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Climate Activism Favors Pro-environmental Consumption[*]

Marco A. Marini[†] Samuel Nocito[‡]

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Abstract

We investigate whether climate activism favors pro-environmental consumption by examining the impact of Fridays for Future (FFF) protests in Italy on second-hand automobile transactions in the strike-affected areas. Leveraging data on 10 million automobile transactions occurring before and after FFF, we exploit rainfall on the day of the events as exogenous source of attendance variation. Our findings reveal that local participation to the events is associated with a reduction in the per capita CO2 emissions of purchased cars, an uptick in the market share of low-emission vehicles and a corresponding decrease in the market share of high-emission counterparts. Notably, we uncover heterogeneous effects across gender and age groups. Results are primarily driven by a rise in the purchase of petrol cars, with electric cars contributing to a lesser extent, thereby displacing the demand for diesel vehicles. This evidence indicates substitution effects between goods prospectively subject to more stringent environmental regulations toward those obeying milder restrictions. The study provides valuable insights into the mechanisms underlying individuals' consumption choices under the influence of social protests.

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1 Introduction

The unprecedented environmental degradation caused by human activities has recently sparked an upswing of pro-environmental protests. These include spontaneous demonstrative actions as well as more structured movements aimed to solicit national and transnational institutions to act against such impelling environmental crises. Noteworthy examples are the *Environmental Movement*, gaining notoriety with the inaugural *Earth Day* in 1970, and *Greenpeace*, established in 1971, known internationally for its mediatic actions against global threats as deforestation as well as deploitation of marine ecosystems. More recently, *Fridays for Future* (henceforth FFF), initiated by climate activist Greta Thunberg, has engaged in some of the most globally widespread climate protests on record in favor of the environment (Forbes, 2019).

Pro-environmental movements have, in many cases, led to effective national and transnational legislative changes. For example, the ratification of the *Clean Air Act* and *Clean Water Act* in the U.S. and, more recently, the European ban on new fossil fuel-powered vehicles from 2035 (Reuters, 2023). However, it is less clear whether, and to what extent, climate activism can effectively influence consumer behavior, particularly encouraging consumers to choose cleaner products over their dirtier alternatives.

Disentangling the influence of climate activism on consumers' choices poses several challenges. To start with, to establish empirically a clear-cut causal relationship between environmental movements and consumption patterns in specific regions or markets can be gruelling. Regional pro-environmental events and climate strikes are often correlated with a higher proclivity toward eco-friendly consumption, thus making causal inferences relatively hard to ascertain.

In this paper, we study the impact of FFF climate protests occurred in 2019 in a group of Italian towns on the local second-hand automobile markets. To overcome some of the aforementioned challenges, we use precipitation levels on the day of the event as an exogenous source of variation of protest participation, drawing from an instrumental variable approach (see, for instance Madestam *et al.* (2013)). Since the day of every FFF is generally decided at global level, it cannot be altered by local organizations according to weather conditions. Therefore, rainfall serves as a credible instrument, capable of influencing the decision to participate to an outdoor event, meanwhile remaining unrelated to economic outcomes.

Our analysis draws from three distinct data sources composing a panel data set at the municipality-year-month level used to investigate the impact of FFF on consumption. In particular, we use data on FFF protests taking place in Italy throughout 2019, exploiting all available information, including the number of participants. We also employ rainfall data on the day of the strikes to account for weather-related variations in FFF attendance. Finally, we tap into a rich data set of second-hand automobile transfers, made available by the Italian Ministry of Infrastructure and Transport and spanning from January 2017 to February 2020. The data encompass nearly 10 million automobile transactions, offering comprehensive insights into consumer behaviour in the second-hand automobile market. In order to study all changes occurred in consumers' choices, we categorize vehicles into quartiles based on New European Driving Cycle (NEDC) CO2 emissions, which distinguish between low and high-emission automobiles. Such a taxonomy allows us to disentangle the effects of FFF on consumers' decisions in terms of market shares.

We find that FFF led to a reduction in CO2 per capita emissions of purchased cars following the FFF March 2019 event. This reduction corresponds to approximately half of the standard deviation (SD) when compared to those municipalities not hosting FFF. Moreover, climate strikes have increased the share of low-emission cars by 37.5 per cent of SD while decreasing that of high-emission cars by 43 per cent of SD. Heterogeneity analyses shed light on gender and age-related variations in these patterns.

Our results offer a plausible *rationale* of the underlying mechanism linking FFF to consumers' behaviour. By looking at the changes in consumption choices, we observe how the pressure exerted by FFF on climate policies prompt individuals to adapt *ex-ante* their consumption patterns, in particular in view of newly *European Emission Standards* (EES). Specifically, FFF induce a rise in the share of second-hand petrol cars (28.5% of SD) at the expense of diesel (minus 35% of SD). It is also observed, although to a lower extent, an increase in the share of gas (e.g., methane or LPG) and electric cars. By differentiating car sales into EES classes, we can, therefore, conclude that FFF favors consumers' choices towards cleaner cars, in a way, however, that is mediated by their concern toward the stricter environmental regulations appearing on the horizon.

Our paper contributes to the recent literature studying the economic impact of social and political protests.[1] Among others, Madestam *et al.* (2013) examine the economic consequences of Tea Party movement in U.S., exploiting the rainfall on the day of the rallies as an exogenous source of attendance variation. They highlight how Tea Party protests influence both the political narrative as well as political decisions, leading to a shift of fiscal policy at the state and federal levels. This supports the idea that social and political movements exert a tangible economic influence through their capacity to shape the political agenda.[2] Hungerman and Moorthy (2023) use variations in weather to study the long-term effects of environmental activism, symbolized by *Earth Day*

[1]Our findings also relate to the literature dealing with the social drivers of consumers' preferences (Akerlof and Kranton, 2000; Bénabou and Tirole, 2006; Costa Pinto *et al.*, 2014). Consumers' preferences and their choices are affected by a multitude of social drivers that reflect not only individual self-interest but also pro-social behaviour, identity, salience, and societal norms. We do not directly contribute to this literature from a theoretical perspective. Nevertheless, our results provide indirect evidence of the fact that consumers follow their self-interest mitigated by expectations which are influenced by the social pressure exerted on local politics. This, in turn, may end up having an impact on their pro-environmental and pro-social behaviour.

[2]Acemoglu *et al.* (2018) investigate the economic repercussions of the Arab Spring in Egypt. Their framework revolves around the idea that political uprisings can disrupt economic stability. They use a synthetic control method to compare Egypt's economic performance to that of similar countries not experiencing the Arab Spring. The primary economic result is that the Arab Spring led to a decline in foreign direct investment, tourism and overall economic stability in Egypt.

events. They find that bad weather on the 1970 *Earth Day* is associated with weaker support to the environment and is, therefore, related to higher levels of carbon monoxide in the air and to a greater risk of congenital abnormalities in the infants born in the following decades. Thus, this work illustrates how grassroots movements dealing with environmental concerns can have measurable economic consequences over time. Fabel *et al.* (2022) study the political impact of FFF, in particular focusing on FFF local events in Germany. The authors employ a panel regression approach, examining the changes in environmental policies in counties with and without significant FFF activity. The main economic finding is that FFF led to a higher share of votes for the Green Party.[3]

To our knowledge, our work is the first to investigate the impact of climate activism on consumption choices. Specifically, we study the mechanisms through which FFF protests impact consumers' choices pushing them toward products with a milder environmental footprint. Our results provides support to the idea that some of the consumption shifts are based upon a self-interested *rationale*, driven by consumers' anticipation of more stringent future environmental regulations. Our analysis is based on global protests taking place simultaneously in several towns all over the world. This implies that our local average treatment effect is generalizable to other countries and areas of the world, enhancing the external validity of the results. All in all, our investigation provides valuable insights on the interaction between climate activism, consumer behaviour and environmental policies. Understanding these dynamics is crucial for policymakers, social scientists and society at large, as it contributes to unveil the complex interplay between social activism and economic behaviour.

