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Keywords: Fridays for Future, climate activism, green consumption, carbon emissions, automobiles

JEL classification: D72, D12, Q53, R41

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Abstract

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1 Introduction

The unprecedented environmental degradation caused by human activities has recently sparked an upswing in pro-environmental protests. These include not only spontaneous demonstrative actions but also more structured movements aimed at persuading national and transnational institutions to act against such dramatic environmental crises. Noteworthy examples are the *Environmental Movement*, which gained notoriety through the inaugural *Earth Day* in 1970, and *Greenpeace*, established in 1971, known internationally for its media-based actions against global threats such as deforestation and exploitation of marine ecosystems. More recently, *Fridays for Future* (FFF), a movement created by climate activist Greta Thunberg, has engaged in some of the most globally widespread climate protests on record in support of the environment (Forbes, 2019).

Pro-environmental movements have, in many cases, led to effective national and transnational legislative changes. Well-known examples are the ratifications of the *Clean Air Act* and *Clean Water Act* in the US 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 by 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, empirically establishing a clear-cut causal relationship between environmental movements and consumption patterns in specific regions or markets can be grueling. Local pro-environmental events and climate protests 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 the FFF climate protests that occurred in 2019 in a group of Italian towns on the local second-hand automobile markets. To address some of the aforementioned challenges, we use precipitation levels on the day of the event as an exogenous source of variation in protest participation, drawing from an instrumental variable approach (see, for instance Madestam *et al.* (2013)). Since the day of every FFF event is generally decided at a global level, it cannot be altered by local organizations based on weather conditions. Therefore, rainfall serves as a credible instrument that is capable of influencing the decision to participate in an outdoor event, while remaining unrelated to economic outcomes.[1]

Our analysis draws from three distinct data sources making up a panel data set at 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 protest to account for weather-related variations in FFF attendance. Finally, we tap into a rich data set of second-hand automobile sales, made available by the Italian Ministry of Infrastructure and Transport and spanning the period from January 2017 to February 2020. The data encompass nearly 10 million automobile transactions, offering comprehensive insights into consumer behavior in the second-hand automobile market. In order to study all changes occurring 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. The use of this 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 both the total number of cars purchased per 1,000 inhabitants and their average CO2 emissions following the FFF event in March 2019. These reductions correspond to approximately half of the standard deviation

[1]While Mellon (2024) notes potential exclusion-restriction issues with rainfall as an instrument, our single-day approach falls within the exceptions. For example, Busse *et al.* (2015) highlight how weather variations at the time of purchase can affect vehicle preferences. However, since our study specifically examines the impact of precipitation on March 15, 2019, the date of the first Fridays for Future event, this isolated weather event is unlikely to influence post-FFF consumer choices differently from participation in the protest, thus adhering to the exclusion restriction and isolating the effect of FFF.

(SD) in the total number of automobiles per 1,000 inhabitants, and one fourth of the SD in CO2 per car when compared to those municipalities not hosting FFF events. Moreover, climate protests have increased the share of low-emission cars by 37.5% of SD while decreasing that of high-emission cars by 43% of SD. Heterogeneity analyses shed light on the gender- and age-related variations in these patterns.

We explore two potential mechanisms driving the effect of the FFF movement on consumption. A first mechanism depicts FFF protests as pivotal events exerting an influence on social norms in communities, which, in turn, induce citizens to adopt greener behaviors (see, for instance, Carattini *et al.* (2019)). A second proposed mechanism suggests that the political pressure exerted by the FFF movement may prompt consumers to rationally anticipate stricter future environmental regulations, thus opting for lower-emission vehicles, which are generally subject to milder restrictions.

To check for the first channel, we use the data on local volunteer associations collected by Pulejo (2023), distinguishing between those with a specific environmental scope. We find that the FFF movement has not induced significant changes in pro-environmental voluntary action in local communities. Despite this, when examining consumption choices, we observe a reduction in the number of cars purchased per capita. This suggests that there may be a mechanism triggered by a stronger environmental awareness. However, among consumers buying a car, we do not observe a statistically significant effect on the choice of electric cars (the greener option), finding instead a substitution effect between automobiles subject to different traffic regulations.

In view of this evidence, for the second channel, we further explore the changes in consumers' choices, thus finding that FFF may have prompted individuals to adapt their consumption patterns ex-ante, particularly in anticipation of the new European Emission Standards (EES). Specifically, FFF led to an increase in the share of second-hand petrol cars (28.5% of SD) at the expense of diesel cars (a decrease of 35% of SD).[2]

[2]Increases are also observed, albeit to a lesser extent, in the share of gas-powered vehicles (e.g., those powered by methane or LPG).

By differentiating car sales into EES classes, we conclude that FFF has led consumers toward cars that are likely to be less subject to severe traffic restrictions, rather than towards a drastic transition to electric vehicles. This effect is potentially mediated by their concerns about stricter environmental regulations looming on the horizon.

Finally, we observe that individuals aged 18-25, who are potentially closest to the spirit of the FFF movement, are the most affected by the protest, adopting pro-environmental purchasing behaviors that might not be directly connected to a rational anticipation of tighter regulations. In fact, for these individuals, we observe a significant reduction in the number of cars purchased and, when they buy a car, a disregard for diesel vehicles, without a clear substitution effect supporting the second mechanism.

Our paper contributes to the recent literature studying the economic impact of social and political protests.[3] Among others, Madestam *et al.* (2013) examine the economic consequences of the Tea Party movement in the US, 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 and political decisions, leading to a shift in fiscal policy at 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.[4] Hungerman and Moorthy (2023) use variations in weather to study the long-term effects of environmental activism, symbolized by *Earth Day* events. They find that bad weather on *Earth Day* in 1970 is associated with

[3]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; Marini *et al.*, 2022). Consumers' preferences and their choices are affected by a multitude of social drivers that reflect not only individual self-interest but also pro-social behavior, 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 that 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 behavior.

