde{X}'_{lt} \cdot \mu$ which implies that shocks are quasi-randomly assigned conditional on shock-level unobservable $\bar{\varepsilon}_t$, the average lagged firm exposure σ_{t-16}, and shock-level observables $\widetilde{X}_{lt}$. In our design, it means that shocks are randomly assigned, conditional on state-level characteristics and period fixed effects. Importantly, a systematic relation between the occurrence of wildfires and state characteristics would not conflict with the identification strategy given the set of controls.

Testing shock exogeneity. To test the exogeneity of the shocks, we implement two falsification tests. The first one is a shock balance test following Borusyak, Hull, and Jaravel 2022 with the objective to falsify that shocks predict predetermined variables. We perform the test on the state and the firm level.[60] If the shocks are as-good-as-randomly assigned to firms and states within periods, we expect them to not predict these predetermined variables. On the state level, we can deal with correlation of predetermined variables and shocks by including the respective variable as control.

At the state level, we find a significant relationship between a state's wildfire exposure and the share of Republican votes, the urban population share, the share of the population commuting by public transport, and greenhouse gas regulations. 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 no statistically significant correlation between wildfires and the lagged outcome variables, consistent with the quasi-randomness assumption.[61]

The second falsification test is a pre-trend test. We regress predetermined outcome variables on the instrumented main regressor including all controls and fixed effects.[62] We thereby test whether the results capture some long-run common causal factor behind both preferences and technological change or lobbying. If our identification strategy is valid, we expect no significant correlation between predetermined outcome variables and future values of the instrumented index. Except for one variable, we cannot reject that there is no relationship between future instrumented changes in willingness to act and the lagged dependent variables. We note

[60] We regress predetermined variables on the shocks, that is, $Fire\ Shock_{lt}$ on the state level and Z_{it} on the firm level. The outcome variables at the firm-level are measured in period $t-12$, and at the state-level in period $t-8$. The regressions include time fixed effects as well as state-quarter and firm fixed effects, respectively in the state- and firm-level regressions.

[61] The results are presented in Table 9 in Online Appendix F.

[62] The outcome variables are measured in period $t-16$, that means for any outcome variable y we regress $\log(y_{t-16}) - \log(y_{t-24})$ on instrumented $\Delta^{\log}_{8,s_t} ENV_{it}$ and controls. Thus, in comparison to the baseline estimation, the pre-trend test solely differs by shifting the outcome variables backwards.

a marginally significant positive relationship for anti-environmental lobbying growth. This suggests that firms that raised their spending on anti-environmental lobbying more in the past tend to face a stronger greening of household preferences in the future. The overall result of the test lends credibility to a causal interpretation of our estimates.[63]

Many uncorrelated shocks. This condition states that shocks should not be concentrated in few observations. The assumption implies that market shares should not be concentrated in a few number of states. The effective number of leveraged shocks can be estimated by the inverse of the Herfindhal index, HHI, of the average firm exposure to states, σ_{lt-16}. Our effective sample size is large (above 700) and our largest importance weight, σ_{lt-16}, is below 1%. This suggests that given the small number of units (16 firms) and treatment groups (50 states), the shocks are not too clustered and the frequency of observation is sufficient to reach consistency (Borusyak, Hull, and Jaravel 2022).[64]

Relevance condition. The relevance condition requires that the instrument has power, that is $\mathbf{E}[\Delta^{\log}_{8,s_t} ENV_{it} \cdot Z_{it} | X_{it}] \neq 0$. We check this by computing the Montiel-Pflueger first-stage F-statistic which roughly amounts to 146,[65]suggesting a strong positive correlation between exposure to wildfires and green household preferences. The 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). Online Appendix E provides an overview of the literature on the relationship between natural disasters and environmental interest. In the same section, we explore the relation of the shocks and the two-year change in willingness to act on the state level.

4.3 Treatment correlation and robust standard errors

The wildfire shocks generate dependencies in the instrument and in the residuals for firms with similar exposures. 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

[63]The results of the pre-trend falsification tests are presented in Table 10 in Online Appendix F.

[64]We report the related statistics in Table 6 in Online Appendix B.

[65]While the firm-level sample for lobbying outcomes is smaller than the sample considered in the innovation regressions, the reshape guarantees that the first-stage Montiel Pfluger F-statistics is the same across outcomes.

errors (Borusyak, Hull, and Jaravel 2022).[66] 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.[67]

5 Results

We are now equipped to discuss our results. Subsection 5.1 analyzes the instantaneous effects of willingness to act. Subsection 5.2 takes a dynamic perspective analyzing local projection results. We scrutinize potential explanations for the average effects by separating firms into those with a relatively high share of clean knowledge and those with a low share in Subsection 5.3. Subsection 5.4 assess the magnitudes of the results by comparing them to the effect of fuel prices.

5.1 Static baseline results

The static results are shown in Table 4. The first panel depicts changes in average annual knowledge stock growth for clean, dirty, and gray technologies.[68] The second panel focuses on lobbying activities specifically targeting environmental issues: anti-environmental and pro-environmental lobbying expenditure growth.[69] All regressions include time fixed effects, firm fixed effects, and the lagged market share at the firm level. Column (1) applies a bare-bone OLS specification that includes no further covariates. These estimates suggest a positive correlation between growth in household environmental willingness to act and growth in both firm anti-environmental lobbying and clean knowledge stock. There is neither a significant effect on dirty and gray innovation nor on pro-environmental lobbying.

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 or political influence tools. Furthermore, this

[66] Borusyak, Hull, and Jaravel 2022 prove that the shock-level regression delivers the same standard errors as the procedure by Adao, Kolesár, and Morales 2019.

[67] 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.

[68] Outcome variables and the index for preferences are specified as log-change over two years. We scale estimates to present effects on the average annual growth rate measured over the two-year horizon.

[69] 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. 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.

empirical strategy also takes care of confounding factors that affect both household preferences and firm strategies, such as a state's environmental policy stance.

Using an instrumental variable approach changes estimates especially for innovation and in particular for clean knowledge. The positive effect of the greening of household preferences on clean knowledge growth intensifies. This finding can be explained with forward-looking firm decisions: Firms accelerate clean knowledge growth when they expect a faster greening of demand tomorrow. The OLS estimate then captures a negative correlation between contemporaneous growth in clean knowledge and green household preferences.

Our instrument constructed from wildfire exposure is most likely correlated with state-level policies and firm strategies other than through household willingness to act, threatening the exclusion restriction of the empirical approach. We, therefore, control for potentially correlated variables.[70] In Column (3), we augment the model with a set of demographic controls, such as the share of young people in the population, the employment rate, 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.[71] Transportation controls also include the state-level end-use 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 latter two controls we aim at mitigating risks that our results are confounded by systematic variations in environmental regulation similar to firm exposure to wildfires. Finally, Column (5) controls for the score of Republicans in the last presidential elections to account for differences in political orientation that vary on the state-time dimension affecting both firm and household responses to fire exposure.

In all three specifications, the controls leave most of the results of similar magnitude and significance. An apparent exception is the change in the size of the effects on pro-environmental lobbying which arises when adding transportation and environmental policy controls. This finding is consistent with the view that wildfires lead to policy shifts that make pro-environmental lobbying less attractive. When controlling for political changes, however, the reduction is muted.

The significant results for clean knowledge and anti-environmental lobbying in our preferred specification with the full set of controls, Column (5), are economically meaningful. A 1% increase in the two-year growth rate of the index of willingness to act on average implies a

[70] Section 3 describes the controls and the data sources in more detail.

[71] The choice of transportation could be affected by the likelihood of wildfires and clearly determines the demand for cars.

TABLE 4: Effect of greener household preferences on firms

	OLS	IV			
	(1)	(2)	(3)	(4)	(5)
Panel A: Knowledge stocks					
Clean knowledge stock					
$\Delta^{\log}_{8,s_t} ENV$	7.88***	19.81**	18.04**	18.51***	18.43***
	(1.59)	(7.53)	(7.05)	(6.78)	(6.75)
Dirty knowledge stock					
$\Delta^{\log}_{8,s_t} ENV$	2.35	-0.16	-0.96	-1.88	-1.75
	(2.08)	(2.80)	(2.79)	(3.75)	(3.74)
Gray knowledge stock					
$\Delta^{\log}_{8,s_t} ENV$	-3.37	-6.53	-6.07	-9.32	-9.35
	(2.67)	(5.64)	(5.47)	(7.61)	(7.57)
Panel B: Environmental lobbying					
Anti-environmental lobbying					
$\Delta^{\log}_{8,s_t} ENV$	2.51***	2.69**	2.79***	3.46***	3.54***
	(0.58)	(1.03)	(0.89)	(1.09)	(1.09)
Pro-environmental lobbying					
$\Delta^{\log}_{8,s_t} ENV$	-5.04+	-7.75	-6.56	5.90	5.79
	(3.42)	(10.51)	(10.46)	(11.20)	(11.09)
FE: year-quarter	X	X	X	X	X
FE: state-quarter	X	X	X	X	X
Firm trend	X	X	X	X	X
Lagged firm controls	X	X	X	X	X
Lagged demographic controls			X	X	X
Lagged transportation controls				X	X
Lagged political controls					X
N (states - periods)	1970	1970	1970	1970	1970
Montiel-Pflueger first-stage F		211	108	149	146

Significance codes: ***: 1%, **: 5%, *: 10%, +: 15%

Notes: Column (1) depicts OLS and Columns (2) to (5) shift-share IV results. Standard errors clustered at the state level are given in parentheses. All changes are in two-year differences (8 quarters). The variable $\Delta^{\log}_{8,s_t} ENV$ represents the eight-quarter difference in the log-transformed index of environmental willingness to act that is constructed in Section 3. In Columns (2) to (5), $\Delta^{\log}_{8,s_t} ENV$ is instrumented with the change in wildfire exposure computed using satellite data from NASA's FIRMS dataset. Each row reports the results for a different outcome variable. The unit of analysis are firms, i.e., U.S. automotive groups. Outcome variables are extensively described in Section 3.

rise of the annual growth rate of anti-environmental lobbying by 6%, and a rise in the annual growth rate of clean innovation by 20%.[72] Taken together, the static results suggest that firms use a combination of innovation and lobbying to deal with greener household preferences with ambiguous impacts on the green transition. To enable a more comprehensive understanding of the effect of willingness to act, the next section takes a long-run perspective.

5.2 Dynamics

Figure 3 depicts dynamic responses of key variables. There is a clear adjustment of the direction of innovation (Figure 3a). While the annual growth rate of clean knowledge accelerates by roughly 20% immediately after the shock, it converts back to the counterfactual level absent a change in household preferences after roughly ten quarters. On average, the initial increase in clean knowledge is compensated with a reduction in the medium term.

The initial non-response of dirty and gray innovation turns into a long-lasting adjustment. Dirty knowledge growth reduces by 20% eight quarters after the greening of household preferences and remains depressed in the long run. Simultaneously, gray knowledge growth increases steadily cumulating into a 20% higher growth rate five years after the shock to household preferences.