The remainder of the paper is organized as follows. Section 2 illustrates the background of FFF and the data used in our empirical analysis. Section 3 details the adopted empirical strategy. Section 4 discusses the main results along with robustness

[3]Additionally, Valentim (2023) focuses on the role of repeated exposure to FFF protests in Germany, highlighting how such repeated exposure has further increased the share of Green Party votes.

specifications, heterogeneity analyses (4.1), and mechanisms at work (4.2). Section 5 concludes.

2 Background and Data

Our analysis leverages on three distinct data sources. Firstly, we use data on FFF protests taking place in Italy on 2019. Secondly, we exploit rainfall data on the day of the strikes as a source of exogenous variation on the attendance of FFF.[4] Finally and most importantly, we make use of a rich data set of Italian second-hand automobile transactions. Thus, we merge all above mentioned sources to build up a panel data set at the municipality-year-month level.

2.1 Fridays for Future

FFF is a global movement aimed to address the challenge of climate change through student-led strikes and demonstrations. FFF have begun thanks to Greta Thunberg, a Swedish teenager, who in August 2018 started a solitary strike outside the Swedish Parliament. Her determination and passion for climate activism quickly spread globally, inspiring millions of students worldwide to join the cause (Guardian, 2019). Since its start, the movement's core principle has been centered around the request of stronger climate actions from governments, advocating for policies aligned with the goals of Paris Agreement. In 2019, young people have rallied under the flag of FFF all over the world, organizing strikes and demonstrations and advocating for more comprehensive climate policies and sustainable practices. This involved almost 17 thousand cities and 13 million people during 6 global strikes.[5] In Italy, 404 municipalities hosted a FFF event in 2019, with 273 (3.5 per cent of all Italian municipalities) participating to the

[4] As for the rainfall data, these come from Agri4Cast which is a Joint Research Center financed by the European Commission. Agri4Cast provides historical data on precipitations (in millimetres). URL: https://agri4cast.jrc.ec.europa.eu/DataPortal/Index.aspx?o=.

[5] In 2019, there were 6 global strikes in the following dates: March 15, May 24, September 20, September 27, November 29, and December 6.

first event in March 2019. The strikes primarily targeted government inaction, asking for more ambitious policies to reduce greenhouse gas emissions, promote renewable energy sources to actively fight the upgrowing climate crises. It is fair to say that FFF have exerted a considerable pressure on Italian policymakers, prompting them to prioritize climate-related issues in their political agenda (la Repubblica, 2019). The strikes created a sense of urgency, leading to increased political discussions on climate issues, both at national and international level (BBC, 2021).

To investigate the local influence of such protests, we used data on FFF participation in Italy in 2019. Specifically, we collected data from the FFF map of strikes reported by the organization's website.[6] People involved in FFF reported strikes directly on the organization's webpage by completing a specifically designated form or using the Game-Changer platform.[7] Typically, these reports were submitted shortly after the events were taking place. In addition, FFF activists tracked their events worldwide, with a specific team responsible for managing this task.[8] In particular, activists reported the cities of the strikes and the number of participants.[9] One caveat regarding the reported number of participants is that it may be either over or underestimated or, in a very few cases, even missing. However, we can consider such error as essentially random. As explained in Section 3, we employ both the number of participants and a dummy variable indicating event hosting as treatment variables.[10]

[6] See: https://map.fridaysforfuture.org/list-towns.

[7] See: https://fridaysforfuture.org/action-map/register-report-strikes/. Game-Changer platform is available at: https://www.gamechanger.eco/action/start.

[8] In recent years, FFF activists also promoted the use of a Twitter-bot, Twiff, to make the reporting process even easier and more efficient. For more details, see: https://actionnetwork.org/groups/twiff-manual.

[9] We retrieved data on FFF participation to Italian strikes and we double checked on national media that those events actually took place, without finding any inconsistency in the overall data.

[10] Specifically, the former measures the treatment's intensity, where the latter represents an absorbing state not invalidating the goodness of the empirical strategy (Angrist and Imbens, 1995; Angrist *et al.*, 2000; Callaway *et al.*, 2021). It is important to stress that the date of FFF events is independent of local conditions (e.g., weather) as is determined at global level. On the other hand, the decision to host the event in a specific town can be affected by weather conditions. Therefore, the dummy variable measures whether FFF actually occurred in a particular location, and this information is typically reported after the date of the event. Employing both measures enhances the robustness of our empirical investigation.

2.2 Automobiles Data

To examine the impact of FFF on consumption choices, we employ a rich data set of Italian second-hand automobile transactions. We concentrate on this market for two main reasons. Firstly, we consider this as easily comparable across European and extra-European countries, potentially allowing the investigation to be extended to further geographical areas, enhancing its external validity. Secondly, by using data on second-hand cars we could access their exact dates of purchase, something not accessible for new automobiles, for which only the registration date is available. This poses a significant limitation when using data on new automobiles since the registration date often does not coincide with the purchasing date, leading to potentially biased estimates when investigating the influence of FFF on consumption choices.

Data on the second-hand automobile market are gathered by the Italian Ministry of Infrastructure and Transport and we could access information on all automobile transfers occurred between January 2017 and February 2020, totalling nearly 10 million transactions.[11] For every transaction many details were available on both the buyer and the automobile. About the buyer, we have the information on their municipality of residence (i.e., the location where the car was purchased), the date of purchase, age and gender. About the car, we could access the date of registration, engine power and level of CO2 emissions. The latter information relies on the New European Driving Cycle (NEDC), designed to evaluate emission levels and fuel economy in passenger cars. The NEDC represents the standard driving patterns in Europe and is based upon four repeated urban driving cycles and one extra-urban driving cycle.[12] Thus, we use the latter measure to differentiate consumers' choices of more or less polluting cars.

Specifically, we categorize cars into quartiles based on the NEDC CO2 emission

[11] Data are available up to 2022 but we cut the sample before Covid-19 lockdown to avoid introducing bias in estimates.