[4]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.

weaker support for the environment and is, therefore, related to higher levels of carbon monoxide in the air and to a greater risk of congenital abnormalities in 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 local FFF 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.[5]

With respect to these studies, we investigate the direct impact of climate activism on consumption choices. Specifically, we examine the mechanisms through which FFF protests influence consumers' choices, pushing them toward products with a less pronounced environmental footprint. Our results provide support for the idea that some of the consumption shifts can be based on a self-interested *rationale*, driven by consumers' anticipation of more stringent future environmental regulations. Our analysis is based on global protests occurring simultaneously in several cities around the world. This implies that our methodology can be applied to study effects in other countries and regions, thereby enhancing its external validity. Moreover, the Italian second-hand automobile market is easily comparable to those of other European countries, potentially allowing the investigation to be extended further. Overall, our investigation provides valuable insights into the interaction between climate activism, consumer behavior, and environmental policies. Understanding these dynamics is crucial for policymakers, social scientists, and society at large, as it helps to unveil the complex interplay between social activism and economic behavior.

The remainder of the paper is organized as follows. Section 2 provides details about the background of the FFF movement and the data used in our empirical analysis, while

[5]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.

Section 3 details the identification strategy. Section 4 discusses the main results along with placebo analyses and robustness specifications, Section 5 describes mechanisms and heterogeneous effects, and Section 6 provides concluding remarks.

2 Background and Data

Our baseline analysis leverages three main distinct data sources. First, we use data on FFF protests taking place in Italy in 2019. Second, we exploit rainfall data on the day of the rally as a source of exogenous variation on the attendance of FFF events. Finally and most importantly, we make use of a rich data set of Italian second-hand automobile transactions. Thus, we merge all of the abovementioned sources to build up a panel data set at municipality-year-month level.[6]

2.1 Fridays for Future and Rain Data

FFF is a global movement aimed at addressing the challenge of climate change through student-led strikes and demonstrations. FFF began through Greta Thunberg, a Swedish teenager, who initiated a solitary strike outside the Swedish Parliament in August 2018. Her determination and passion for climate activism quickly spread globally, inspiring millions of students worldwide to join the cause (Guardian, 2019). Since it began, the movement's core principle has been centered around demands for stronger climate action from governments, advocating for policies aligned with the goals of the Paris Climate Agreement. In 2019, young people rallied under the banner of the FFF movement all over the world, organizing strikes and demonstrations and advocating for more comprehensive climate policies and sustainable practices. This involved almost 17 thousand

[6]The monthly panel structure allows us to (descriptively) capture the dynamics of the effect over time and to apply a more refined model specification, as detailed in Section 3. Nevertheless, mainly for the sake of robustness of the analysis, we also provide additional results in Appendix.1 employing a two-period dataset (pre- and post-FFF), which ultimately are consistent with our baseline results presented in Section 4.

cities and 13 million people during six global strikes.[7] In Italy, 404 municipalities hosted an FFF event in 2019, with 273 (3.5% of all Italian municipalities) participating in the first event in March 2019. The strikes primarily targeted government inaction, asking for more ambitious policies to reduce greenhouse gas emissions and promote renewable energy sources to actively fight the growing climate crisis. It is fair to say that FFF events have exerted 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 discussion on climate issues, at both 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 list of strikes reported by the organization's website.[8] People involved in FFF actions reported strikes directly on the organization's webpage by completing a specifically designated form or using the Game-Changer platform.[9] Typically, these reports were submitted shortly after the events took place. In addition, FFF activists tracked their events worldwide, with a specific team responsible for managing this task.[10] In particular, activists reported the cities where strikes were taking place and the number of participants.[11] One caveat regarding the reported number of participants is that this information can be either over- or under-estimated or, in some cases, is even missing. However, we can consider such errors as essentially random.[12] As explained in Section 3, we use both the number

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

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

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

[10] In recent years, FFF activists have 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.

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

[12] We attempted to contact several local police headquarters to inquire about the reported and observed numbers of protesters, as well as the central police authority, but unfortunately we were unable to obtain any information.

of participants and a dummy variable indicating event hosting as treatment variables. Specifically, the former measures the treatment's intensity, whereas the latter represents an absorbing state that does not invalidate the goodness of the empirical strategy (Angrist and Imbens, 1995; Angrist *et al.*, 2000; Callaway *et al.*, 2024). Therefore, the dummy variable measures whether FFF events 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.

It is important to emphasize that FFF events are typically strikes organized by students in their city of study, and the date of the event is determined globally, thus independently of local conditions such as weather. On the other hand, the decision to host the event in a specific city may be influenced by weather conditions, and it is unlikely that organizers would change the location of the protest based on a rain forecast.[13] For this reason, as detailed in Section 3, we use precipitation on the day of the FFF event as an exogenous source of variation in protest attendance at municipal level.

In particular, we use the Agri4Cast precipitation data produced by the Joint Research Centre (JRC) of the European Commission for the Monitoring Agricultural Resources Unit (MARS).[14] The data contain rainfall observations from weather stations, which are interpolated onto a 25x25 km grid, providing daily records for the European Union and neighboring countries (Toreti, 2014). To link these data to Italian municipalities, we use geo-spatial analysis to identify the nearest rainfall grid to the centroid of each municipality provided by the Italian National Statistics Institute (Istat).[15] Specifically, we identify all grid cells within a 5-km radius of the centroid of each municipality and retain only the nearest grid cell. Once identified, the municipality-level data are merged with the corresponding rainfall data from the grid cell. This process ensures

[13]Nevertheless, participants might choose to attend an FFF event in a nearby city where it is not raining. This possibility is taken into account in our robustness check analyses.