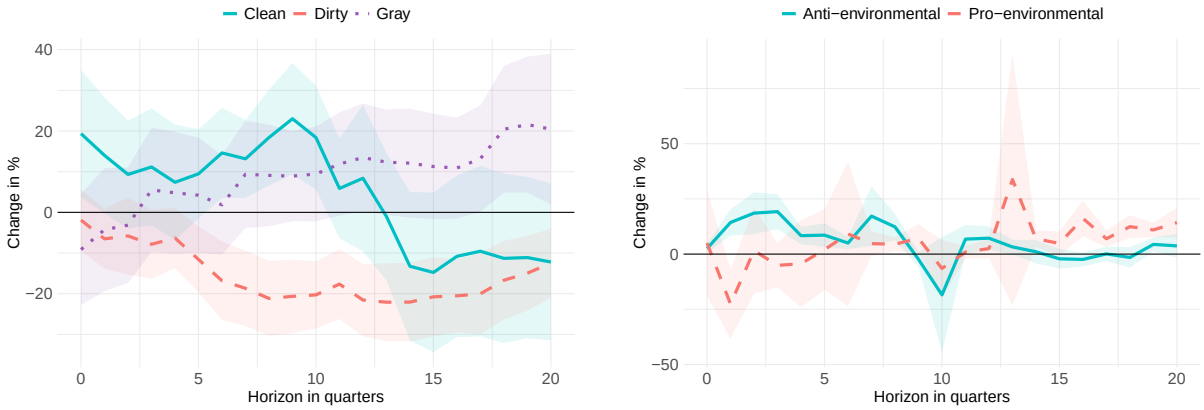
The reallocation of environmental lobbying expenditures towards anti-environmental lobbying immediately after the rise in household willingness to act persists for seven quarters (Figure 3b). In the long run, however, we detect no effect on anti-environmental lobbying.[73] Conversely, we observe a slow yet steady increase in pro-environmental lobbying culminating in a 15% higher pro-environmental lobbying growth 5 years after the greening of preferences.

In sum, results point to firms using a combined strategy of innovation and lobbying to cope with a greening of household preferences on average. Relatively more anti-environmental lobbying in the short run helps guard revenues from established products. The development of new gray and clean technologies, in turn, deals with a change in household preferences in the long run. Pro-environmental lobbying then boosts the value of the newly developed low-emission technologies. The heterogeneity analysis which follows next examines how the use of innovation and lobbying depends on firm characteristics.

[72] Coefficients are transformed to reflect elasticities.

[73] Similar to the effect on clean innovation, the reversal to the non-shock counterfactual value means a negative deviation of anti-environmental lobbying expenditures in the medium term in response to greener household preferences.

FIGURE 3: Effect of greener household preferences on innovation and lobbying



(A) Knowledge stocks (B) Environmental lobbying

Note: Graphs show cumulative impulse responses of key variables to a 1% increase in the two-year growth rate of the index of household willingness to act according to the specification $\log(y_{it+h}) - \log(y_{it-8}) = \beta^h \Delta^{\log}_{8,s_t} ENV_{it} + \gamma^h X_{it} + \varepsilon_{it+h}$, for quarters h=0, ..., 20 after the shock. Shaded areas are 95% error bands with standard errors clustered at the state level. Coefficients are transformed to reflect percentage changes in the outcome variable. Standard errors are transformed using the delta method.

5.3 Firm heterogeneity

In this section, we explore the mechanisms behind our results by grouping firms according to the composition of their knowledge stock.[74] We consider the distribution of the share of combustion-engine-related knowledge in firm total knowledge stocks based on averages over the whole time span from 2006 to 2019.[75] We split the sample into firms with a share of knowledge on combustion-engine-related technologies (gray and dirty) above the median firm and firms with a share below the median firm.[76]

The exercise sheds light on the role of path dependence in innovation and how it affects lobbying behavior of firms. In line with the literature, two hypotheses are conceivable. One possibility is that firms with a cleaner knowledge stock react with more clean innovation to greener

[74] In Online Appendix G, we examine how the importance of revenues from combustion engines—which proxies for adverse firm exposure to greener household preferences—alters firm responses. We find that more severely affected firms engage both in a more pronounced rise in gray innovation and in anti-environmental lobbying. Here, the two strategies arise as complements.

[75] We argue that this approach better captures firms' technological orientation than a momentary picture of their knowledge stock. Alternative classifications—such as using period-by-period measures or pre-2006 shares of combustion-engine-related technologies—do not produce significant results (available upon request). We conjecture that this is related to a rapid change in the industry in our period of analysis. A caveat of our approach, however, is that our grouping variable is partly based on post-shock information, which may introduce bias; therefore, we take these results as suggestive.

[76] The Montiel-Pflueger first-stage F-statistics equal 25 for the above median group and 94 for the below median group.

preferences,[77] while firms specialized in combustion-engine-related technologies, i.e., firms which are further away from the innovation frontier of the technology that caters to greener household preferences, instead use lobbying as a less costly alternative to protect current cash flows (Bombardini, Cutinelli-Rendina, and Trebbi 2021).

A second likely scenario is that it is the largest and more profitable firms that engage in competition-deterring strategies. As discussed in Subsection 3.1, these firms correspond to the clean-knowledge firms which happen to be dominant in both clean and dirty market segments. The literature has established that such big firms profit more form non-productive strategies such as leveraging political connections (Akcigit, Baslandze, and Lotti 2023) or strategic patenting (Argente et al. 2025). Taken together, while clean-knowledge firms have the potential to innovate cleaner products, they may be especially inclined to choosing non-productive measures instead.

We find evidence for both hypotheses. Clean-knowledge firms engage in a persistent increase in their clean knowledge stock amounting to a 37% increase in the average annual growth rate five years after the shock to household willingness to act (Figure 4a). Similarly, firms specialized in combustion-engine technologies drive the aggregate rise in gray technologies (Figure 4c). While the point estimates are not significant at the 5% level, the results uncover a systematic trend of gray knowledge growth. Simultaneously, both types of firms equally reduce their innovation efforts on dirty technologies (Figure 4d). Hence, both types of firms redirect innovation efforts to the greener technology where they hold a knowledge advantage.

In combination with the productive adjustment of knowledge stocks, the graphs suggest the use of competition-deterring strategies especially by clean-knowledge firms. First, these firms more heavily rely on lobbying to cope with greener household preferences in two distinct ways: They leverage more anti-environmental lobbying immediately after the greening of household preferences[78] and more pro-environmental lobbying in the long run.[79] Hence, innovation and lobbying emerge as complements for clean-knowledge firms.[80] These findings are consistent with the idea that market leaders opt for lobbying to protect their market shares. Firms with

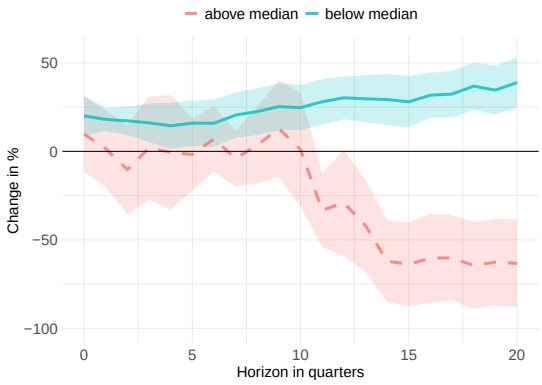
[77] This logic follows the theory in Aghion et al. 2005 which predicts that firms close to the technological frontier should innovate when facing high competitive pressures.

[78] The largely constant effect over time means that there is no reduction in anti-environmental lobbying expenditures in subsequent periods in response to the shock.

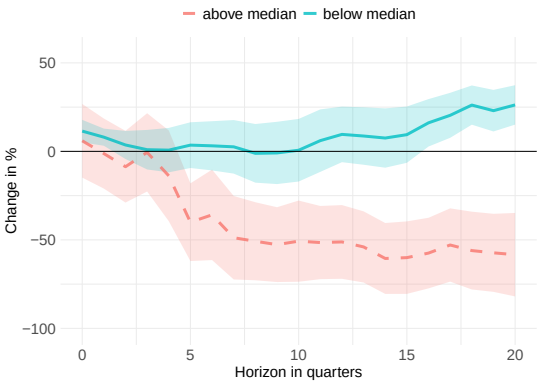
[79] Clean-knowledge firms do profit from guarding revenues from dirty products since they (i) derive a high share of their revenues from selling fuel cars and (ii) tend to hold a higher share of the combustion-engine market. Compare the more in depth discussion in Subsection 3.1.

[80] The finding is furthermore congruent with recent empirical insights on environmental lobbying and innovation. Kwon, Lowry, and Verardo 2023 document that firms that innovate green technologies do use anti-environmental lobbying. Lobbying protects current cash flows derived from selling dirtier goods, while clean innovation qualifies as a long-run preparation for a green transition.

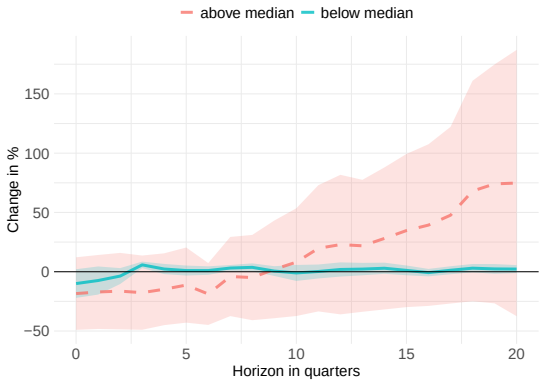
FIGURE 4: Effects of greener household preferences: Firm heterogeneity



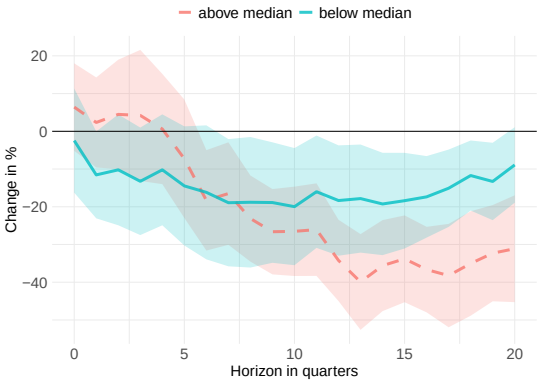
(A) Clean knowledge stock: Number of patents



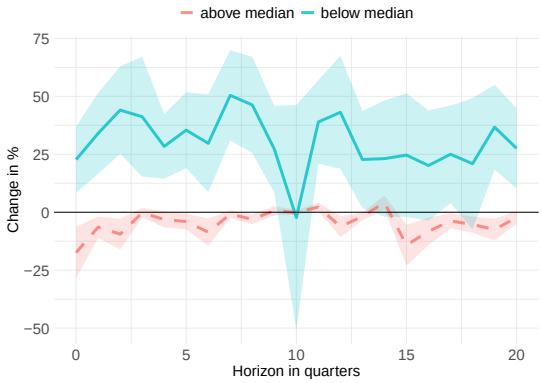
(B) Clean knowledge stock: Citation weighted



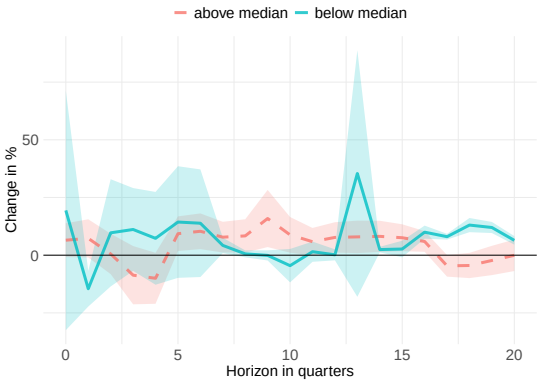
(C) Gray knowledge stock



(D) Dirty knowledge stock



(E) Anti-environmental lobbying



(F) Pro-environmental lobbying

Note: Graphs show cumulative impulse responses of key variables to a 1% increase in the two-year growth rate of the index of household willingness to act according to the specification $\log(y_{it+h}) - \log(y_{it-8}) = \beta^h \Delta^{\log}_{8,s_t} ENV_{it} + \gamma^h X_{it} + \varepsilon_{it+h}$, for quarters h=0, ..., 20 after the shock for two separate samples. *Above median* refers to firms with a share of combustion-engine-related knowledge stock above the median firm, and *below median* indicates the sample of firms with a lower share of such technologies. The full sample period from 2006 to 2019 is used to measure the average share of combustion-engine-related knowledge stock. Shaded areas are 95% error bands with standard errors clustered at the state level. Coefficients are transformed to reflect percentage changes in the outcome variable. Standard errors are transformed using the delta method.

a high knowledge stock on combustion-engine technologies—if anything—lower their spending on anti-environmental lobbying and raise pro-environmental lobbying temporarily in the medium run.