[12] In September 2018, NEDC has been replaced by Worldwide Harmonized Light Vehicles Test Cycles (WLTC). However, in our analysis, we refer to NEDC since the WLTC is not available for cars registered before 2017 while the NEDC is still available for automobiles registered after 2017.

distribution. For simplicity, we refer to the first quartile as having low CO2 emissions and to the fourth quartile as that associated to high emissions. The second and third quartile denote mid-low and mid-high emissions levels, respectively. Table A.1 in the Appendix presents summary statistics on automobile micro data, with the average NEDC CO2 emission level at 133 for the whole sample, 103 for the first quartile, and 174 for the fourth quartile. Electric automobiles constitute 0.6 per cent of sales, while petrol cars account for 38.7 per cent and diesel vehicles for 54 per cent.[13] The average age of buyers is 46.6 (SD: 14.4), whereas female buyers comprise 35 per cent of the sample. Table A.2 in the Appendix shows summary statistics of the panel data at the municipality-year-month level.[14]

3 Empirical Strategy

To establish a causal relationship between FFF and the choice of cars, we employ precipitation levels on the day of the event (i.e., March 15, 2019) as instrumental variable (IV) (Madestam *et al.*, 2013). The rationale of this choice lies in the assumption that rainfall is exogenous to individual participation decisions and has a direct impact on the attendance of the FFF event. This assumption is plausible provided that the date of the FFF-event is decided by the organization at the global level, whereas cannot be changed by local organizations according to weather conditions. Therefore, rainfall serves as a plausible instrument, as it influences the decision to participate in outdoor events without being directly related to the economic outcomes. Formally, we estimate the following first-stage equation on the panel data at the municipality-year-month

[13] The market of second-hand electric cars is not so large in Italy. For this reason, we decided to include full-hybrid and mild-hybrid electric cars into the electric segment.

[14] For reasons explained in detail in section 3, our panel data include never treated municipalities and treated municipalities who became treated in the first FFF strike occurring on March 15, 2019 (i.e., 273 municipalities out of 404 ever treated in 2019). Therefore, we drop municipalities hosting an FFF strike for the first time in one of the subsequent dates of 2019.

level:

$$FFF_{m,t} = \alpha_0 + +\alpha_1 Rain_{m,t} + \delta_p + \delta_t + \delta PLT + \delta RainProb_m + \gamma X_m + \varepsilon_{m,t} \quad (1)$$

where subscript m indicates the municipality and t relates to time (i.e., year-month). $FFF_{m,t}$ represents the treatment variable expressed as number of FFF-strikers per capita, thus measuring the intensity of the treatment for municipalities participating to the protest (Angrist and Imbens, 1995; Angrist *et al.*, 2000). Alternatively, we also express the treatment variable FFF as a dummy which takes the value of one if municipality m is involved in the FFF event. The treatment dummy can be interpreted as an absorbing state (Callaway *et al.*, 2021), providing an easier interpretation of the results.[15] $Rain_{m,t}$ measures precipitations (in mm) on the day of the FFF-event and serves as an instrument for $FFF_{m,t}$ to solve the potential selection bias and reverse causality issues.[16] δ_p, δ_t, and δPLT represent province fixed effects (FE), time FE and a province linear trend, respectively. In particular, the inclusion of δ_p and δ_t allows to control for every idiosyncratic component at the province as well as at the year-month level. Including local time trend, δPLT, helps to control for any variation in the dependent variable at the province level in any given year-month. For example, we control for monthly variations in automobile/fuel prices in a given province or any other monthly variation in local economic activities. We further include a set of municipality characteristics to enhance the precision of our estimates to compare treated and control municipalities within a given province with similar characteristics. Specifically, we include $\delta RainProb_m$, which is a set of dummy variables corresponding to the deciles

[15]Notice also that, since the number of strikers is self-reported by participants and is missing for a few treated municipalities, the treatment dummy provides robustness to our results.

[16]In the appendix, we also provide robustness check estimations in which we consider as an instrument a dummy variable that takes a value of one if precipitations were greater than 0.1 inches (i.e., 2.54 mm) on the day of the strike, as in Madestam *et al.* (2013). Results are qualitatively and quantitatively similar, although the dummy instrument is slightly weaker when compared to the continuous rainfall instrument.

of the historical rain probability distribution (1980-2018).[17] Furthermore, we add the matrix of municipality controls, X_m measured in 2018, that captures the pre-determined green attitude, the economic situation, and the level of automobile usage.[18] We perform population-weighted regressions with clustered standard errors at the municipality level.

Finally, we estimate the second stage equation to measure the causal relationship of interest:

$$Y_{m,t} = \beta_0 + \beta_1 \widehat{FFF_{m,t}} + \delta_p + \delta_t + \delta PLT + \delta RainProb_m + \gamma X_m + \varepsilon_{m,t} \tag{2}$$

where the variable $Y_{m,t}$ measures different economic outcomes, namely: the share of purchased cars belonging to each CO2 emission quartile, the total CO2 emissions per capita of purchased cars, and the share of purchased cars by engine types.[19] Given the nature of our data, it is fair to say that we do not observe consumers' decisions to buy

[17]As in Madestam *et al.* (2013), to derive this distribution we take the fraction of historical rainy days as defined by the 0.1-inch threshold over the period 1980-2018. More in detail, the dummies were constructed as follows. We first generated a dummy variable equal to 1 if precipitation in the municipality exceeded 0.1 inches for the first day of each week in March from 1980-2018 and 0 otherwise. We then took the mean over all dates, leaving us with the likelihood of rain in a given municipality for the relevant time period. Finally, we created decile dummy variables based on this distribution.

[18]Specifically, X_m includes the share of votes to green parties, the share of recycled waste, the number of per capita vehicles, the share of work trips within the municipality, the share of cars, the number of per capita taxpayers, the Gini index, the resident population, the number of per capita public high school and a set of dummies for each decile of the distribution of the population aged 18 years old. These control variables measure predetermined pro-green attitudes as well as the likelihood of hosting an FFF event that is promoted by high school students, automobile usage, economic conditions, and originate from various sources: Statistics Institute (ISTAT), Ministry of Economics and Finance (MEF), Eligendo (Ministry of Interior), and the Institute for Environmental Protection and Research (ISPRA). In the Appendix Table A.6, we provide robustness check estimates without including municipality controls, thus providing evidence that the results are not driven by the chosen set of municipality characteristics.

[19]In figure 1, we also present estimates investigating the dynamics of the effect. Specifically, we estimate the following event-study specification:

$$Y_{m,t} = \beta_0 + \sum_{j=a}^{-1} \beta_j FFF^j_{m,t} + \sum_{j=0}^{b} \beta_j FFF^j_{m,t} \cdot RainyFFF_{m,t} + \delta_p + \delta_t + \delta PLT + \delta RainProb_m + \gamma X_m + \varepsilon_{m,t}$$

with $a = -14$, $b = 11$, and we follow McCrary (2008) binding up the end-points. We interact post-treatment dummies (lags) with the rain dummy, $RainyFFF$, that takes a value of one if rainfall was greater than 0.1 inches on the day of the FFF event. This exercise does not necessarily aim to infer a causal relationship but provides valuable insights into the dynamic nature of the impact of FFF.

or not an automobile; we only observe them when making such a choice. Therefore, our estimates have to be seen as conditional upon the choice of buying a car.