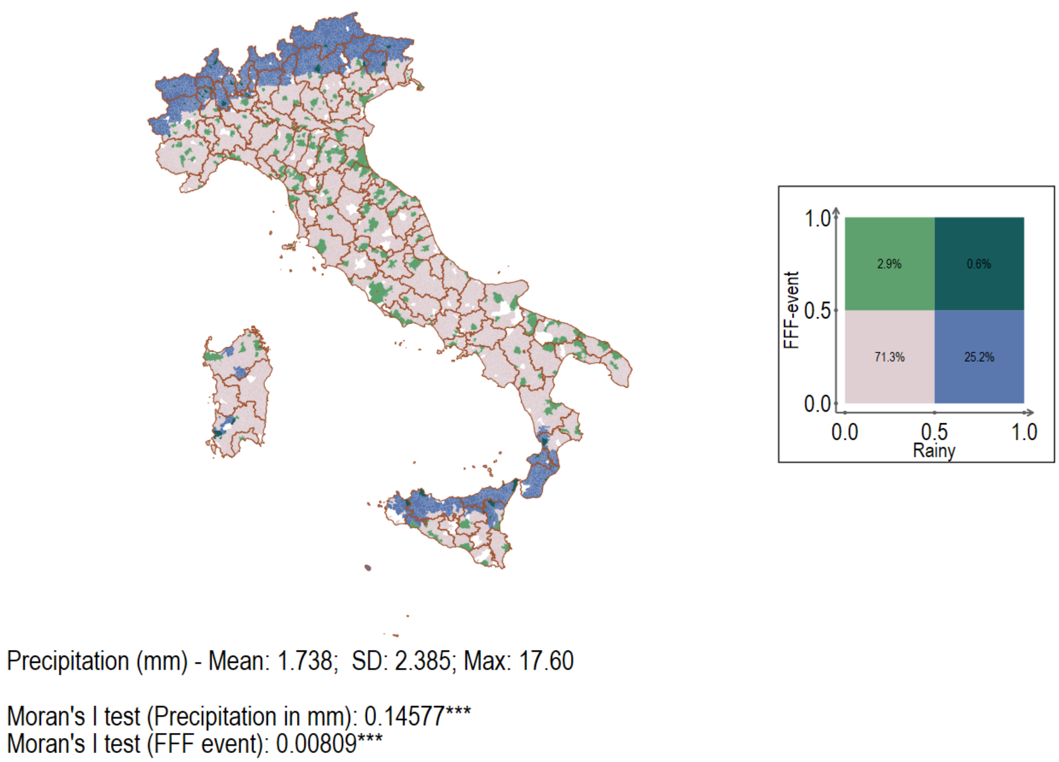
[14]These data can be accessed at: https://agri4cast.jrc.ec.europa.eu/DataPortal/Index.aspx?o=.

[15]Shape-files and centroids are available on Istat's website (in Italian) at the following URL: https://www.istat.it/it/archivio/222527.

that each municipality is linked to the precipitation data from the nearest grid cell within a 5-km radius.

The map in Figure 1 depicts in green the municipalities where an FFF event took place on March 15, 2019 and, in blue, those exposed to rain on the same day. The map indicates that, whereas the FFF events took place all over the country, the rainfall predominantly affected northern municipalities and a few southern regions and the islands, with average precipitation of 1.74 millimeters (SD: 2.39) in municipalities where it rained that day, with a maximum of 17.6 millimeters.

Figure 1: Fridays for Future and Precipitation



Notes: This figure illustrates graphically what happened on March 15, 2019, in Italy (i.e., the day of the first global FFF event). Specifically, the map displays in green the municipalities that hosted the FFF event and in blue those where it rained. The map legend on the right reports the percentage of always-takers in the top-right corner (those hosting the event despite the rain), the percentage of never-takers in the bottom-left corner (those not involved in FFF events despite there being no rain), and the percentages of compliers in the top-left and bottom-right corners. Finally, at the bottom of the graph on the left, we also report the results of the univariate Moran's I test with a binary spatial weights matrix to ensure that each municipality is connected to at least one other municipality. Two municipalities are defined as close if the distance between them is no more than 145.2 km. We report separately the results for the FFF event dummy variable and for the variable measuring precipitation (in mm) on the day of the FFF event. *** p<0.01, ** p<0.05, * p<0.1

The bottom left of the map shows a univariate Moran's I test for which we use a binary spatial weights matrix, thus ensuring that each municipality is connected to at least one other (Moran, 1950). Specifically, two municipalities are defined as "close" if the distance between them is no more than 145.2 km. This threshold is calculated as the minimum of the maximum non-zero inverse distances for all municipalities. The Moran's index ranges from -1, indicating perfect negative spatial correlation, to 1, which indicates perfect positive spatial correlation, where similar values cluster together. We report the results, in turn, for the dichotomous variable of the FFF event and for the continuous variable measuring rainfall in millimeters. The value of the Moran's I test is equal to 0.1458 ($p<0.001$) for rainfall (mm) and 0.0081 ($p<0.001$) for the FFF event variable. These results suggest that, although the spatial auto-correlation is positive and statistically significant, its magnitude is small and thus plausibly negligible.[16]

The legend for Figure 1 divides municipalities into four groups. In the top-right corner, we have the "always takers" (0.6%)—i.e., municipalities that host a Fridays for Future event despite the rain—while the bottom-left corner shows the "never takers" (71.3%)—i.e., municipalities not hosting an FFF-event even when there is no rain. Finally, in the top-left (2.9%) and bottom-right (25.2%) corners of the legend, there are the municipalities in which the decision to comply and participate in the event is influenced by weather conditions. This provides a comprehensive description of the compliant municipalities that contribute to the local average treatment effect estimated through the instrumental variable approach described in Section 3.

[16] More precisely, the spatial auto-correlation of rainfall is statistically significant but negligible in magnitude regardless of the distance matrix adopted. Specifically, even considering an inverse distance matrix accounting for global interdependence, where the $i-j$ entry is equal to the inverse of the distance between municipalities i and j, this provides a Moran's Index equal to 0.1266.

2.2 Automobile 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.[17] First, we consider this market to be easily comparable across European and non-European countries, potentially allowing the investigation to be extended to further geographical areas, enhancing its external validity. Second, by using data on second-hand cars we were able to access exact dates of purchase, something not accessible for new automobiles, for which only the registration date is available. This imposes a significant limitation when using data on new automobiles since the registration date—often used as a proxy for the purchase date—does not necessarily coincide with the actual purchase date.[18] Specifically, if the FFF event occurs after the unobservable purchase date but before the observable registration date, these cases would be considered erroneously as having been influenced by the FFF event, even though the purchasing decision was made prior to the event and could not have been affected by it. This misalignment could lead to biased estimates when investigating the impact of FFF on consumption choices in relation to new automobiles.[19]

Data on the second-hand automobile market are gathered by the Italian Ministry of Infrastructure and Transport and we were able to access information on all automobile sales occurring between January 2017 and February 2020, totaling nearly 10 million transactions.[20] For every transaction, many details were available about both the buyer and the automobile. For the buyer, we have information about the municipality of residence (i.e., the location where the car was purchased), the date of purchase, age and gender. For the car, we were able to access the date of registration, engine

[17]In Italy, the market for used cars is bigger than the market for new vehicles. Before Covid-19, the purchasing ratio was 1.6 used cars for every new one (il Sole 24 Ore, 2023).