Second, there is evidence indicating that the short- and medium-run response of clean innovation by firms specializing in EV technologies is intended to deter competition. First, parts of the rise is driven by low-quality patents. To see this, compare Figure 4b which shows the response of the clean knowledge stock calculated with citation-weighted patents.[81] While there is a positive effect in the medium term in our baseline measure, there is no such rise when looking at quality-weighted knowledge stocks. Second, the reduction in the knowledge stock after the initial increase points to an unusually low growth in clean patents afterwards: Firms seem to rush to file patents earlier than usual. This suggests that before a productive increase in innovation in the long run, clean-knowledge firms engage in some strategic patenting of low-quality innovation in the short run.

A last finding worth noting is that the long-run non-response of the average firm's clean knowledge stock (Figure 3a) masks two opposing firm responses: Clean-knowledge firms increase their clean knowledge persistently, while combustion-engine-knowledge firms decrease it starting 10 quarters after the change in preferences.[82] Revenue pressures and cheaper gray technologies may explain this pattern.

5.4 Comparison to the effect of fuel prices

As a last piece of evidence on the effectiveness of greener household preferences, we compare our results to the effect of fuel prices.[83] The analysis follows Aghion et al. 2016 where variation in exposure comes from heterogeneous predetermined revenue shares of firms on the country-level.[84]

Figure 5 depicts the dynamic responses to a 50% increase in the two-year growth of fuel prices in comparison to the baseline analysis: a 1% increase in the two-year growth of the index on household willingness to act. It stands out that firm responses to greener household preferences closely resemble a 50% increase in fuel price growth.

[81] The information on citations stems from *PatentsView*. For further details consult Subsection 6.4.

[82] When looking at citation-weighted knowledge stocks (Figure 4b), the reduction begins already 4 quarters after the shock, suggesting that before reducing patenting all together, these firms file low-quality patents.

[83] We use data on quarterly energy and fuel prices on country level from the International Energy Agency's "End-use energy prices and taxes for OECD countries" table.

[84] In contrast to Aghion et al. 2016, we use shares predetermined to each period and not to the whole period of analysis. Revenues are proxied with the number of new cars from the S&P global registration data.

Clean innovation growth increases constantly for ten quarters before it declines to its counterfactual level without change in household preferences (Figure 5a). Dirty innovation growth reduces persistently (Figure 5b), whereas gray innovation growth rises steadily until the end of the considered horizon (Figure 5c).[85] The response of anti-environmental lobbying is qualitatively similar to greener household preferences but less pronounced (Figure 5d). One outstanding difference is the rise in pro-environmental lobbying in the long run in response to a faster greening of household preferences which cannot be detected as a reaction to faster growth in fuel prices (Figure 5e).

6 Robustness

In this section, we present some robustness analyses: results when using an alternative strategy to identify changes in household preferences using data on observed sales in Subsection 6.1, alternative instruments in Subsection 6.2, and an alternative index composed of different Google Trend keywords in Subsection 6.3. We close the section by discussing results based on different knowledge stock measures in Subsection 6.4.[86]

6.1 Alternative measure of household preferences

Our main analysis aims at estimating the effect of a greening in preferences on lobbying and innovation, and we interpret our results in light of demand being the main driver behind identified firm responses. By using online search data to proxy demand, we capture changes in preferences that do not translate into a purchase, for example, due to budget constraints, but are nevertheless critical for firm strategies.[87]

On the downside, our measure of environmental willingness to act is arguably more closely related to alternative channels, for instance, voter behavior. As a robustness exercise, we propose an alternative proxy of green demand based on observed vehicle registrations. Similarly to our main analysis, we leverage the exact same instrument with the idea to isolate demand shocks from the equilibrium data.[88]

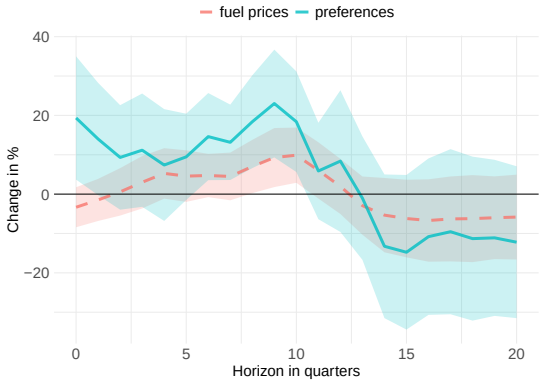
[85] The instantaneous fuel price results are similar to Aghion et al. 2016.

[86] In Online Appendix G, we briefly study how results change when adding Tesla, the only firm with neither sales nor knowledge in combustion engines, to the sample.

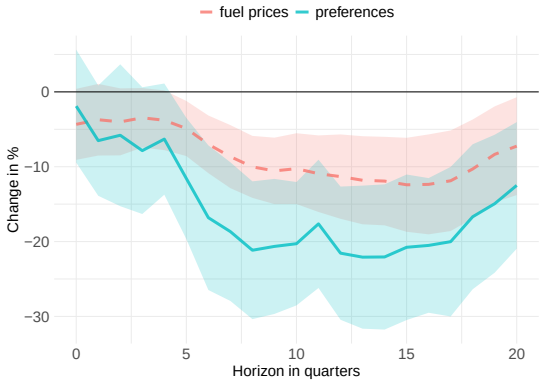
[87] A recent contribution relating natural disasters directly to inventors shows that inventors' expected changes in demand and environmental policies affect the direction of innovation (Keding and Ritterrath 2025).

[88] Separating demand from supply shocks is a well-known challenge in empirical economics since what is reflected in the data is an outcome of their interaction. One solution, which we follow here, is to use data on observed quantities and combine it with an instrument that presumably shifts demand

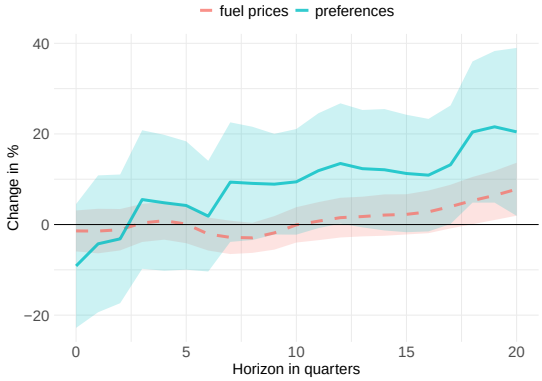
FIGURE 5: Effect of fuel prices versus greener household preferences



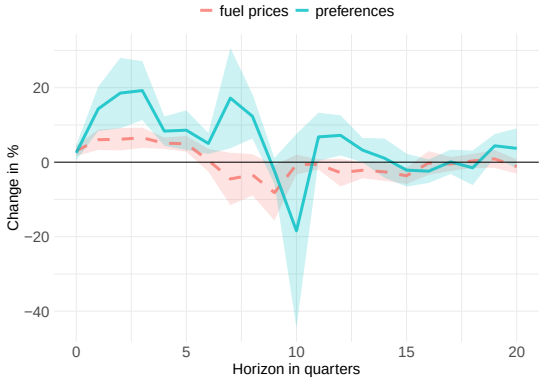
(A) Clean knowledge stock



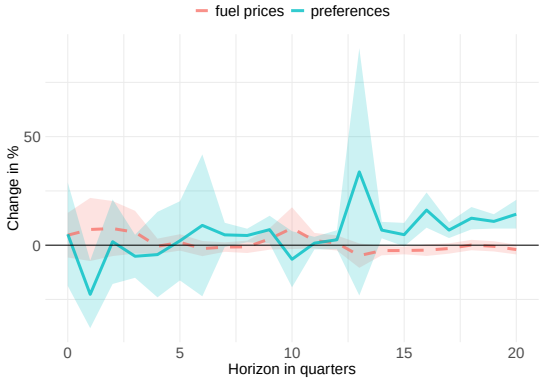
(B) Dirty knowledge stock



(C) Gray knowledge stock



(D) Anti-environmental lobbying



(E) Pro-environmental lobbying

Note: This figure reports the impulse responses of outcome variables following an increase in the growth rate of our index of household willingness to act by 1% and a rise in the growth rate of fuel prices by 50%. Coefficients are derived according to the following specification: $\log(y_{it+h}) - \log(y_{t-8}) = \beta^h V_{it} + \gamma^h X_{it} + \varepsilon_{it+h}$, for quarters h=0, ..., 20 after the shock where V stands in for the respective main regressor. Shaded areas are 95% error bands. Standard errors are clustered at the state level. Coefficients are transformed to reflect percentage changes in the outcome variable. Standard errors are transformed using the delta method.

Another challenge arises from some firms not selling any electric vehicle, so that their directly measured demand would be null, even though households were willing to buy electric vehicles from the manufacturer if the car would be supplied. To solve this issue, we estimate clean demand using all sales made within the same market segment. We define a segment as a tuple of location and vehicle type, henceforth called a *cell*.[89] The change in clean demand in this cell is given by the change in the number of clean vehicles sold in this cell:

$$\Delta N_{ct}^{clean} = \frac{N_{ct} - N_{ct-8}}{\frac{1}{2}(N_{ct} + N_{ct-8})},$$

with N_{ct} indicating the number of clean vehicles sold in a cell c at time t.[90] 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 to compute firm exposure to changes in clean demand:[91]

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

Panel A in Figure 6 presents the results. Firm responses both in innovation and in terms of lobbying are qualitatively very close to our main results in Figure 3. The effects of a 1% increase in firm-level growth in clean demand is roughly half as big as the effects associated with a 1% increase in the growth of our index of willingness to act. The diminished size may be due either to the diminished importance of political adjustments or by our measure better identifying firm exposure to green household preferences.

6.2 Alternative instrument: droughts and extreme temperatures

We now test the robustness of the results with respect to the instrument using a combination of extreme temperatures and droughts as an alternative. Here, we assume that environmental willingness to act is only affected by extreme temperatures or droughts in the state of consideration. In the baseline strategy, in contrast, we allow wildfires outside the state to be relevant for a state's exposure to wildfires.[92] The main advantage of the latter strategy is to capture the influence of severe yet distant wildfires, for instance through the media. The former strategy,

while ideally leaving supply unchanged.

[89] Examples of cells are (SUV, Ohio) or (Compact, Florida).

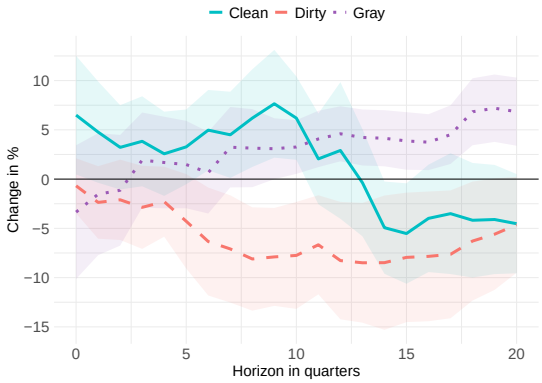
[90] We use a symmetric percent change which has the great advantage of limiting the risk of having a denominator equal to zero.

[91] For the definition of the weights see Section 4.