In our analysis, we include both municipalities that have never been treated and municipalities that first experienced treatment during the initial FFF strike (i.e., 273 municipalities). We exclude municipalities that only received treatment in subsequent events. This exclusion is made to prevent any potential bias in the estimates due to the panel structure of our data and the staggered nature of the treatment, as discussed in previous research (Goodman-Bacon, 2021; De Chaisemartin and d'Haultfoeuille, 2020; Callaway *et al.*, 2021). This choice is forced in the IV framework to avoid potential sources of bias that cannot be addressed by using alternative estimation models available for standard difference-in-differences settings (Roth *et al.*, 2023). Therefore, the treatment status ($FFF_{m,t}$) switches on after the first FFF event (March 2019) onwards. However, it is possible that some of the treated municipalities participate in subsequent events. This scenario does not pose any threat to the validity of our empirical strategy since our monotone instruments (i.e., FFF dymmy or FFF strikers) can be considered as an absorbing state of subsequent events. However, this does not allow us to investigate the effect on consumers to be exposed to multiple FFF-strikes. In order to carry this analysis forward without running into a (potentially problematic) staggered treatment context, we build a panel of municipalities over two periods (pre/post-March 2019) and we construct a treatment variable ($NFFF_{m,t}$) counting the number of FFF-events hosted by the municipality m in the post-first-FFF-event period. Finally, we estimate the following first-stage equation to estimate the multi-level treatment effect:

$$NFFF_{m,t} = \alpha_0 + \sum_{e=1}^{6} \alpha_1^e Rain_{e,m} + \delta_p + \delta_t + \sum_{e=1}^{5} \delta^e RainProb_{e,m} + \gamma X_m + \varepsilon_{m,t} \quad (3)$$

In equation 3, we consider as excluded instrument the rainfall on the first FFF-event and we include as control the precipitations of each subsequent FFF-event in 2019 as well as the probability of rain related to each month of the subsequent events.[20]

[20]In the equation 3, the probability of rain is considered for five months since two out of six FFF-

Second-stage results are shown in the Appendix Table A.10.

4 Results

Table 1 presents our main IV results.[21] Panel A displays estimates using the FFF treatment dummy, while panel B presents the results obtained using the number of per capita FFF strikers as a treatment variable.[22] Column 1 provides evidence that the FFF event leads to lower CO2 per capita emissions. This implies that cars purchased in the months following the FFF event in March 2019 exhibit a total technical CO2 emissions per capita reduced by half a SD when compared to counterfactual municipalities (Panel A). In columns 2 and 3, we present results on the share of purchased cars belonging to the first and fourth quartile of CO2 emissions distribution (i.e., low and high CO2), respectively. We do not find any statistically significant effect on the share of cars belonging to the second and third quartile of CO2 emissions distribution, with coefficients close to zero in magnitude. Therefore, for brevity, we do not report these result.[23] We find that FFF caused an increase in the share of low-emission cars at the expense of cars belonging to the high-emission quartile. Specifically, in Panel A, the share of low-emission cars increases by 37.5 per cent of the SD, while the share of high-emission cars decreases by 43 per cent of SD. In Appendix Tables A.6, A.7 and A.8, we provide robustness check analyses. Firstly, in Table A.6, we exclude control mu-

strikes occurred in September.

[21] Appendix Tables A.3, A.4, and A.5 report the corresponding first-stage, OLS, and the reduced-form estimates, respectively.

[22] In Panel B, the number of observations excludes treated municipalities missing information on the number of strikers. Results exhibit qualitative similarity in terms of direction of the results. However, the effect shown in Panel B relates to an increase of 1 striker per capita. Additionally, in Panel B, the F-statistic of the excluded instrument is smaller compared to Panel A, possibly because we dropped some treated municipalities. However, following Angrist and Kolesár (2023), we report the parameter ρ (in absolute value) that measures the degree of endogeneity (see equation 7 in Angrist and Kolesár (2023)). According to Angrist and Kolesár (2023), (see the contour plot shown in Figure 1, Panel B), when we relate the F-statistic to the $|\rho|$ parameter, we obtain evidence that our instrument is valid and should not be rejected even though $F < 10$. The same argument holds for the results shown in the Appendix.

[23] Results are available upon request to the authors.

nicipalities from our model equation. Secondly, in Table A.7, we employ an alternative IV, a dummy variable taking a value of one when rainfall exceeds 0.1 inches (Madestam *et al.*, 2013). In both cases, the results remain robust. Thirdly, in Table A.8, we test the sensitivity of our results by using an alternative control group in which we exclude control municipalities belonging to the same Local Labor System (LLS) as a treated municipality.[24] This exercise allows us to test for potential bias introduced by spillover effects because people living in a control municipality may potentially participate to a FFF event hosted by a neighbouring municipality, which could introduce a downward bias in our estimates. We find qualitatively robust results with a reduced magnitude.

Figure 1 depicts the dynamics of the effects. We observe that outcomes remain stable in the pre-treatment period. Results on total CO2 emissions per capita display a negative jump that persists in the post-treatment period, albeit with some noise. The purchase of low CO2 cars sharply increases immediately after the FFF event, then declines before raising again five months after the event. The purchase of high CO2 emission cars follows a similar pattern, albeit in the opposite direction. These dynamics suggest that the effect is renewed with the occurrence of subsequent FFF events, a phenomenon that we investigate in the Table A.10 of the Appendix, where we find that a repeated exposure to FFF events further increase the magnitude of our effects.[25]

4.1 Heterogeneity Analysis

Figure 2 presents the results of the heterogeneity analysis by age classes. There, we divided consumers into ten different age classes, reported on the vertical axis of each graph, and examine their consumption choices. We find a particularly interesting result that suggests that individuals in the class 18-25 years, who are expected to be potentially closer to the FFF movement and caring more about climate change, show

[24] LLSs are clusters of neighboring municipalities based on commuting patterns defined by the Italian Statistics Institute (ISTAT).

[25] This result is consistent with Valentim (2023).

an increase in the consumption of high CO2 emission cars. A possible rationale of such a counter-intuitive effect is that the FFF movement increased the consumption of low CO2 emission cars on average, leading to their price increase and to a decrease (or a lower increase) of the price of high-emission cars. Consequently, young consumers, typically facing tighter budget constraints, opt in this case for more polluting and relatively less expensive cars. Unfortunately, we did not have access to the purchasing price associated to each transaction to directly test this hypothesis.

In Table A.9 of the Appendix, we analyze heterogeneous effects between males and females. We find results which are similar qualitatively but more intense for females if compared to the sample average and SD as also observed in other studies (Laroche *et al.*, 2001; Brough *et al.*, 2016).

4.2 Mechanism

It can be interesting to briefly discuss the mechanism linking FFF to the observed reduction in the share of high CO2 emission cars toward those with lower emissions. Our results point toward rational-driven consumers' responses triggered by climate protests in their areas of residence. This conclusion can be drawn from the observed consumption changes favored by the FFF protests. They are mainly a switch from diesel to petrol cars and only partially from diesel toward all cars perceived as green by consumers, as those propelled by gas or electricity.

We began the analysis under the premise that a primary goal of FFF is to exert political pressure to tackle the climate change issue caused by high levels of CO2 emissions polluting the atmosphere.[26] We investigated the consumers' reaction to such political pressure by looking at the substitution effect occurring in the market of second-hand cars between different engine types in accordance to European Emission Standards (EES). These are currently the main indicators used for policy targeting.[27]

[26] See: https://fridaysforfuture.org/what-we-do/who-we-are/.

[27] These are typically referred to as Euro 1, Euro 2, Euro 3, Euro 4, Euro 5, and Euro 6, with Euro 1 introduced in January 1993 and Euro 6 introduced in September 2015.