[18]The gap between these two dates usually ranges from a few days to several months.

[19]Nevertheless, in Appendix.1, we show baseline estimates by using data on the purchases of new automobiles that are provided by the Italian Ministry of Infrastructure and Transport.

[20]Data are available up to 2022 but we cut off the sample before the Covid-19 lockdowns to avoid introducing bias into the estimates.

power and level of CO2 emissions. The latter information relies on the New European Driving Cycle (NEDC), which is designed to evaluate emission levels and fuel economy in passenger cars. The NEDC represents the standard driving patterns in Europe and is based on four repeated urban driving cycles and one non-urban driving cycle, providing a value in grams of CO2 emitted per kilometer driven (g CO2/km).[21] 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 distribution. For simplicity, we refer to the first quartile as having low CO2 emissions and to the fourth quartile as being associated with high emissions. The second and third quartiles denote mid-low and mid-high emissions levels, respectively.

Table A.1 in the Appendix presents summary statistics on automobile microdata, with the average NEDC CO2 emission level at 133 g/km for the whole sample, 103 for the first quartile, and 174 for the fourth quartile. Electric automobiles constitute 0.6% of sales, petrol cars account for 38.7%, and diesel vehicles for 54.1%, while mixed-petrol vehicles represent 6.3%, and gas vehicles 0.3%.[22] The average age of buyers is 46.6 years (SD: 14.4), whereas female buyers comprise 35% of the sample.

Table 1 shows summary statistics of the panel data at municipality-year-month level that we use for the empirical analysis.[23] In column (1), we present the summary statistics for the car data for the entire sample. In column (2), we limit the sample, to include only the municipalities hosting an FFF event, whereas in column (3) we include only the municipalities not hosting an FFF event.

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

[22] We also include full-hybrid and mild-hybrid electric cars in the electric segment.

[23] For reasons explained in detail in Section 3, our panel data include never-treated municipalities as well as treated municipalities that 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 on one of the subsequent dates in 2019.

Table 1: Summary Statistics - Car Panel Data

	Municipalities		
	All	Exposed to FFF	Not Exposed to FFF
	(1)	(2)	(3)
Number of cars per 1,000 inhabitants	4.530	4.270	4.540
	(3.849)	(1.280)	(3.910)
Tot. CO2 per car	127.749	132.628	127.572
	(34.138)	(16.332)	(34.601)
Shares of cars by CO2 quartiles (Q):			
Low CO2 (Q1)	0.235	0.255	0.234
	(0.192)	(0.089)	(0.195)
Mid-low CO2 (Q2)	0.225	0.239	0.225
	(0.188)	(0.081)	(0.191)
Mid-high CO2 (Q3)	0.233	0.245	0.232
	(0.190)	(0.083)	(0.193)
High CO2 (Q4)	0.251	0.249	0.251
	(0.204)	(0.091)	(0.207)
Shares of cars by engine types:			
Share of electric cars	0.004	0.005	0.004
	(0.025)	(0.011)	(0.025)
Share of petrol cars	0.342	0.378	0.341
	(0.231)	(0.124)	(0.234)
Share of mixed petrol cars	0.049	0.064	0.048
	(0.093)	(0.055)	(0.094)
Share of diesel cars	0.547	0.536	0.547
	(0.259)	(0.136)	(0.262)
Share of gas cars	0.002	0.004	0.002
	(0.018)	(0.010)	(0.018)
Observations	295,336	10,374	284,962

Notes: The table presents summary statistics using panel data at municipality-year-month level. Each row reports the variable's sample average with standard deviations in parentheses. The sample spans the period from January 2017 to February 2020 and includes treated municipalities affected by the first FFF event (March 15, 2019), along with control municipalities, totaling 7,772 out of 7,904 Italian municipalities. It excludes municipalities treated in subsequent FFF events (i.e., a total of 132 municipalities). Column (1) shows descriptive statistics for the whole sample, column (2) presents statistics for municipalities exposed to the FFF event, and column (3) provides summary statistics for municipalities never exposed to the FFF event. Car data pertain to sales of used automobiles registered by municipalities within the analysis period. The electric category also includes full-hybrid and mild-hybrid electric cars, which are not classified under the mixed-petrol category. Table A.1 reports summary statistics of car sale microdata.

Looking at the descriptive statistics, we can observe some, albeit minimal, differences between municipalities with and without FFF events. The municipalities that hosted FFF events tend to have slightly fewer cars per 1,000 inhabitants (4.270) than those not hosting events (4.540). The average CO2 emissions per car are higher in FFF municipalities (132.628) than in those extraneous to the events (127.572). There is also a higher share of low-CO2 cars (25.5%) in municipalities involved in FFF events when compared to those with no events (23.4%). However, the share of high-CO2 cars is almost identical between the two groups.[24] Slight differences across groups are observed in the central quartiles of the CO2 distribution, particularly for mid-low (Q2) and mid-high (Q3) CO2 levels. Regarding engine types, FFF municipalities are characterized by a slightly higher share of electric cars (0.5% vs. 0.4%) and petrol cars (37.8% vs. 34.1%), while the shares of mixed petrol, diesel, and gas cars are similar in both groups.