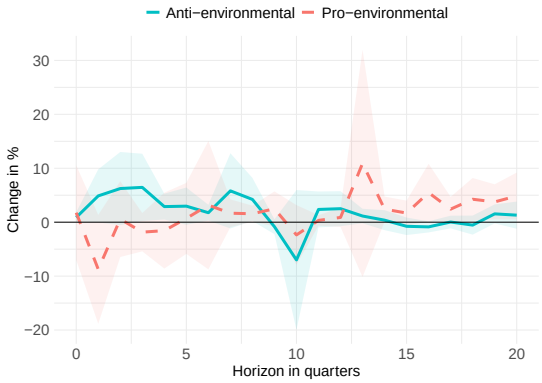
[92] This difference is mainly justified by the nature of natural disasters. Most of the population is not directly threatened by wildfires but rather exposed through media coverage and public debate. On the contrary, extreme temperatures typically affect everyone in a region and media coverage is presumably low.

FIGURE 6: Robustness

Panel A: Vehicle registrations to measure household preferences

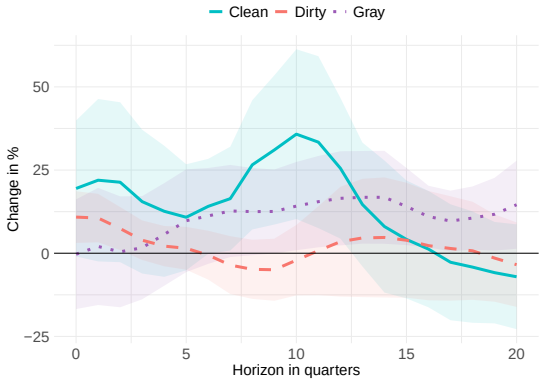


(A) Knowledge stocks

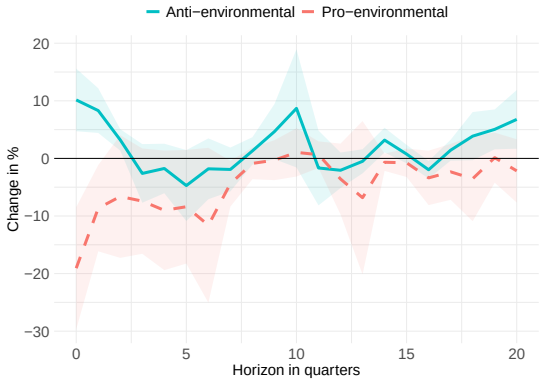


(B) Environmental lobbying

Panel B: Alternative instrument

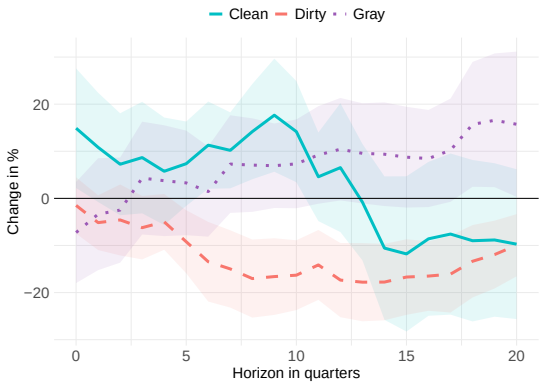


(A) Knowledge stocks

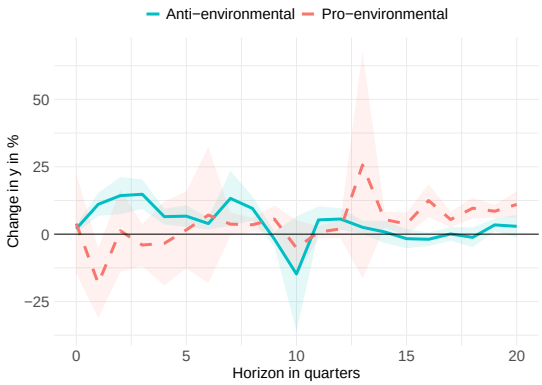


(B) Environmental lobbying

Panel C: Alternative index



(A) Knowledge stocks



(B) Environmental lobbying

Note: Graphs show cumulative impulse responses of key variables to a 1% increase in our index of willingness to act measured using $\log(y_{it+h}) - \log(y_{it-8}) = \beta^h \Delta^{\log}_{8,s_t} ENV_{it} + \gamma^h X_{it} + \epsilon_{it+h}$, for quarters h=0, ..., 20 after the shock. Shaded areas are 95% error bands with standard errors clustered at the state level. Each panel represents a different robustness analysis. Coefficients are transformed to reflect percentage changes in the outcome variable. Standard errors are transformed using the delta method.

in turn, ensures that households are directly affected by the meteorological event.

Data on extreme temperatures and precipitations come from the National Oceanic and Atmospheric Administration (NOAA) Monthly U.S. Climate Divisional Database (Vose et al. 2014). We summarize 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 in one instrument. The first-stage F-statistic of 13 suggests that the instrument is relevant, albeit less so than the one built from wildfires.

Results are displayed in Panel B in Figure 6. The results are qualitatively similar to our benchmark regression. In particular, findings confirm that greener household preferences persistently spur gray innovation, while on average clean innovation only adjusts temporarily. After closer inspection, the dynamics in dirty knowledge, too, are close to the benchmark results: An immediate non-significant increase in dirty knowledge growth—which is not present in our main analysis—leads to a cumulative non-response in the long run despite reductions in the quarterly growth rates in the medium run.

The dynamic responses in lobbying also mimic the benchmark results. They feature a positive effect on anti-environmental lobbying in the short run which is, however, compensated more quickly in the medium term. The dynamics of pro-environmental lobbying overall is shifted downwards due to an initial strong decline. Such a decline may be explained by less pro-environmental lobbying being required in a world with greener household preferences. The initial drop implies no long-run effect despite a continued increase in pro-environmental lobbying in the medium term.

The magnitudes of the results are similar to our benchmark estimates. On the one hand, the instrument has less power and we conjecture an upward bias. On the other hand, 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, the estimates from the alternative instrument may be biased downwards.

6.3 Alternative index

Panel C in Figure 6 depicts the main results using the *mixed* index based on the search terms: *Electric Car*, *Climate Change*, and *Recycling*.[93] Using this alternative definition allows us to distinguish the effect of a specific interest impacting household behavior from the effect of a more gen-

[93] Subsection D.1 details the construction of the index and summary statistics. Unfortunately, our instrument is not strong enough for a more general index on environmental interest that abstracts from terms indicating a willingness to change. We, therefore, focus on this mixed version.

eral interest. The results for both innovation and lobbying outcomes, when regressed against this broader index, replicate the patterns we document in the main specification, and the direction and timing of the effects is equivalent to our baseline findings.[94]

6.4 Alternative knowledge stock measures

Another 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 with high-quality patents presumably reflecting more innovative effort than low-quality ones. The literature, therefore, reverts to citation weighted patents or leverages stock market information (Kogan et al. 2017); where the latter measure is designed to capture the private value of innovation to the firm.

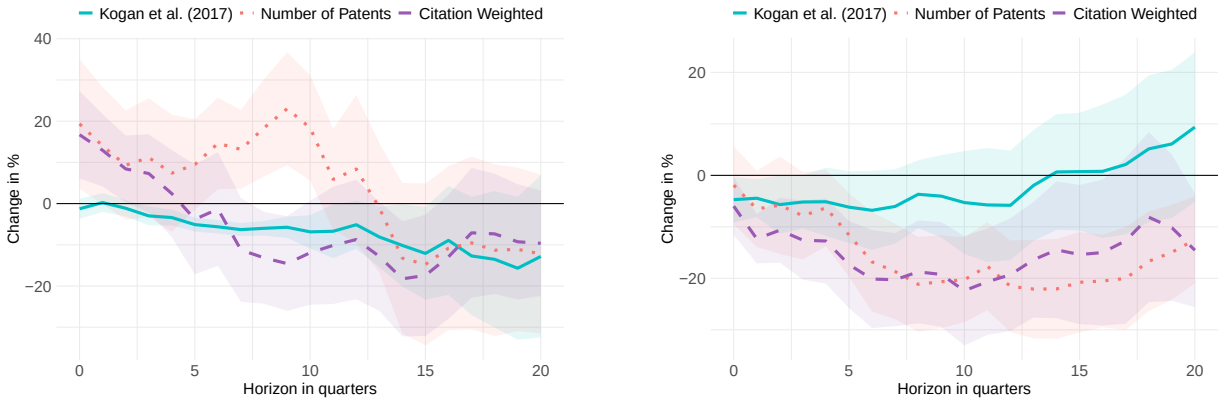
Our choice to use the number of patents is motivated by two considerations. First, citation-weighted patents open the door for self-citation to impact results which would imply that innovation of bigger firms are implicitly given more weight in the regressions. Second, stock-market weighted patents eventually contain information on realized or expected macroeconomic changes relevant for the specific firm. For example, a clean patent may have assigned a higher stock-market weight than a dirty patent solely because the market values clean innovation more in expectation of a green transition.[95]

We contrast the effect of household willingness to act on our baseline measure of knowledge to a stock-market measure based on Kogan et al. 2017 and a citation-weighted measure in Figure 7. The first thing to note is that the dynamics and the magnitudes of the effects on clean and dirty knowledge stocks are similar for all three measures. Regarding the clean knowledge stock, one important difference stands out, though. There is a clear discrepancy of the response in the medium term: While the number-of-patents measure displays a positive effect in the medium run, the two quality-adjusted measures suggest a negative effect. In fact, this finding lends support to the interpretation of the increase in clean innovation being a non-productive strategic rise in clean patents. There might be more clean patents filed in the medium term, however, their quality is unusually low.

[94] The instrument remains strong yielding a Montiel-Pflueger F-statistic of 87.

[95] Since stock market information is firm specific, this concern is not taken care of by time fixed effects.

FIGURE 7: Alternative measures of knowledge stocks



(A) Clean knowledge stock

(B) Dirty knowledge stock

Notes: This figure reports the cumulative impulse responses of the clean and dirty knowledge stocks based on various definitions of *knowledge* following a 1% increase in the growth rate of the willingness to act index according to the specification $\log(y_{it+h}) - \log(y_{it-8}) = \beta^h \Delta^{\log}_{8,s_t} ENV_{it} + \gamma^h X_{it} + \epsilon_{it+h}$, for quarters h=0, ..., 20 after the shock. Shaded areas are 95% error bands with standard errors clustered at the state level. Coefficients are transformed to reflect percentage changes in the outcome variable. Standard errors are transformed using the delta method.

7 Conclusion

How do firms react to greener household preferences? We examine firm responses in the automotive industry to exogenous changes in green household preferences in the U.S. from 2006 to 2019. To quantify greener preferences, we construct a novel index of households' environmental willingness to act based on Google Trends search data.

We find that a greening of household preferences persistently affects firms' innovation and lobbying behavior. On average, innovation shifts away from conventional combustion-engine-related (*dirty*) technologies to *gray* technologies which make combustion engines less polluting. An immediate aggregate rise in EV-related (*clean*) innovation is compensated in subsequent periods so that clean knowledge stock growth remains unaffected in the long run.

We show that firms innovate more in the low-emission alternative—gray or clean —where they have a knowledge advantage. Our results indicate that firms use competition-deterring strategies, such as lobbying and non-productive patenting, to complement the productive adjustment in innovation. Finally, we document that the effect of a 1% increase in the growth rate of the index on household willingness to act resembles a 50% increase in the growth rate of fuel prices.