Table 2 presents the results on the shares of purchased cars associated to different types of engine. Our results show an overall decrease in the number of per capita purchased cars, equivalent to half of the SD. Moreover, FFF induce an increase in the consumption of petrol cars (28.5% of SD) at the expense of diesel ones (a decrease of 35% of SD). We additionally observe a positive (although mild) rise in gas-powered cars (e.g., methane or LPG) and a positive but barely significant effect on electric cars. These findings provide a robust evidence of a substitution effect taking place between diesel and petrol cars as effect of climate protests. In Italy, gasoline is typically more expensive than diesel at the pump. However, diesel cars are viewed as more polluting and are usually subject to stricter urban regulations than petrol cars (il Sole 24 Ore, 2020). Therefore, on average, second-hand car buyers appear to rationally anticipate the local introduction of environmental-related traffic restrictions. To further investigate this mechanism, Table 3 shows our results on car transactions categorized by EES. In particular, Panel A reports transactions of petrol cars, while Panel B, in turn, those of diesel. We find an increase in the share of E6 petrol cars (Panel A, Column 6) by 40% of SD and a decline in the share of E5 petrol and diesel cars and in that of E4 diesel ones.[28] Therefore, our results provide evidence of a substitution effect between cars subject to more stringent traffic restrictions (particularly in urban areas) in favor of those subject to milder regulations. The data confirm that such a rational response by consumers was significantly fostered by FFF.

In summary, our analysis provides evidence that consumers react to FFF in a rational manner, anticipating the effects that the political pressure of protests may exert on local policymakers, who, as a result, could be keen to introduce tighter anti-pollution policies. To avoid incurring in serious mobility limitations, consumers react by switching toward safer options, in particular toward cars which are prospectively less subject to severe traffic restrictions.

[28] We also find a positive and statistically significant effect on E3 petrol cars. We do not have an obvious explanation for this result, that could be related to a sort of backfire effect observed among individuals aged 18-25.

5 Concluding Remarks

Our study delves into the consumption effects of climate activism, with a focus on the FFF movement, which has recently galvanized global climate protests. While environmental concerns have increasingly dominated the public discourse, the impact of such movements on consumers' choices for eco-friendly products remains understudied. We investigated the consumption effects of FFF protests in Italy in 2019 by employing an instrumental variable approach based on precipitation levels to establish causality.

Our findings reveal a significant and tangible impact of FFF events on consumer behaviour, particularly on second-hand automobiles purchase. After FFF, we observe a significant reduction in CO_2 emissions of purchased cars, associated to a rise in the share of low-emission vehicles and a fall in high-emission ones. Heterogeneity analyses shed light on gender and age-related variations of consumption patterns.

Our investigation highlights how the observed shifts in the consumption patterns are consistent with rational motives, influenced by consumers' expectations of more stringent local traffic regulations to mitigate pollution triggered by climate protests. These results offer useful insights into the interplay between climate activism, consumer decisions, and environmental policy.

Our case study exhibits a high degree of external validity in various contexts, as the FFF movement is global and several strikes took place concurrently worldwide. Additionally, the second-hand automobile market demonstrates substantial comparability across different countries, making it applicable to other geographical areas.

In a landscape where environmental concerns are growing, understanding the nexus between social activism and economic change is of paramount importance. Our study contributes to this vital discourse, offering implications for policymakers, economists, and society as they navigate the intricate relationship between social activism and economic changes. All in all, our findings hold significance for policymakers aiming to promote environmentally sustainable consumption, locally and globally.

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Tables and Figures

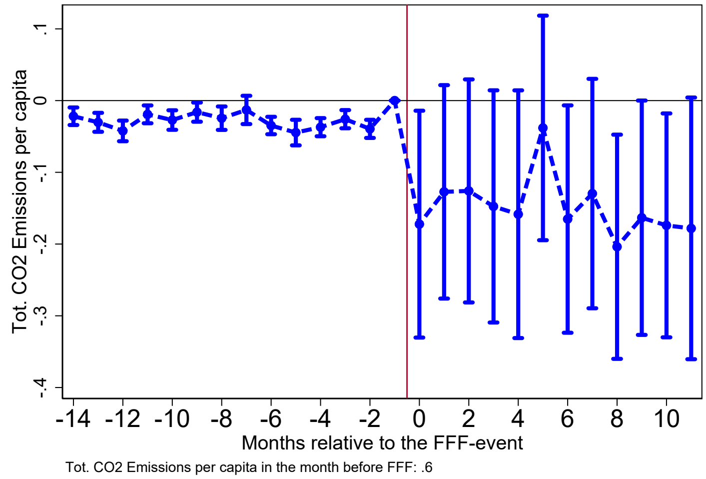
Table 1: IV Baseline Results

	(1) Total CO2 (per capita)	(2) Low CO2 (Quartile 1)	(3) High CO2 (Quartile 4)
Panel A: FFF-dummy	-0.292***	0.072***	-0.088***
	(0.097)	(0.028)	(0.033)
Observations	295,336	295,336	295,336
F-stat of the Excl. Instrument	14.62	14.62	14.62
$\lvert\rho\rvert$	0.614	0.620	0.630
Avg. outcome	0.615	0.235	0.251
Outcome SD	0.554	0.192	0.204
Panel B: FFF-strikers	-9.802**	1.913**	-2.332**
	(4.178)	(0.900)	(1.107)
Observations	288,648	288,648	288,648
F-stat of the Excl. Instrument	7.236	7.236	7.236
$\lvert\rho\rvert$	0.906	0.838	0.855
Avg. outcome	0.616	0.234	0.251
Outcome SD	0.560	0.194	0.206
Province FE	YES	YES	YES
Time FE	YES	YES	YES
Prob. of Rain	YES	YES	YES
Mun. Controls	YES	YES	YES

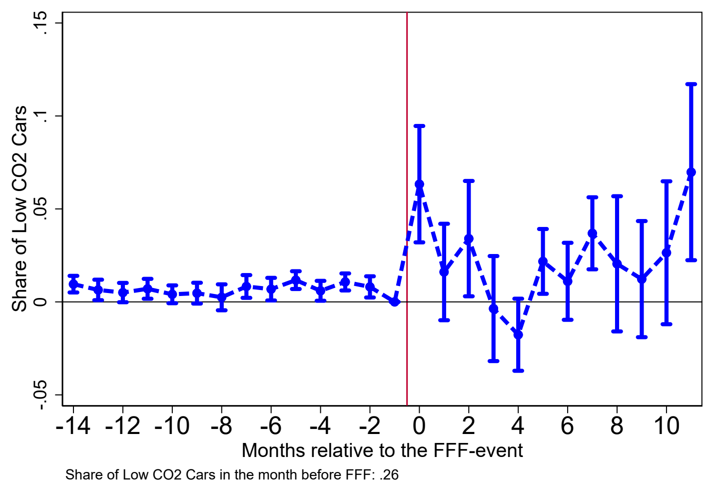
Notes: Panel data at the municipality year-month level. The panel includes never treated municipalities and treated municipalities by the first FFF-event. Quartile outcomes are expressed as share of cars in each quartile. Table shows IV estimates where the endogenous variable (i.e., FFF-dummy or FFF-strikers per capita) is instrumented by rainfall (mm) on March 15, 2019. Estimates are weighted by municipality's population. Standard errors clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1