3 Identification Strategy

To establish a causal relationship between FFF events and car choice, we employ precipitation levels on the day of the event (i.e., March 15, 2019) as an instrumental variable (Madestam *et al.*, 2013). The rationale behind this choice is the assumption that rainfall, being exogenous to individual participation decisions, directly impacts the attendance of the FFF event.[25] This assumption is plausible provided that the date of the FFF event is decided by the organization at global level, and cannot be changed by local organizations based on weather conditions. Therefore, rainfall on the specific day of the first FFF event serves as a plausible instrument (IV), as it influences the decision to participate in the outdoor event without being directly related to the economic outcomes. While Mellon (2024) identifies various potential exclusion-restriction violations

[24] Figure A.1 in the Appendix illustrates the geographical distribution of these variables in the pre-FFF period.

[25] In the literature, the direct impact of rainfall on electoral turnout is also well recognized (e.g., Gomez *et al.* (2007); Hansford and Gomez (2010); Fraga and Hersh (2010)). Damsbo-Svendsen and Hansen (2023) provide a comprehensive meta-analysis of 34 studies on electoral turnout and rainfall, with the vast majority demonstrating a negative association.

when using rainfall as an instrumental variable, our analysis—which leverages precipitation on a single day—falls within the exceptions outlined in his analysis, also taking into account the nature of both our endogenous variable and the outcomes.[26]

Formally, we estimate the following first-stage equation on the panel data at municipality-year-month level:

$$FFF_{m,\tilde{t}} = \alpha_0 + \alpha_1 Rain_{m,\tilde{t}} + \delta_p + \delta_t + \delta_{PLT} + \delta_{RP_m} + \gamma X_m + \xi_{m,t} \tag{1}$$

where subscript m indicates the municipality and t relates to time (year-month).[27]

The endogenous treatment variable, $FFF_{m,\tilde{t}} = FFF_m \cdot \mathbb{1}\{t \geq \tilde{t}\}$, takes a value of one if municipality m is involved in the FFF event (FFF_m) from the year-month of the event ($\tilde{t}$) onward. Alternatively, we also express the treatment variable FFF as the number of FFF strikers, thus measuring the intensity of the treatment for municipalities participating in the protest (Angrist and Imbens, 1995; Angrist *et al.*, 2000). The treatment dummy can be interpreted as an absorbing state (Callaway *et al.*, 2024), providing an easier interpretation of the results.[28] The variable $Rain_{m,\tilde{t}} = Rain_m \cdot \mathbb{1}\{t \geq \tilde{t}\}$ measures precipitation (in mm) on the day of the FFF event ($Rain_m$) and is switched on for $t \geq \tilde{t}$, where $\tilde{t}$ is the time (year-month) at which the FFF event took place. This

[26]For example, Busse *et al.* (2015) have shown that weather variations at the time of purchase can cause consumers to overvalue certain vehicle characteristics. They predict that consumers will overvalue warm-weather vehicle types (e.g., convertibles) when the weather is warm and sunny at the time of purchase, and cold-weather vehicle types (e.g., four-wheel-drive vehicles) when the weather is cold and snowy. Our empirical strategy relies on precipitation that occurred on a specific day (i.e., March 15, 2019), which is unlikely to affect consumer choices before or after that date, thus avoiding any violation of the exclusion restriction. Additionally, studies using rainfall as an instrument to predict income (Miguel *et al.*, 2004; Barrios *et al.*, 2010) do not violate the exclusion restriction in our context, as consumption is part of income. Therefore, using precipitation on the FFF day in Italy ensures that its influence on income is mediated solely through the FFF event, without affecting income through FFF-unrelated components.

[27]Accordingly, the reduced-form equation can be represented as follows:

$$Y_{m,t} = \lambda_0 + \lambda_1 Rain_{m,\tilde{t}} + \delta_p + \delta_t + \delta_{PLT} + \delta_{RP_m} + \gamma X_m + \psi_{m,t} \tag{2}$$

[28]Note also that, since the number of strikers is self-reported by participants and missing for some treated municipalities, the treatment dummy is preferred. However, the use of both measures provides robustness to our results.

serves as an instrument for $FFF_{m,\tilde{t}}$ to resolve the potential selection bias and reverse causality issues.[29] δ_p, δ_t, and δ_{PLT} represent province fixed effects (FE), year-month FE and a province linear trend, respectively. In particular, the inclusion of δ_p and δ_t makes it possible to control for every idiosyncratic component at province level and at year-month level. The inclusion of local time trend, δ_{PLT}, helps to control for any variation in the dependent variable at 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 or weather conditions. 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 δ_{RP_m}, which is a set of dummy variables corresponding to the deciles of the historical rain probability distribution (1980-2018).[30] Furthermore, we add the matrix of municipality characteristics, X_m, measured in 2018. Specifically, X_m includes the share of votes for green parties, the share of recycled waste, the per capita number of vehicles, the share of work trips within the municipality, the share of cars, the per capita number of taxpayers, the Gini index, the resident population, the number of public high schools per 1,000 inhabitants, and a set of dummies for each decile of the distribution of the population aged 18 years old.[31] These predetermined control variables measure pro-green attitudes as well as the likelihood of hosting an FFF event that is promoted by high school students. These variables

[29]In section 4.3, we also provide robustness check estimations in which we consider as an instrument a dummy variable that takes a value of one if precipitation was greater than 0.1 inches (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.

[30]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 specifically, 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.

[31]Specifically, the distribution of the population aged 18 years is derived from the population of all municipalities. Therefore, each decile dummy represents municipalities belonging to the corresponding decile of the distribution.

also control for automobile usage and local economic conditions. The data originate from various sources, including the National Statistics Institute (ISTAT), the Ministry of Economy and Finance (MEF), Eligendo (Ministry of Interior), and the Institute for Environmental Protection and Research (ISPRA). We perform population-weighted regressions with clustered standard errors at municipality level.[32] Finally, we estimate the second-stage equation to measure the causal relationship of interest:

$$Y_{m,t} = \beta_0 + \beta_1 \widehat{FFF}_{m,\tilde{t}} + \delta_p + \delta_t + \delta_{PLT} + \delta_{RP_m} + \gamma X_m + \varepsilon_{m,t} \tag{3}$$

where the variable $Y_{m,t}$ measures different economic outcomes: for example, the share of cars purchased belonging to each CO2 emission quartile or the total number of cars purchased per 1,000 inhabitants. Given the nature of our data, it is fair to say that we are not observing consumers' decisions as to whether to buy an automobile, we are merely observing them when making such a choice. Therefore, our estimates should 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 applied 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.*, 2024). 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 ($FFF_{m,\tilde{t}}$) switches on after the first FFF event (March, 2019). Although it is possible that some of the treated municipalities might have participated in subsequent events, this scenario does not pose any threat to the validity of our em-

[32] In section 4.3, we provide robustness check estimates by clustering standard errors at a higher geographical dimension to account for potential spatial auto-correlation of rainfall.

pirical strategy. Our monotone instruments (i.e., FFF event dummy or FFF strikers) can be considered as an absorbing state of subsequent events. Consequently, we cannot use Equation (3) to investigate the effect on consumers exposed to multiple FFF strikes. Nevertheless, in Appendix.2, we describe an alternative identification strategy to estimate multivalued treatment effects.