To summarize, our results, on the one hand, point to the effectiveness of greener house-

hold preferences to spur a green transition of innovation. On the other hand, the possibility for firms to protect profits through lobbying and strategic patenting makes greener household preferences—contrary to intuition—complicate a green transition.

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Online Appendix

A Data construction

This section provides further information on Google Trends and the classification of patents.

A.1 Google Trends

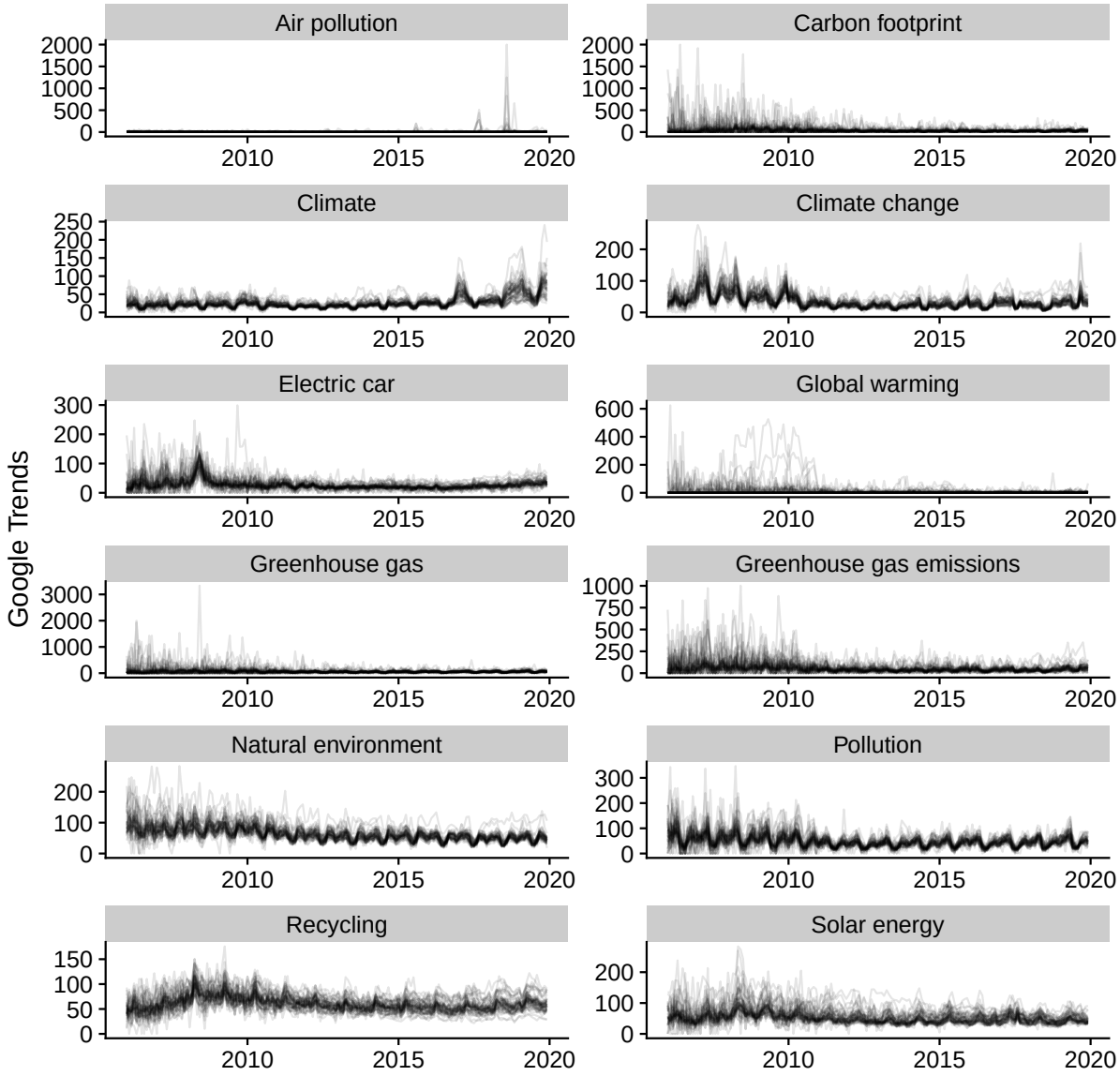
We utilize data from Google Trends, a publicly available online tool provided by Google that allows users to explore and analyze the popularity of search queries over time. Google Trends provides insights into the relative search interest for specific terms or topics based on the frequency of searches 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 relative 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 US states from January 2006 to December 2019. Figure 8 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 very 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.[96] 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 value may outreach the U.S. value. With the same geographic benchmark included in each query, we can, however, 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.

[96]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 8: 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 keyword in the same time period in the U.S. 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.

A.2 Patents classification

TABLE 5: Patent classification into clean, gray, and dirty by CPC code

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

Notes: The table reports the Cooperative Patent Classification (CPC) used to classify patents into clean, gray, and dirty technologies. The classification follows Aghion et al. 2016.

B Additional summary statistics and figures

TABLE 6: Summary statistics

Panel A: Shocks

	Mean	SD	P1	P99
$Fire\ Shock_{lt}$	−0.0001	0.0002	−0.0005	0.0004
$Fire\ Shock_{lt}$ (w. period FE)	0.0000	0.0002	−0.0005	0.0004

Panel B: Predetermined shares

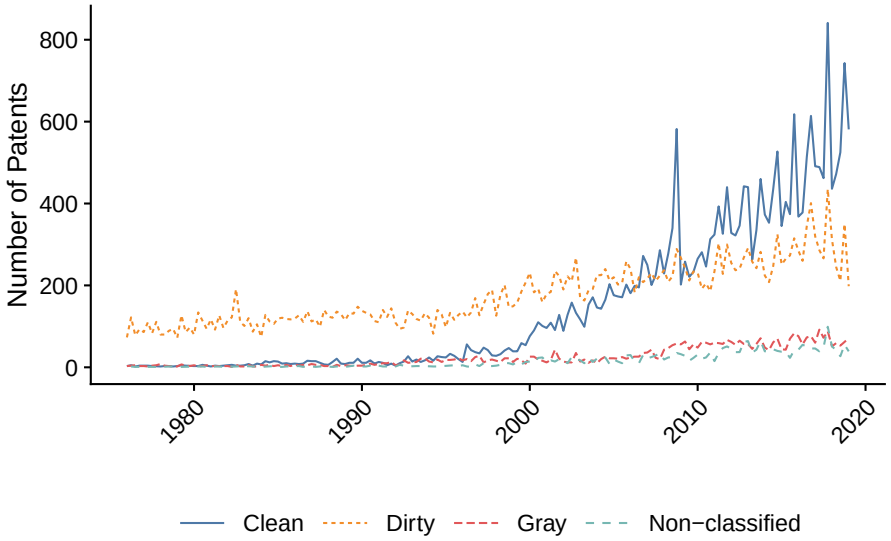
	Mean	Max
$1/HHI$	775.98	776.98
σ_{lt-16} in percent	0.05	0.39
Treatment Groups	50.00	50.00

Panel C: Main regressors

	Mean	SD	P1	P25	P50	P75	P99
$\Delta^{log}_{8,s_t} ENV$	0.0000	0.0525	-0.1780	-0.0140	0.0008	0.0163	0.1772
$\Delta^{log}_{8,s_t} FuelPrice$	0.0000	0.0022	-0.0058	-0.0010	-0.0000	0.0010	0.0067

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 σ_{lt-16}. Panel B reports the *effective sample size* computed as the inverse of the Herfindahl index of the average state exposure share σ_{lt-16}. 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). Panel C summarizes the distribution of quarterly changes in firm-level exposure to (i) our index of environmental willingness to act built using Google Trends and (ii) changes in fuel prices.

FIGURE 9: Number of granted patents by type, 1976-2019



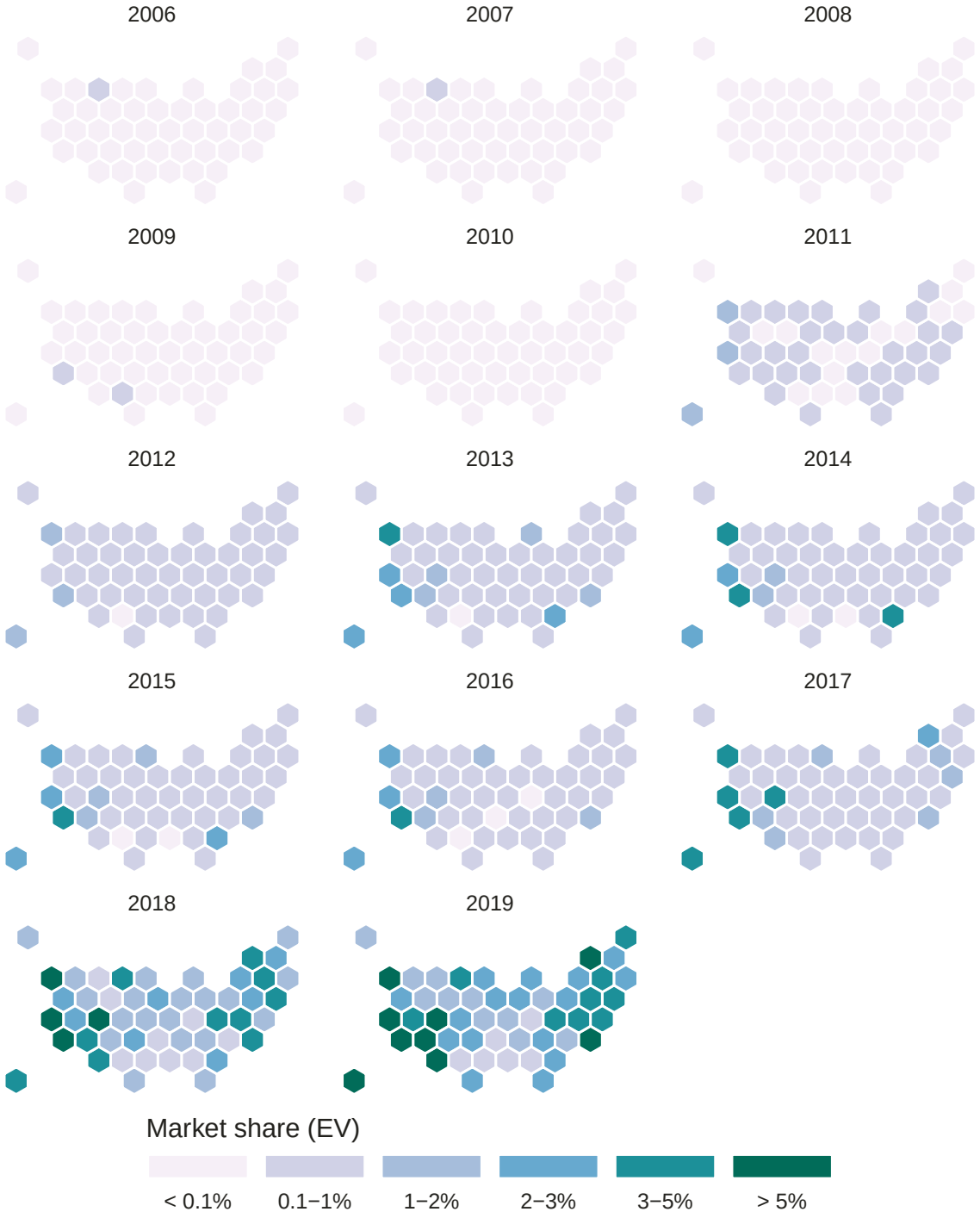
Notes: The figure illustrates the number of granted patents for *clean*, *dirty*,*gray* and *non-classified* technologies over time filed with the U.S. patent office. Dirty patents are defined as innovations related to internal combustion engines while clean innovations are related to electric and hybrid vehicle patents. Gray patents are innovations that aim to reduce emissions from fossil fuel vehicles.