Figure 1: Event Study

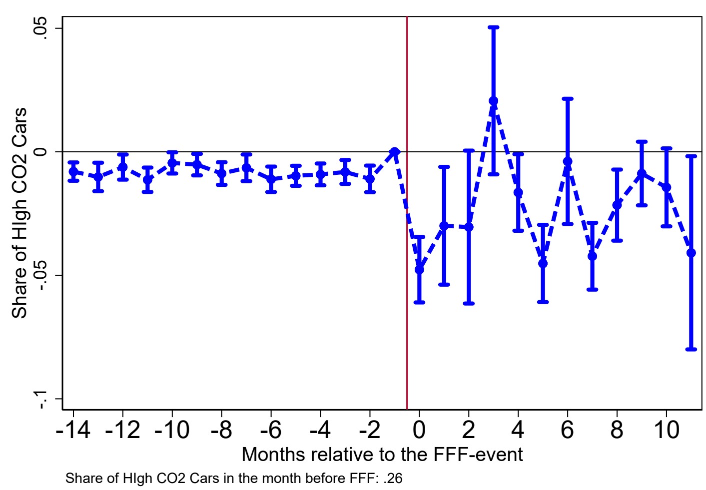
(a) Total CO2 Emissions per capita



(b) Share of Low CO2 Cars (Q1)



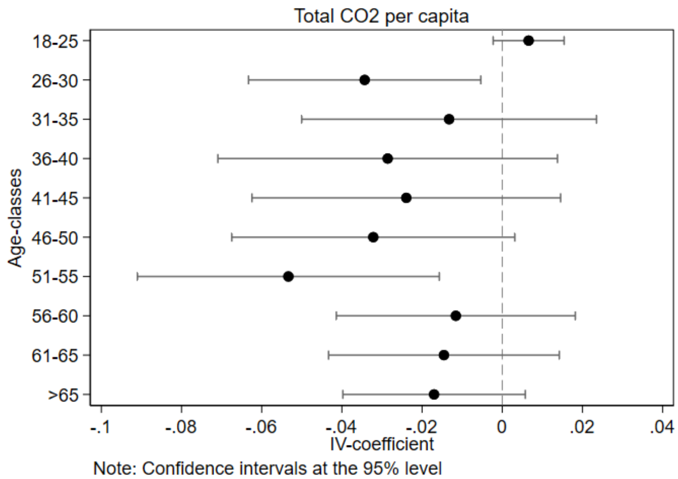
(c) Share of High CO2 Cars (Q4)



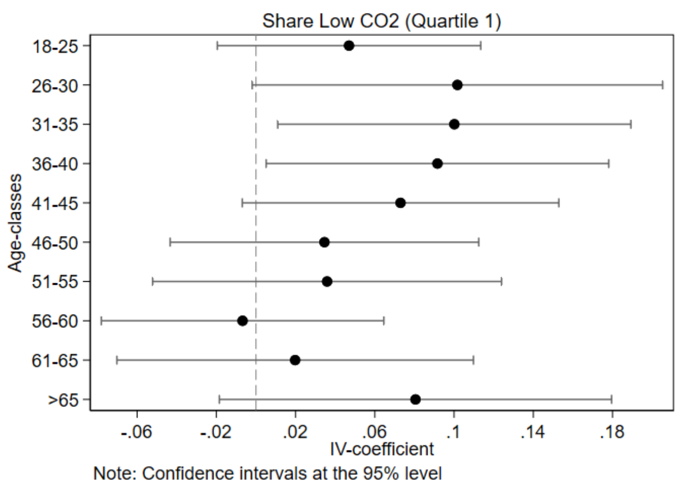
Note: Panel (a) shows results on the total CO2 per capita; panel (b) reports the results on the share of cars belonging to the first emissions' quartile (low); panel (c) provides estimates on the share of cars belonging to the fourth emissions' quartile (high). Population weighted estimates. The straight line indicates the first FFF-event. 95% confidence intervals are obtained after clustering the standard errors at the municipality level.

Figure 2: Heterogeneity - Age Classes

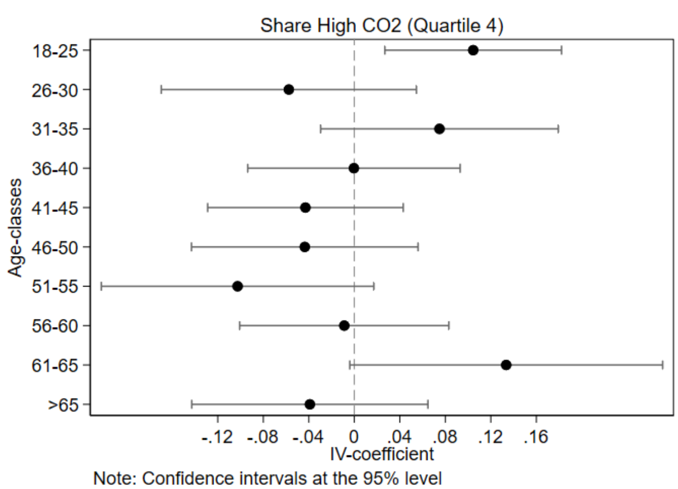
(a) Total CO2 Emissions per capita



(b) Share of Low CO2 Cars (Q1)



(c) Share of High CO2 Cars (Q4)



Note: Panel (a) shows results on the total CO2 per capita; panel (b) reports the results on the share of cars belonging to the first emissions' quartile (low); panel (c) provides estimates on the share of cars belonging to the fourth emissions' quartile (high). Population weighted estimates. 95% confidence intervals are obtained after clustering the standard errors at the municipality level.

Table 2: Mechanism - Engine Types (IV)

	(1) N. of Auto (per capita)	(2) Share Electric	(3) Share Petrol	(4) Share Mixed-Petrol	(5) Share Diesel	Share Gas
Panel A: FFF-dummy	-0.002***	0.004+	0.066**	0.007	-0.090**	0.005***
	(0.001)	(0.002)	(0.031)	(0.007)	(0.036)	(0.001)
Observations	295,336	295,336	295,336	295,336	295,336	295,336
F-stat of the Excl. Instrument	14.62	14.62	14.62	14.62	14.62	14.62
$\|\rho\|$	0.568	0.376	0.451	0.327	0.590	0.801
Avg. outcome	0.005	0.004	0.342	0.049	0.547	0.002
Outcome SD	0.004	0.025	0.231	0.093	0.259	0.018
Panel B: FFF-strikers	-0.067**	0.075	1.682*	0.121	-1.886*	0.118**
	(0.029)	(0.057)	(0.951)	(0.164)	(1.008)	(0.047)
Observations	288,648	288,648	288,648	288,648	288,648	288,648
F-stat of the Excl. Instrument	7.236	7.236	7.236	7.236	7.236	7.236
$\|\rho\|$	0.893	0.547	0.752	0.343	0.759	0.916
Avg. outcome	0.005	0.004	0.341	0.049	0.547	0.002
Outcome SD	0.004	0.025	0.233	0.094	0.261	0.018
Province FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Prob. of Rain	YES	YES	YES	YES	YES	YES
Mun. Controls	YES	YES	YES	YES	YES	YES

Notes: Panel data at the municipality year-month level. The panel includes never treated municipalities and treated municipalities by the first FFF-event. Table shows IV estimates where the endogenous variable (i.e., FFF-dummy or FFF-strikers per capita) is instrumented by rainfall (mm) on March 15, 2019. Population weighted estimates with standard errors clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1 , + p<0.15

Table 3: Mechanism - EES Classes (IV)