Table 2 presents summary statistics and a balance test for the municipality characteristics included in the matrix X_m described above. Column (1) provides descriptive statistics for the full sample, while columns (2) and (3) show statistics for municipalities either exposed or not exposed to the FFF event, respectively. Columns (4) and (5) display statistics for municipalities with and without rainfall on the FFF day. Column (6) reports the balance test results, with each variable regressed on the continuous measure of rainfall in millimeters, including all fixed effects and controls.[33] Variables are balanced with respect to the rainfall instrument, with the exception of the coefficients of the share of votes for green parties and the number of taxpayers, which are statistically significant but economically small in magnitude.[34] In section 4.3, we provide robustness check estimates without including these control variables, thus providing evidence that the results are not driven by the chosen set of municipality characteristics.

[33]For simplicity, columns (4) and (5) divide municipalities according to the presence of rainfall while—consistently with the main IV analyses—the balance test in column (6) uses rainfall in millimeters. The tested variable is excluded from the controls in its respective regression. The results for the FFF variables in the balance test align with the first-stage estimates presented in Section 4. Importantly, for consistency with the manuscript's analyses, Table 2 is based on the monthly panel dataset. However, the municipality-level controls are cross-sectional, measured in 2018. Performing this balance analysis solely on the municipality sample (7,772 in total) would, in any case, yield unchanged estimates.

[34]It should be noted that control variables are measured in the pre-treatment period (2018), while the rainfall measure pertains to a single day in March 2019, which does not violate the exclusion restriction and falls within one of the exceptions discussed in Mellon (2024). Results are largely similar when the balance test is performed using a simple bivariate regression with clustered standard errors. In this case, the only variables that appear slightly unbalanced are those related to certain demographic characteristics (i.e., population and the highest deciles of the population aged 18 years), which is largely expected, given the observed precipitation during the FFF event (see Figure 1) and the demographic heterogeneity between northern and southern Italian municipalities. Therefore, including fixed effects, as in Hungerman and Moorthy (2023), is more appropriate in this context. Nevertheless, our identification strategy relies on the conditional independence assumption (CIA), which requires that treatment and control groups be comparable after conditioning on covariates.

Table 2: Summary Statistics and Balance Test

	Municipalities					
	All (1)	Exposed to FFF (2)	Not Exposed to FFF (3)	Not Exposed to rain (4)	Exposed to rain (5)	Balance test (6)
Precipitation (mm) on the FFF day	0.142 (0.830)	0.073 (0.629)	0.144 (0.836)	0.000 (0.000)	0.549 (1.565)	-
FFF variables:						
FFF event	0.011 (0.105)	0.316 (0.465)	0.000 (0.000)	0.013 (0.111)	0.007 (0.083)	-0.030*** (0.008)
FFF strikers	19.702 (1,065.4)	1,542.83 (9,303.78)	0.000 (0.000)	23.621 (1,199.25)	8.562 (522.88)	-1,500.387** (688.41)
FFF strikers per 1,000 inhabitants	0.139 (6.787)	10.898 (59.080)	0.000 (0.000)	0.120 (2.832)	0.192 (12.416)	-1.336*** (0.497)
Municipal characteristics:						
Population (2018)	7,148.27 (42,607.5)	74,403.34 (214,000)	4,699.86 (7,105.41)	8,083.89 (48,328.02)	4,455.33 (17,560.96)	-4,792.315 (4,260.47)
Share of votes for green parties (2018)	0.327 (0.121)	0.352 (0.106)	0.327 (0.121)	0.347 (0.116)	0.270 (0.116)	-0.004*** (0.001)
Share of recycled waste (2018)	0.614 (0.201)	0.613 (0.180)	0.614 (0.202)	0.616 (0.202)	0.607 (0.200)	0.002 (0.002)
Gini index (2018)	0.384 (0.041)	0.408 (0.036)	0.383 (0.041)	0.384 (0.038)	0.382 (0.050)	0.000 (0.000)
Number of vehicles (2018) - per capita	0.897 (0.135)	0.897 (0.321)	0.897 (0.123)	0.893 (0.122)	0.906 (0.166)	-0.013 (0.015)
Share of cars (2018)	0.752 (0.052)	0.756 (0.042)	0.752 (0.052)	0.753 (0.052)	0.748 (0.051)	0.001 (0.001)
Number of taxpayers (2018) - per capita	0.702 (0.075)	0.702 (0.065)	0.702 (0.075)	0.697 (0.069)	0.719 (0.087)	0.001** (0.001)
Number of high schools (2018) - per 1,000 inh.	0.132 (0.257)	0.308 (0.215)	0.126 (0.256)	0.144 (0.258)	0.099 (0.252)	0.003 (0.002)
Share of work trips within mun. (2018)	0.338 (0.182)	0.567 (0.218)	0.329 (0.175)	0.351 (0.178)	0.298 (0.186)	0.000 (0.002)
Population aged 18 y.o. - Deciles of the distribution:						
Decile 1	0.105 (0.306)	0.004 (0.060)	0.108 (0.311)	0.096 (0.294)	0.131 (0.337)	0.000 (0.000)
Decile 2	0.119 (0.324)	0.011 (0.104)	0.123 (0.329)	0.111 (0.314)	0.143 (0.350)	0.000 (0.001)
Decile 3	0.095 (0.293)	0.018 (0.134)	0.098 (0.297)	0.091 (0.288)	0.106 (0.308)	0.002 (0.001)
Decile 4	0.089 (0.285)	0.018 (0.134)	0.092 (0.288)	0.086 (0.281)	0.097 (0.296)	-0.001 (0.001)
Decile 5	0.100 (0.300)	0.037 (0.188)	0.102 (0.303)	0.097 (0.296)	0.108 (0.311)	0.002 (0.002)
Decile 6	0.095 (0.294)	0.015 (0.120)	0.098 (0.298)	0.092 (0.289)	0.106 (0.308)	0.002 (0.003)
Decile 7	0.098 (0.297)	0.051 (0.221)	0.099 (0.299)	0.097 (0.296)	0.099 (0.299)	-0.002 (0.003)
Decile 8	0.102 (0.303)	0.066 (0.248)	0.103 (0.304)	0.106 (0.307)	0.092 (0.289)	0.003 (0.005)
Decile 9	0.098 (0.297)	0.099 (0.299)	0.098 (0.297)	0.109 (0.311)	0.067 (0.250)	-0.003 (0.005)
Decile 10	0.099 (0.298)	0.681 (0.466)	0.078 (0.268)	0.116 (0.320)	0.050 (0.219)	-0.004 (0.006)
Observations	295,336	10,374	284,962	219,184	76,152	295,336