TABLE 7: Summary statistics of outcome variables

	Mean	SD	P25	P50	P75	P95	Max
Clean knowledge stock	295	412	24	82	500	1170	2098
Dirty knowledge stock	263	323	45	79	489	895	1374
Gray knowledge stock	46	60	6	19	60	188	258
Total lobbying (k$)	905	881	280	640	1356	2447	7860
Pro-env. lobbying (k$)	303	589	0	20	500	1337	7617
Anti-env. lobbying (k$)	108	251	0	17	60	509	2557

Notes: The table summarizes the main outcomes in our analysis as quarterly averages over firms. The first three rows refer to the knowledge stocks for clean, dirty, and gray technologies. The last three rows depict the average lobbying, pro-environmental lobbying, and anti-environmental lobbying expenditures in thousands of dollars. See Section 3 for a description of the dataset.

FIGURE 10: Market share of electric vehicles



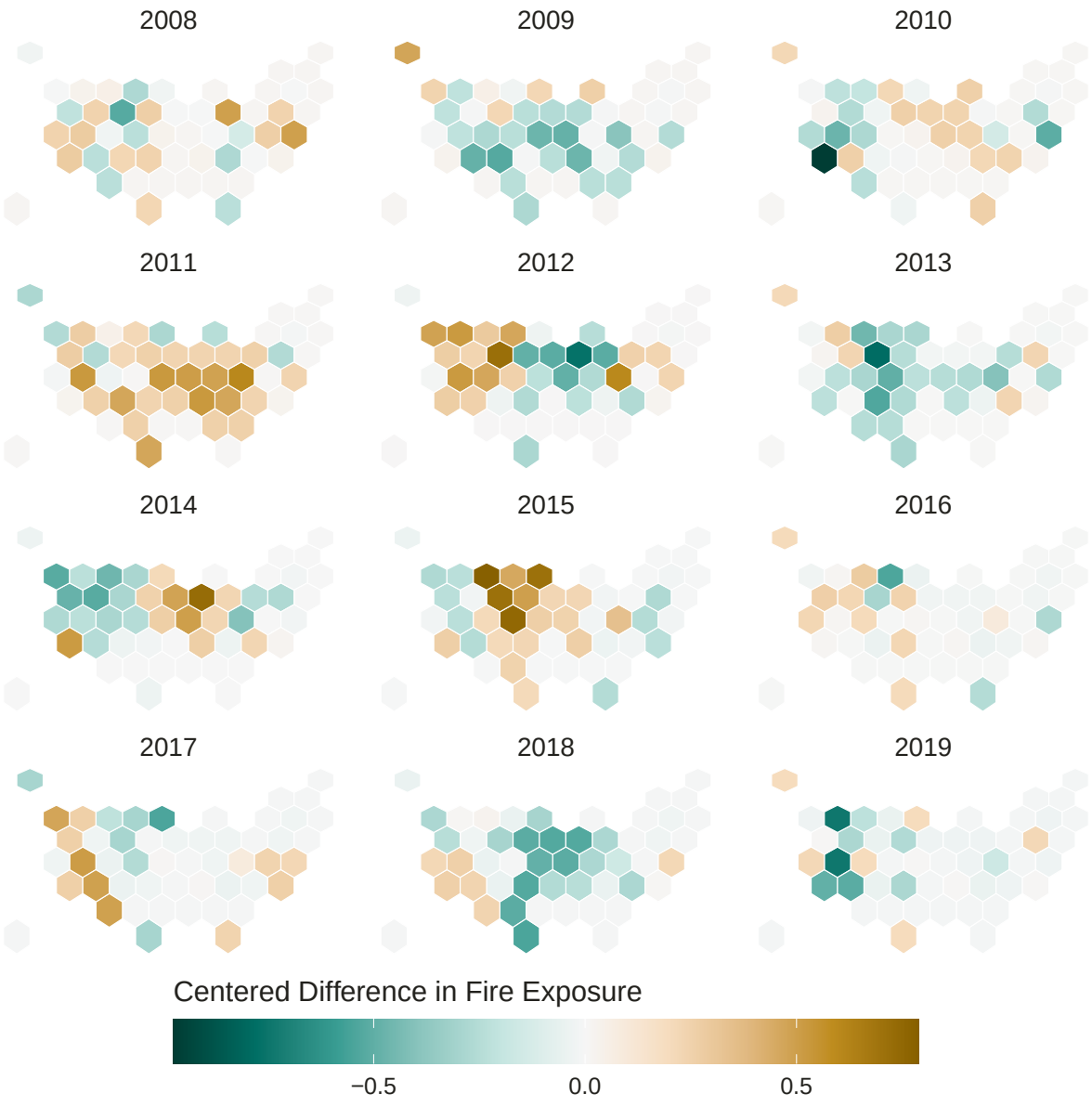
Notes: The figures show the market shares of electric vehicles in each U.S. states between 2006 and 2019. The market shares are computed as the fraction of clean cars registered over total passenger cars registrations in the state.

FIGURE 11: 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 with respect to its competitors and negative if it is under-represented in the state.

FIGURE 12: Centered 2-year difference of fire exposure (yearly average)



Notes: The figures show the centered difference of fire exposure. The measure is centered with respect to a yearly and state-quarter fixed effects. We report annual averages for each state. Brown shades indicate over-exposure, while green shades indicate under-exposure.

C Distribution of firm characteristics

Figure 13 visualizes the discrepancy between the composition of knowledge stocks and firm sales. Presented are firm-specific averages over time. On the one hand, most firms hold shares of clean technologies in their knowledge portfolio with values between 30% and 55% (Figure 13a). On the other hand, clean sales are negligible relative to revenues from combustion vehicles with most of the firms clustering at shares around 1% (Figure 13b). This mismatch is in line with the evidence that clean patents not necessarily translate into more clean products (Kwon, Lowry, and Verardo 2023) and that firms may use clean patenting as competition-deterring strategies (Argente et al. 2025). Figure 13c takes a dynamic perspective on revenues from clean sales and clean innovation. The figure highlights the divergence of Tesla from the average firm with a 100% clean knowledge stock and revenue structure.

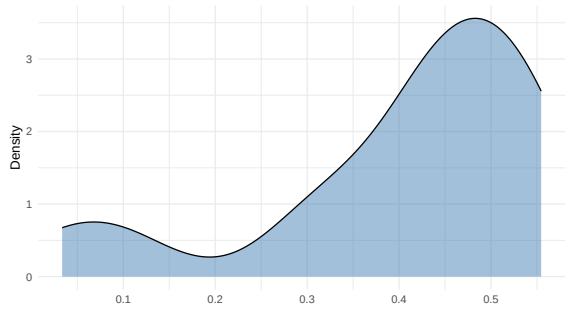
D Index evaluation

This section further explores the index. Subsection D.1 elaborates on alternative yet related indices. We explore further correlations of the index of willingness to act with data on attitudes in Subsection D.2 and with consumption in Subsection D.3.

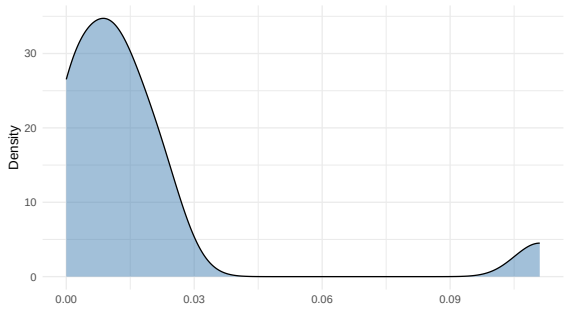
D.1 Alternative indices

In a similar fashion to our main index, we derive two more indices for different combinations of keywords to compare their performance. One, we construct 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*. Two, we build a mixed index comprising the keywords: *Electric Car*, *Climate Change*, and *Recycling*. Table 8 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. In the next section, we discuss how each index relates to survey data on attitudes on the state level.

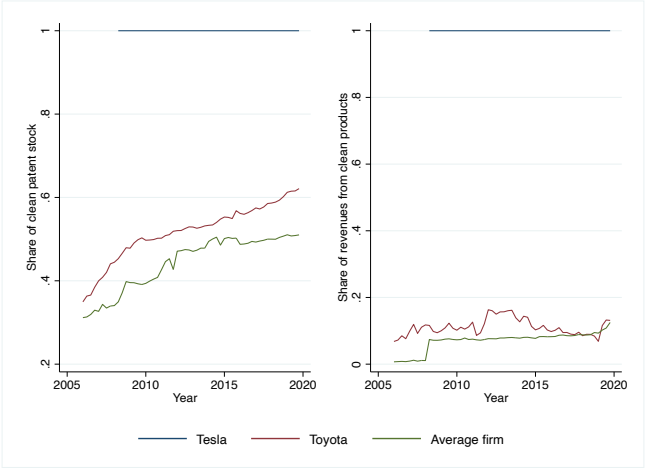
FIGURE 13: Distribution of firm characteristics



(A) Clean share in firm knowledge stock



(B) Clean share in firm sales



(C) Clean share in firm sales and knowledge stocks over time

Notes: Panel (A) and (B) show kernel estimates of the density distribution of firm-specific averages over time. Here, we use the sample of firms used in the baseline estimations, i.e., Tesla is not included. The left side of Panel (C) presents the share of the clean knowledge stock in the overall knowledge stock for Tesla, Toyota, and the average firm. The right side of Panel (C) pictures the share of revenues coming from the sales of electric and hybrid vehicles.

D.2 Index evaluation with survey data on attitudes

To investigate the proximity of our index to survey data on the state level, we turn to the Gallup survey.[97] The disadvantage of 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.[98] Therefore, we use a broader measure of environmental concerns, which is available at a higher frequency, to compare the indices. The precise question we consider from the Gallup reads:

[97]The Gallup survey measures public opinions and attitudes for the U.S. in representative samples. We use the Gallup Poll Social Series conducted in March 2023 on environmental topics (Gallup 2023).

[98]Questions concerning a willingness to act, such as, "do you recycle", "do you adjust your consumption", are only asked infrequently not allowing for a comparison over time.

TABLE 8: Summary statistics of the indices

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

Notes: The tables summarizes the three indices derived from Google Trends: the Willingness to Act index, the Environmental Interest index and the Mixed index. The first index relies on the keywords *Electric Car*, *Recycling*, and *Solar Energy*, the second on the keywords *Climate Change*, *Climate Crisis*, *Air Pollution*, and *Carbon Emissions*, and the last is composed of the terms *Electric Car*, *Climate Change*, and *Recycling*.

"How worried are you by climate change?". We use the share of participants that answer "A great deal" to construct a survey-based index following the same steps as for our index based on Google Trends data. The 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.

First of all, Figure 1 compares the index built with Gallup data on the federal level to our state-level indices. The dynamics of the federal-level index from the Gallup 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 resurgence starting around 2015. On average, the Gallup suggests to foreshadow our measure of willingness to act: Environmental concerns seem to foster changes in willingness to act.