EU-Emission:	(1) Class E1	(2) Class E2	(3) Class E3	(4) Class E4	(5) Class E5	(6) Class E6
Panel A: Petrol Cars						
FFF-Dummy	0.000	0.006	0.027**	0.009	-0.020*	0.044**
	(0.000)	(0.006)	(0.013)	(0.013)	(0.012)	(0.018)
Avg. outcome	0.000	0.029	0.102	0.079	0.066	0.067
Outcome SD	0.001	0.078	0.136	0.117	0.109	0.112
Panel B: Diesel Cars						
FFF-Dummy	-0.000	-0.003	0.009	-0.032*	-0.056**	-0.008
	(0.000)	(0.004)	(0.014)	(0.017)	(0.024)	(0.020)
Avg. outcome	0.000	0.009	0.110	0.131	0.167	0.131
Outcome SD	0.000	0.044	0.145	0.154	0.169	0.156
Observations	295,336	295,336	295,336	295,336	295,336	295,336
F-stat of the Excl. Instrument	14.62	14.62	14.62	14.62	14.62	14.62
Province FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Prob. of Rain	YES	YES	YES	YES	YES	YES
Mun. Controls	YES	YES	YES	YES	YES	YES

Notes: Panel data at the municipality year-month level. The panel includes never treated municipalities and treated municipalities by the first FFF-event. Table shows IV estimates where the endogenous variable (i.e., FFF-dummy) is instrumented by rainfall (mm) on March 15, 2019. Population weighted estimates with standard errors clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1

Appendix

Table A.1: Summary Statistics - Cars Data

Variable	**Mean**	**(Std. Dev.)**
Panel 1: Whole Sample		
CO2 Emissions (nedc)	133.826	(30.614)
Electric	0.006	(0.074)
Petrol	0.387	(0.487)
Mixed Petrol	0.063	(0.244)
Diesel	0.541	(0.498)
Gas	0.003	(0.054)
Female	0.349	(0.477)
Age	46.651	(14.367)
N. observations: 9,952,224		
Panel 2: CO2 Emissions Quartile 1		
CO2 Emissions (nedc)	103.535	(10.15)
Electric	0.019	(0.135)
Petrol	0.252	(0.434)
Mixed Petrol	0.087	(0.281)
Diesel	0.638	(0.481)
Gas	0.004	(0.067)
Female	0.398	(0.49)
Age	46.432	(14.416)
N. observations: 2,547,942		
Panel 3: CO2 Emissions Quartile 2		
CO2 Emissions (nedc)	120.683	(4.117)
Electric	0.002	(0.043)
Petrol	0.336	(0.472)
Mixed Petrol	0.099	(0.299)
Diesel	0.561	(0.496)
Gas	0.002	(0.046)
Female	0.376	(0.484)
Age	46.831	(14.549)
N. observations: 2,526,197		
Panel 4: CO2 Emissions Quartile 3		
CO2 Emissions (nedc)	138.836	(4.659)
Electric	0.000	(0.022)
Petrol	0.571	(0.495)
Mixed Petrol	0.039	(0.194)
Diesel	0.386	(0.487)
Gas	0.004	(0.062)
Female	0.35	(0.477)
Age	46.948	(14.605)
N. observations: 2,469,566		
Panel 5: CO2 Emissions Quartile 4		
CO2 Emissions (nedc)	174.518	(29.836)
Electric	0.001	(0.027)
Petrol	0.394	(0.489)
Mixed Petrol	0.026	(0.159)
Diesel	0.578	(0.494)
Gas	0.001	(0.035)
Female	0.269	(0.444)
Age	46.39	(13.861)
N. observations: 2,408,519		

Notes: Table reports summary statistic of cars' micro-data based on cars transfers occured between January, 2017 and February, 2020 in Italy.

Table A.2: Summary Statistics - Panel Data

	Mean	SD	Min	Median	Max
FFF-dummy	0.011	0.105	0.000	0.000	1.000
FFF-strikers (per capita)	0.000	0.007	0.000	0.000	0.980
Rainy FFF Day	0.016	0.125	0.000	0.000	1.000
FFF Day Rainfall (mm)	0.142	0.830	0.000	0.000	17.60
Tot. Automobiles (per capita)	0.005	0.004	0.000	0.004	0.345
Tot. CO2 (per capita)	0.615	0.554	0.000	0.569	52.16
Shares of Cars by C02 Quartiles					
Low CO2 (Quartile 1)	0.235	0.192	0.000	0.233	1.000
Mid-low CO2 (Quartile 2)	0.225	0.188	0.000	0.222	1.000
Mid-high CO2 Quartile 3)	0.233	0.190	0.000	0.229	1.000
High CO2 (Quartile 4)	0.251	0.204	0.000	0.240	1.000
Shares of Cars by Engine Types					
Electric	0.004	0.025	0.000	0.000	1.000
Petrol	0.342	0.231	0.000	0.333	1.000
Mixed Petrol	0.049	0.093	0.000	0.000	1.000
Diesel	0.547	0.259	0.000	0.560	1.000
Gas	0.002	0.018	0.000	0.000	1.000
N. of observations: 295,336					

Notes: Rainy FFF-event dummy is equal to 1 if precipitations were greater equal to 0.1 inches (i.e., 2.54 mm). Electric cars also include full-hybrid and mild-hybrid automobiles.

Table A.3: First Stage Estimates

	(1) FFF-Dummy	(2) FFF-strikers (per capita)
FFF-event Precipitations (mm)	-0.030***	-0.001***
	(0.008)	(0.000)
Observations	295,336	288,648
F-stat	77.70	14.14
F-stat of the Excluded Instrument	14.62	7.240
Province FE	YES	YES
Time FE	YES	YES
Province Linear Trend	YES	YES
Prob. of Rain	YES	YES
Mun. Controls	YES	YES

Notes: Panel data at the municipality year-month level. The panel includes never treated municipalities and treated municipalities by the first FFF-event. Population weighted estimates with standard errors clustered at the municipality level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.4: OLS Estimates - Share Emissions

	(1) Total CO2 (per capita)	(2) Low CO2 (Quartile 1)	(3) High CO2 (Quartile 4)
Panel A: FFF-dummy	-0.024***	0.006***	-0.006***
	(0.005)	(0.001)	(0.001)
Observations	295,336	295,336	295,336
F-stat	27.25	9.237	12.73
Avg. outcome	0.615	0.235	0.251
Outcome SD	0.554	0.192	0.204
Panel A: FFF-strikers	0.052	-0.038*	0.045*
	(0.087)	(0.022)	(0.027)
Observations	288,648	288,648	288,648
F-stat	23.31	9.788	11.09
Avg. outcome	0.616	0.234	0.251
Outcome SD	0.560	0.194	0.206
Province FE	YES	YES	YES
Time FE	YES	YES	YES
Prob. of Rain	YES	YES	YES
Mun. Controls	YES	YES	YES

Notes: Panel data at the municipality year-month level. The panel includes never treated municipalities and treated municipalities by the first FFF-event. Table shows OLS estimates. Population weighted estimates with standard errors clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1

Table A.5: Reduced Form Estimates - Share Emissions

	(1) Total CO2 (per capita)	(2) Low CO2 (Quartile 1)	(3) High CO2 (Quartile 4)
FFF-event Precipitations (mm)	0.009***	-0.002***	0.003***
	(0.002)	(0.001)	(0.001)
Observations	295,336	295,336	295,336
F-stat	26.92	9.088	10.61
Avg. outcome	0.615	0.235	0.251
Outcome SD	0.554	0.192	0.204
Province FE	YES	YES	YES
Time FE	YES	YES	YES
Prob. of Rain	YES	YES	YES
Mun. Controls	YES	YES	YES