Notes: The table presents summary statistics at municipality level. Each row reports the variable's sample average with standard deviations in parentheses. The sample includes treated municipalities affected by the first FFF event (March 15, 2019), along with control municipalities, totaling 7,772 out of 7,904 Italian municipalities. It excludes municipalities treated in subsequent FFF events (i.e., a total of 132 municipalities). Column (1) shows descriptive statistics for all municipalities included in the sample, column (2) presents statistics for municipalities exposed to the FFF event, column (3) provides summary statistics for municipalities never exposed to the FFF event, and columns (4) and (5) show descriptive statistics for municipalities not exposed to rain or exposed to rain on the FFF day, respectively. The FFF event is a binary variable that assigns a value of 1 if a municipality m participated in the strike on March 15, 2019. FFF strikes and FFF strikers per 1,000 inhabitants measure the number of strikers, with statistics derived from a sample of 288,648 observations. This sample excludes treated municipalities with missing information on the number of strikers. Consequently, the statistics for treated municipalities cover 97 out of the 273 treated municipalities that reported information on the number of strikers. FFF day precipitation measures rainfall (mm) on the day of the FFF event. Finally, column (6) shows the balance test analysis, which is computed by regressing each variable on the instrument that measures precipitation on the day of the FFF event, including all controls and fixed effects described in Equation (1), except for the specific control being used as the outcome for that particular balance test. Balance test estimates are weighted by the population of each municipality, with standard errors clustered at municipality level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

4 The Effect of FFF on Consumption Choices

4.1 Descriptive Evidence

Figure 2 provides descriptive evidence of the dynamics of the effects.[35] We interact post-treatment dummies (lags) with the rain dummy, $RainyFFF_m$, which takes a value of one if rainfall was greater than 0.1 inches in 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 that we will discuss in Section 4.

We observe that the outcomes remain stable in the pre-treatment period. Results on the number of automobiles per 1,000 inhabitants display a negative jump that persists in the post-treatment period, albeit with some noise.[36] Total CO2 per car shows a significant drop in the three months following the event, then returns to zero, with the negative effect re-emerging from the seventh month onward. The purchase of low-CO2 cars sharply increases immediately after the FFF event, then declines before rising again five months after the event. The purchase of high-CO2-emission cars follows a similar pattern, albeit in the opposite direction. This provides *prima facie* evidence that FFF favored consumers' choices towards cleaner products. Moreover, these dynamics suggest that the effect is renewed with the occurrence of subsequent FFF events. We investigate this phenomenon in Table A.11 in Appendix.2, where we find that repeated exposure to FFF events further increases the magnitude of our effects.[37]

[35]Specifically, we estimate the following descriptive event-study specification:

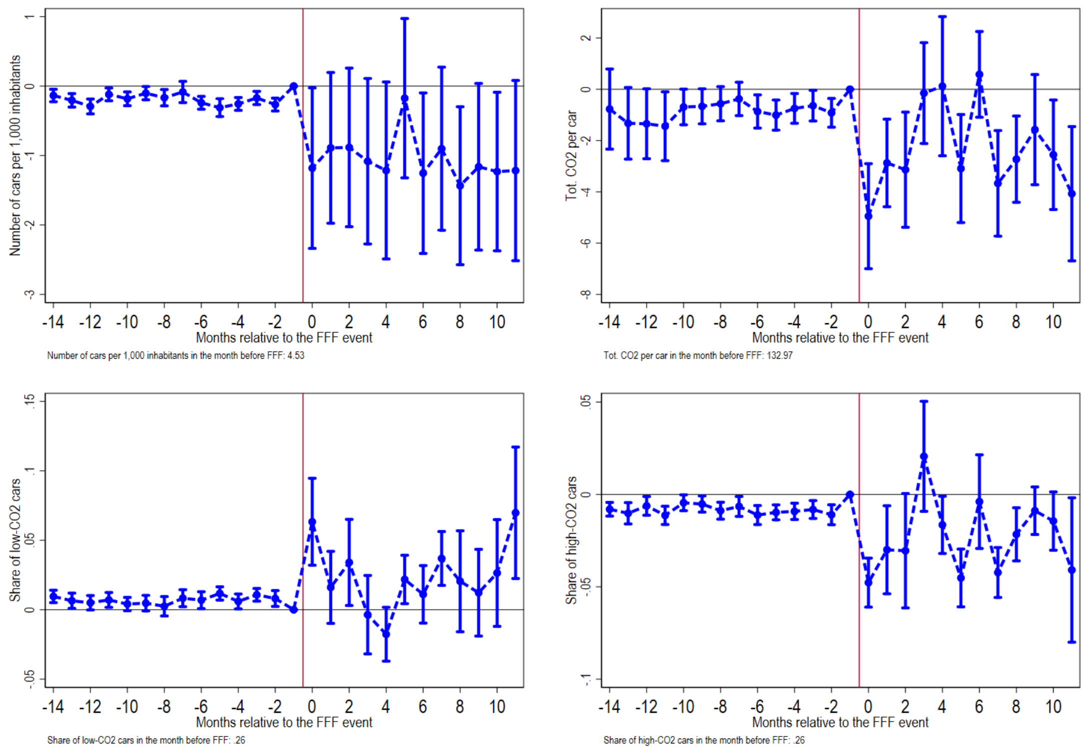
$$Y_{m,t} = \theta_0 + \sum_{j=a}^{-1} \theta_j FFF_{m,t}^j + \sum_{j=0}^{b} \theta_j FFF_{m,t}^j \cdot RainyFFF_m + \delta_p + \delta_t + \delta_{PLT} + \delta_{RP_m} + \gamma X_m + \nu_{m,t} \tag{4}$$