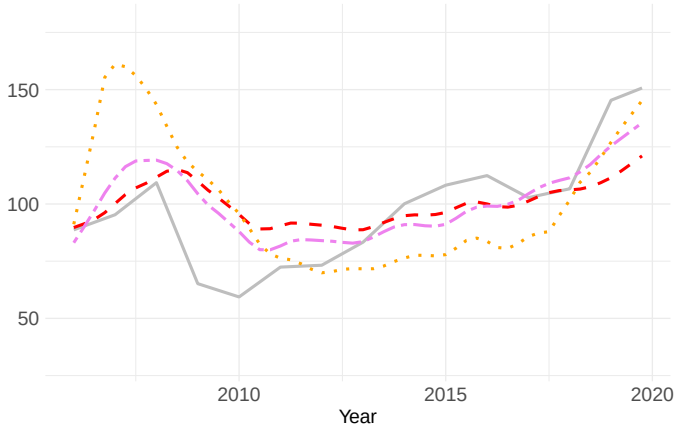
Figure 14 contrasts for highly populated states[99]—California, New York, and Texas—our indices of willingness to act, environmental interest, and the mixed index to the index derived from the Gallup survey. There is a remarkable similarity between the indices and the survey-based index both over time and across states. In the cases of California and New York, the Gallup-based index mimics the indices for willingness to act and the mixed version, while it seems less closely related to the broader measure of environmental interest. As regards the state of Texas, we observe a timely wedge of approximately 2.5 years between the Google Trends indices and the Gallup-based index with the latter foreshadowing the former.

D.3 Correlation with electric vehicle registration data

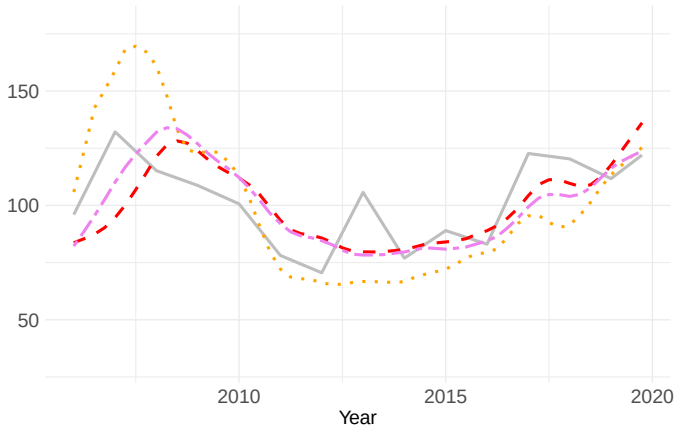
As another test of the usefulness of the index on willingness to act, we evaluate it against data on new vehicle registration provided by S&P Global which we describe in more detail in Section 3.

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

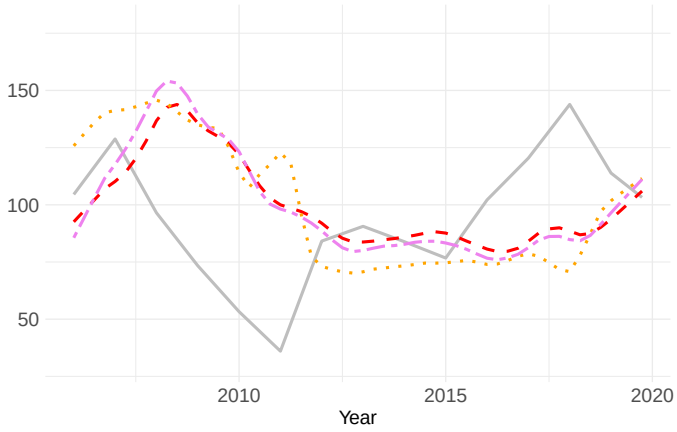
FIGURE 14: Comparison of Google Trends and Gallup indices



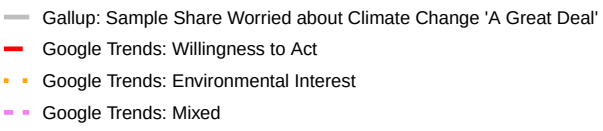
(A) California



(B) New York



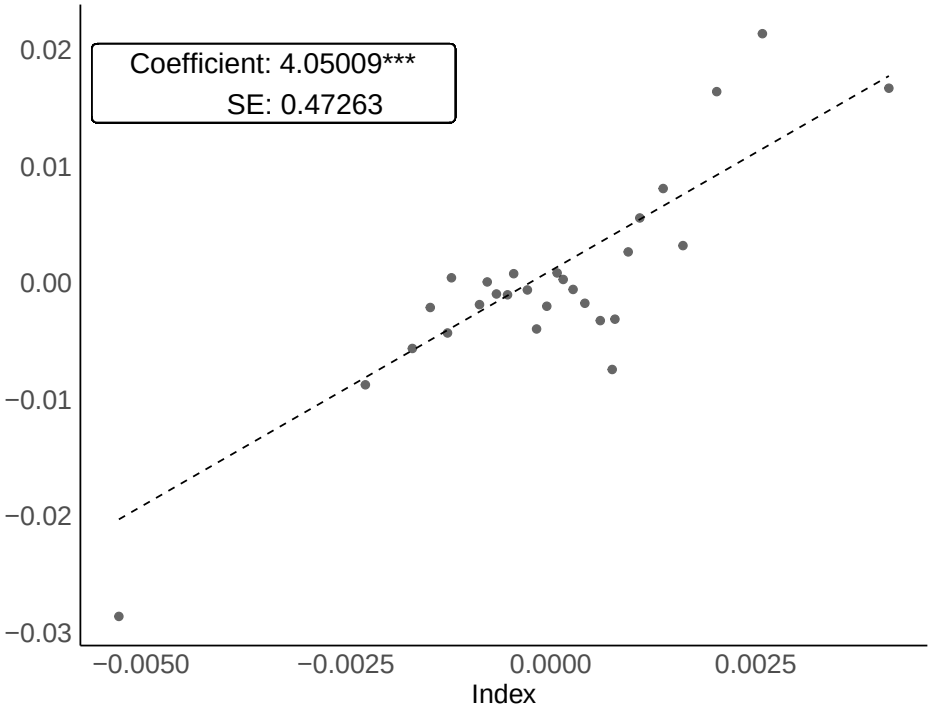
(C) Texas



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".

Figure 15 shows a binned scatter at the state-quarter level between the index and the share of electric vehicles in new vehicle registrations. The estimation accounts for time and state fixed effects. The correlation is strongly significant and economically meaningful: A 1% increase in the index is associated with a 0.04 percentage point increase in the share of electric vehicle registrations. This corresponds to roughly 1.2% relative to the weighted average over states of 3.4%.

FIGURE 15: Index of willingness to act and electric vehicle registration on the state level



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

E Natural disasters and environmental attitudes

With 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 dis-

tant and abstract issue, often disconnected from our daily well-being (Ornstein and Ehrlich 2000; Gifford 2011). However, during extreme weather events, the tangible effects of climate change become readily apparent.

The literature reports that people connect extreme weather events to the broader narrative of climate change in the aftermath of the event for various countries and settings(Lang and Ryder 2016). The experience of extreme weather events, in turn, 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). Beyond shifting attitudes, experiencing extreme weather events appears to also change behavior. For example, Spence et al. 2011 show, in the context of the 2010 flooding in the UK, that first-hand experience of flooding was positively linked to environmental concerns and even greater willingness to save energy to mitigate climate change. Li, Johnson, and Zaval 2011 report that residents in the U.S. and Australia are more likely to make pro-environmental donations under extreme temperatures.

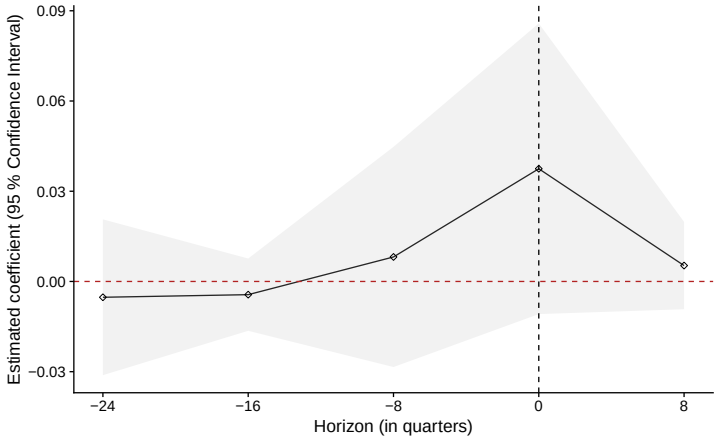
Having given an overview of the literature, we briefly explore the relation of the shocks and the two-year change in willingness to act in our specific setting. To do so, we jointly regress the index on several leads and lags of wildfire exposure, $\Delta_8 Fire\ Exposure_{lt}$, on the state level.[100] One crucial assumption in our framework is that the exogeneity of wildfires is conditional on state-quarter and period fixed effects. This is intuitive as wildfires are not randomly distributed across states and some years are more prone to wildfires than others. Including those fixed effects implies that we leverage the within-state and within-time variation in wildfires to identify the effect of wildfires on environmental preferences. We follow the same approach here. Formally, we estimate a linear relation:

$$\Delta_8^{\log} ENV_{lt} = \alpha_{lq} + \lambda_t + \sum_{k \in \{-24,-16,-8,0,8\}} \beta_k \Delta_8 Fire\ Exposure_{lt+k} + \varepsilon_{lt}$$

The estimation is weighted by the population of state l at time t. The variables α_{lq} and λ_t are state-quarter and time fixed effects, respectively. Albeit not statistically significant, the dynamic pattern in the Figure 16 strongly supports our empirical strategy using the two-year difference in fire exposure as an instrument for the contemporaneous growth in household environmental willingness to act.

[100] This is not exactly the first stage in the main empirical analysis which exploits variation on the firm level.

FIGURE 16: Wildfires and environmental willingness to act



Notes: The figure reports the dynamic effect of wildfires on the index of environmental willingness to act within U.S. states. The difference in fire exposure is calculated over two years as in the main analysis. The data is a panel of U.S. states between 2006 and 2019. The regression includes state-quarter and time fixed effects. The shaded area represents the 95% confidence interval. Wildfire information comes from the NASA's FIRMS satellite data. The figure represents results from an estimation using the two-year difference in periods $t-24$, $t-16$, $t-8$, t, $t+8$.

F Falsification tests

TABLE 9: Shock balance tests

Panel A: State-level balance

Balance variable	Coef.	SE
Share of Republican votes	-0.005**	(0.003)
Share pop. commuting by personal car	-0.002	(0.001)
Share pop. commuting by public transportation	0.007**	(0.003)
Share pop. commuting by bicycle	0.003	(0.011)
Share pop. working remotely	-0.000	(0.002)
# New EV charging stations	0.000***	(0.000)
Share of active pop.	-0.000	(0.000)
Share of young pop.	0.357	(0.605)
Share of urban pop.	-0.006***	(0.002)
Income per capita	0.000***	(0.000)
Gasoline price	0.000*	(0.000)
Diesel price	0.000*	(0.000)
Regulation pollutant	0.010	(0.007)
Regulation ghg	0.022***	(0.006)
Regulation zeroev	0.012	(0.007)
# of state-period: 1970		

Panel B: Firm-level balance

Balance variable	Coef.	SE
Log total lobbying expenditures	0.008	(0.006)
Log pro-environmental lobbying expenditures	-0.001	(0.002)
Log anti-environmental lobbying expenditures	0.007	(0.006)
Log clean patent stock	0.001	(0.003)
Log dirty patent stock	0.002	(0.004)
Log gray patent stock	-0.004	(0.001)
Log non-classified patent stock	-0.001	(0.003)
Log (1+# clean patents)	-0.004	(0.004)
Log (1+# dirty patents)	-0.002	(0.002)
Log (1+# gray patents)	-0.002	(0.004)
Log (1+# clean patents) - log (1+# dirty patents)	-0.001	(0.003)
# of firm-period: 924		

Notes: Significance codes: ***: 1%, **: 5%, *: 10%
The table presents the results of the shock balance test as described in Section 4. Each row considers a different outcome and reports the OLS point estimates and standard errors in parentheses. In Panel A, regressions are ran at the state level including time and state-quarter fixed effects. Standard errors are clustered at the state level. In Panel B, regressions are ran at the firm level including firm and period fixed effects. Standard errors are clustered at the firm level.