Notes: Panel data at the municipality year-month level. The panel includes never treated municipalities and treated municipalities in the first FFF-event for the first time. Table shows OLS estimates. Population weighted estimates with standard errors clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1

Table A.6: IV Robustness Check (1) - No Municipality Controls

	(1) Total CO2 (per capita)	(2) Low CO2 (Quartile 1)	(3) High CO2 (Quartile 4)
Panel A: FFF-dummy	-0.220***	0.093***	-0.118***
	(0.077)	(0.030)	(0.038)
Observations	295,336	295,336	295,336
F-stat of the Excl. Instrument	12.75	12.75	12.75
$\|\rho\|$	0.645	0.745	0.746
Avg. outcome	0.615	0.235	0.251
Outcome SD	0.554	0.192	0.204
Panel B: FFF-strikers	-5.525**	2.590**	-3.283**
	(2.410)	(1.151)	(1.514)
Observations	288,648	288,648	288,648
F-stat of the Excl. Instrument	6.428	6.428	6.428
$\|\rho\|$	0.779	0.892	0.900
Avg. outcome	0.615	0.235	0.251
Outcome SD	0.554	0.192	0.204
Province FE	YES	YES	YES
Time FE	YES	YES	YES
Prob. of Rain	NO	NO	NO
Mun. Controls	NO	NO	NO

Notes: Panel data at the municipality year-month level. The panel includes never treated municipalities and treated municipalities by the first FFF-event. Table shows IV estimates where the endogenous variable (i.e., FFF-dummy or FFF-strikers per capita) is instrumented by rainfall (mm) on March 15, 2019. Population weighted estimates with standard errors clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1

Table A.7: IV Robustness Check (2) - Alternative Instrument

	(1) Total CO2 (per capita)	(2) Low CO2 (Quartile 1)	(3) High CO2 (Quartile 4)
Panel A: FFF-dummy	-0.266**	0.090**	-0.096**
	(0.115)	(0.036)	(0.039)
Observations	295,336	295,336	295,336
F-stat of the Excl. Instrument	7.171	7.171	7.171
$\lvert\rho\rvert$	0.699	0.696	0.721
Avg. outcome	0.615	0.235	0.251
Outcome SD	0.554	0.192	0.204
Panel B: FFF-strikers	-5.757*	2.450**	-3.005**
	(3.256)	(1.202)	(1.396)
Observations	288,648	288,648	288,648
F-stat of the Excl. Instrument	7.656	7.656	7.656
$\lvert\rho\rvert$	0.587	0.705	0.773
Avg. outcome	0.616	0.234	0.251
Outcome SD	0.560	0.194	0.206
Province FE	YES	YES	YES
Time FE	YES	YES	YES
Prob. of Rain	YES	YES	YES
Mun. Controls	YES	YES	YES

Notes: Panel data at the municipality year-month level. The panel includes never treated municipalities and treated municipalities by the first FFF-event. Table shows IV estimates where the endogenous variable (i.e., FFF-dummy or FFF-strikers per capita) is instrumented by a rain dummy that takes a value of 1 if a municipality experienced precipitations greater that 0.01 inches in the day of the FFF event (i.e., March 15, 2019). Population weighted estimates with standard errors clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1

Table A.8: IV Robustness Check (3) - Alternative Control Group

	(1) Total CO2 (per capita)	(2) Low CO2 (Quartile 1)	(3) High CO2 (Quartile 4)
Panel A: FFF-dummy	-0.162***	0.031**	-0.054***
	(0.046)	(0.015)	(0.019)
Observations	295,336	295,336	295,336
F-stat of the Excl. Instrument	37.30	37.30	37.30
$\|\rho\|$	0.299	0.263	0.359
Avg. outcome	0.594	0.232	0.254
Outcome SD	0.381	0.198	0.212
Panel B: FFF-strikers	-7.499***	1.159**	-1.958**
	(2.707)	(0.576)	(0.838)
Observations	288,648	288,648	288,648
F-stat of the Excl. Instrument	11.21	11.21	11.21
$\|\rho\|$	0.848	0.629	0.750
Avg. outcome	0.594	0.232	0.254
Outcome SD	0.381	0.198	0.212
Province FE	YES	YES	YES
Time FE	YES	YES	YES
Prob. of Rain	YES	YES	YES
Mun. Controls	YES	YES	YES

Notes: Panel data at the municipality year-month level. The panel includes never treated municipalities and treated municipalities by the first FFF-event. Table shows IV estimates where the endogenous variable (i.e., FFF-dummy or FFF-strikers per capita) is instrumented by rainfall (mm) on March 15, 2019. Population weighted estimates with standard errors clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1

Table A.9: IV Baseline - Heterogeneity by Gender

	(1) Total CO2 (per capita)	(2) Low CO2 (Quartile 1)	(3) High CO2 (Quartile 4)
Panel A: Female			
FFF-dummy	-0.068**	0.086**	-0.061*
	(0.027)	(0.040)	(0.036)
Avg. outcome	0.205	0.242	0.170
Outcome SD	0.183	0.264	0.231
Panel B: Male			
FFF-dummy	-0.224***	0.055**	-0.096***
	(0.078)	(0.025)	(0.035)
Avg. outcome	0.410	0.209	0.272
Outcome SD	0.514	0.212	0.242
Observations	295,336	295,336	295,336
F-stat of the Excl. Instrument	14.62	14.62	14.62
Province FE	YES	YES	YES
Time FE	YES	YES	YES
Prob. of Rain	YES	YES	YES
Mun. Controls	YES	YES	YES

Notes: Panel data at the municipality year-month level. The panel includes never treated municipalities and treated municipalities by the first FFF-event. Table shows IV estimates where the endogenous variable (i.e., FFF-dummy) by rainfall (mm) on March 15, 2019. Population weighted estimates with standard errors clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1

Table A.10: IV Baseline: Multi-valued Treatment Effect

	(1) Total CO2 (per capita)	(2) Low CO2 (Quartile 1)	(3) High CO2 (Quartile 4)
Panel A: Precipitations (mm) IV			
N. of FFF-events (exposure)	-1.037**	0.013**	-0.019***
	(0.511)	(0.006)	(0.008)
F-stat of the Excluded Instrument	8.556	8.556	8.556
$\|\rho\|$	0.969	0.883	0.906
Panel B: Rain Dummy IV			
N. of FFF-events (exposure)	-0.682*	0.011**	-0.015***
	(0.359)	(0.005)	(0.005)
F-stat of the Excluded Instrument	7.669	7.669	7.669
$\|\rho\|$	0.874	0.768	0.762
Observations	15,544	15,544	15,544
Avg. outcome	11.68	0.249	0.269
Outcome SD	9.931	0.068	0.079
Province & Time FEs	YES	YES	YES
FFF Rain Dummies	YES	YES	YES
Prob. of Rain	YES	YES	YES
Mun. Controls	YES	YES	YES

Note: The excluded instrument is the rain in the first FFF-event (precipitations in mm in Panel A, and rain dummy in panel B), regressions also include controls for rain in the subsequent FFF events in 2019. Probability of rain includes dummies for each decile of the probability distribution of each FFF-event month. Population weighted estimates with standard errors clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1