TABLE 10: Falsification test for the IV regression on predetermined outcomes

	Knowledge stocks			Lobbying	
	Clean	Dirty	Gray	Pro Env.	Anti Env
$\Delta^{\log}_{8s_t} ENV$	16.14	-5.570	19.53	9.335	82.80**
	(11.59)	(6.472)	(11.69)	(8.147)	(35.48)
N (states - periods)	1200	1200	1200	1200	1200

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

Notes: The table reports coefficients from the shift-share IV falsification tests. We regress outcome variables measured over the period from $t-24$ to $t-16$ on the two-year change in the environmental preferences index measured from $t-8$ to t. The change in environmental preferences index is instrumented with the change in wildfire exposure. Clustered standard errors at the state level are in parentheses. All regressions include year-quarter and state-quarter fixed effects and the full set of controls: firm trends, lagged firm controls, demographic, transportation, and political controls as in our baseline regression.

G Additional Results

This section discusses the results of an interaction term analysis based on the share of sales from combustion engines in firm revenues, Subsection G.1, and results in the sample with Tesla, Subsection G.2.

G.1 Importance of dirty product sales

We want to dig a bit deeper into how firm responses depend 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 combustion vehicles. We expect these firms to react more strongly to a shift in preferences. Moreover, we hypothesize that dirtier firms have an increased incentive to prevent stricter environmental regulations 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:

$$\begin{aligned}\log(y_{it+h}) - \log(y_{it-8}) =& \beta^h \Delta^{\log}_{8,s_t} ENV_{it} + \delta^h Dirty_Share_{it-12} \\ &+ \gamma^h \Delta^{\log}_{8,s_t} ENV_{it} \times Dirty_Share_{it-12} + \zeta^h X_{it} + \varepsilon^h_{it+h} \end{aligned} \tag{7}$$

for different horizons $h = 0, ..., 20$. The variable *Dirty_Share* represents the predetermined share of revenues from dirty products in total revenues.[101] As instrument we use the share of revenues from dirty sales times the wildfire shock, Z_{it}.

Figure 17 depicts the coefficient on the interaction term in Model (7) transformed to reflect the total effect of a 1% increase in the growth of the index of willingness to act on the outcome variable in percent at two distinct values of *dirtiness*: the average and the maximum value of the share of dirty sales.

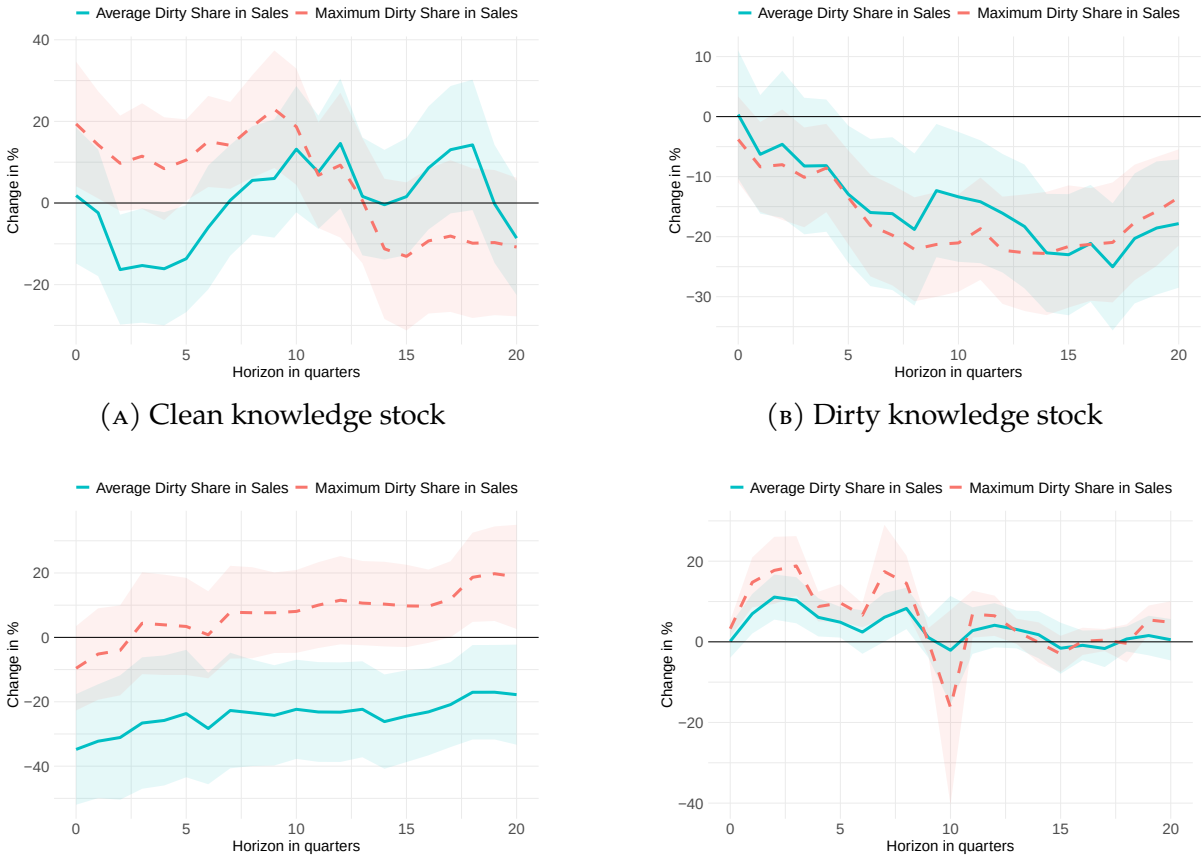
In essence, the results suggest that firms with a dirtier product portfolio respond more with a reallocation of innovation towards clean and gray technologies. The decline in dirty knowledge, however, is not driven by the composition of firm revenues. Furthermore, firms that rely more on dirty products in their revenue portfolio increase their anti-environmental lobbying expenditures more in response to greener household preferences.

We interpret this result as more severely affected firms responding more strongly by both

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

a shift in innovation towards technologies which reduce emissions and by protecting their profits from dirtier product sales. From the perspective of the composition of revenues, anti-environmental lobbying and innovation are complements: Both strategies help secure cash flows, one in the short run and the other in the long run.

FIGURE 17: Total effect of greener household preferences by share of revenues from dirty products



(A) Clean knowledge stock

(B) Dirty knowledge stock

(C) Gray knowledge stock

(D) Anti-environmental lobbying

Note: Graphs show the total effect on key variables to a 1% increase in the index of willingness to act at the firm average of the share of dirty sales, 0.66, and the maximum, 1. That is, graphs depict the function $\beta^h + \gamma^h \times \overline{Dirty_Share}$ of the specification $\log(y_{it+h}) - \log(y_{it-8}) = \beta^h \Delta^{\log}_{8,s_t} ENV_{it} + \delta^h Dirty_Share_{it-12} + \gamma^h \Delta^{\log}_{8,s_t} ENV_{it} \times Dirty_Share_{it-12} + \zeta^h X_{it} + \varepsilon^h_{it}$, 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.

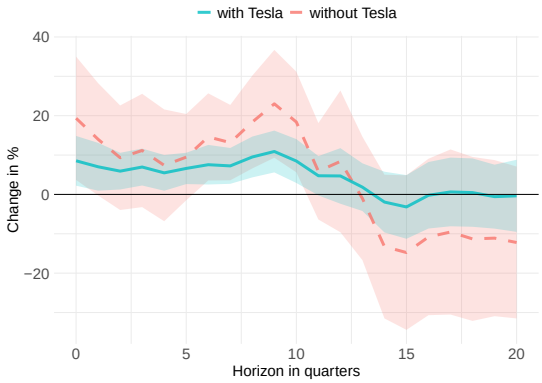
G.2 Sample with Tesla

Tesla stands out in two respects. Neither does the firm sell combustion engines nor does it innovate related technologies.[102] We exclude Tesla from the baseline sample to focus the study on adjustments in the direction of innovation and lobbying. Adding Tesla to the sample changes the average firm response of dirty and gray knowledge. Both average effects vanish. Since Tesla does not conduct any research on combustion-engine-related technologies, the decrease in the size of the estimates comes at no surprise. In contrast, average results on clean knowledge stock growth remain similar.

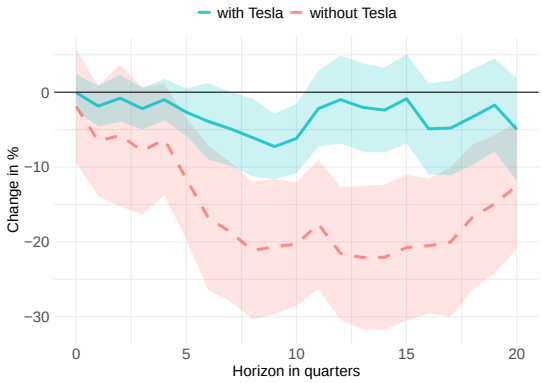
As regards the political economy side, the average firm response in anti-environmental lobbying is largely unchanged. However, pro-environmental lobbying is lowered persistently after a greening of household preferences. One candidate explanation is that greener household preferences necessitate less pro-environmental lobbying for a firm that sells the goods which cater to greener preferences.

[102] Compare Online Appendix C.

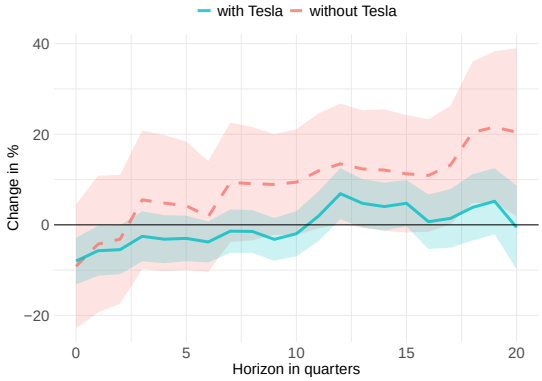
FIGURE 18: Effect of greener household preferences in sample with and without Tesla



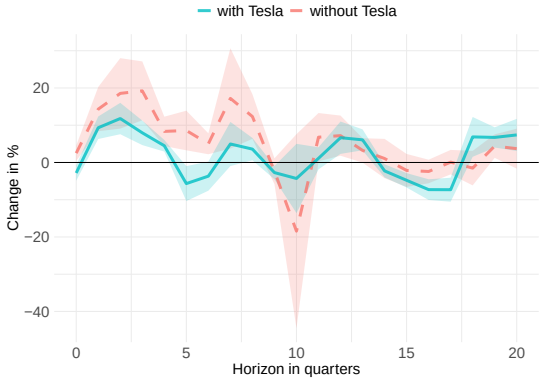
(A) Clean knowledge stock



(B) Dirty knowledge stock



(C) Gray knowledge stock



(D) Anti-environmental lobbying



(E) Pro-environmental lobbying

Note: This figure reports the impulse responses of total knowledge stock and clean knowledge stock following an increase in our index of household environmental willingness to act according to the following specification: $\log(y_{it+h}) - \log(y_{t-8}) = \beta^h \Delta^{\log}_{8,s_t} ENV_{it} + \gamma^h X_{it} + \varepsilon_{it+h}$, for quarters h=0, ..., 20 after the shock. Shaded areas are 95% error bands, where standard errors are clustered at the state level. Coefficients are transformed to reflect percentage changes in the outcome variable. Standard errors are transformed using the delta method.