with $a = -14$, $b = 11$, and we follow McCrary (2008) in binding the end-points. The term $FFF_{m,t}^j$ is an event-study indicator, namely $FFF_{m,t}^j = FFF_m \cdot \mathbb{1}\{t = \tilde{t} + j\}$, where FFF_m is a dummy indicating whether the municipality m hosted the FFF event, whereas $\tilde{t}$ denotes the time (year-month) when the FFF event took place.

[36]The increase in standard errors after the FFF event is likely due to the interaction of the treatment effect with the rain variable, which introduces greater variability in the post-FFF period.

[37]This result is consistent with the findings of Valentim (2023) about repeated exposure to local FFF events on the share of votes for green parties in Germany.

Figure 2: Descriptive Event Study



Notes: This figure presents estimates of the event-study Equation (4) using panel data at municipality-year-month level. Post-treatment dummies (lags) are interacted with the rain dummy, which takes a value of one if rainfall was greater than 0.1 inches (2.54 mm) 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. The regression controls for province fixed effects, year-month fixed effects, a province linear time trend, and a set of predetermined characteristics of the municipality including: dummy variables corresponding to the deciles of the historical rain probability distribution (1980-2018), the share of votes for green parties, the share of recycled waste, the per capita number of vehicles, the share of work trips within the municipality, the share of cars, the per capita number of taxpayers, the Gini index, the resident population, the per capita number of public high schools, and a set of dummies for each decile of the population aged 18 years, all of which were measured in 2018. The top-left graph shows results for the total number of cars purchased per 1,000 inhabitants; the top-right graph shows results for total CO2 per car; the bottom-left and bottom-right graphs display results for the share of cars purchased belonging to the first and fourth quartiles of the CO2 distribution, respectively. Event-study estimates are normalized relative to the year-month before the first FFF event. The straight line indicates the first FFF event. Estimates are weighted by the population of each municipality and 95% confidence intervals are obtained after clustering the standard errors at municipality level.

4.2 Instrumental Variable Results

Table 3 presents estimates from the first-stage IV model Equation (1). Column (1) reports results considering a treatment dummy for the FFF event as the endogenous variable. Column (2) examines results using the number of FFF strikers per 1,000 inhabitants as an alternative endogenous treatment, with the number of observations net of treated municipalities that have missing information on the number of strikers. We observe that precipitation on the day of the FFF event typically decreases both the probability of hosting the event and the number of strikers participating in the protest. Additionally, in column (2), the F-statistic for the excluded instrument is smaller compared to column (1), which is likely due to the omission of some treated municipalities.[38] For this reason, each table displaying IV results will also include the estimated parameter $\hat{\rho}$ (in absolute value), which measures the degree of endogeneity according to Angrist and Kolesár (2024):

$$\hat{\rho} = \frac{\sigma_{\hat{\alpha}}}{|\hat{\alpha}|\sigma_{\hat{\beta}}} \times \left(\frac{\sigma_{\hat{\lambda}\hat{\alpha}}}{\sigma^2_{\hat{\alpha}}} - \hat{\beta} \right) \tag{5}$$

where $\sigma_{\hat{\lambda}\hat{\alpha}} = \frac{\sigma^2_{\hat{\alpha}}\hat{\beta}^2 - \hat{\alpha}^2\sigma^2_{\hat{\beta}} + \sigma^2_{\hat{\lambda}}}{2\hat{\beta}}$. Here, $\hat{\alpha}$, $\hat{\lambda}$, and $\hat{\beta}$ are the estimated coefficients from the first-stage Equation (1), the reduced-form Equation (2), and the second-stage Equation (3), respectively.[39] The terms $\sigma_{\hat{\alpha}}$, $\sigma_{\hat{\lambda}}$, and $\sigma_{\hat{\beta}}$ are the corresponding estimated standard errors. Angrist and Kolesár (2024) focus on IV estimators with a single instrument, examining rejection rates for a conventional 5% nominal t-test as a function of $E[F]$ and $|\hat{\rho}|$.[40] They show that rejection rates significantly exceed the nominal level only if the instrument is weak (i.e., $E[F]$ close to 1) and endogeneity is high, by demonstrating that while the median bias increases with a weaker instrument, the precision of the second stage decreases, adequately reflecting this lack of precision in the IV standard error. Essentially, as long as $|\hat{\rho}| < 0.747$, the 95% confidence interval coverage is distorted by no more than 5% for any population F for the first-stage. Alternatively, for any $E[F] \geq 7.01$, rejection rates stay below 10% regardless of the degree of endogeneity.[41] This proves that our inference strategy is reliable even when the F-statistic for the first-stage is smaller than the commonly known rule-of-thumb threshold of 10.

[38] The magnitude of the effect on the number of strikers is similar when we limit the sample to those municipalities hosting the FFF event (intensive margin), but it lacks statistical significance for the same reasons. These results are available upon request from the authors.

[39] Specifically, the coefficients mentioned above should be interpreted as $\hat{\alpha}_1$, $\hat{\lambda}_1$, and $\hat{\beta}_1$ from the corresponding equations, since we have omitted the subscript '1' to simplify the notation.

[40] Here, $E[F]$ is the estimated F-statistic of the excluded instrument of the first-stage equation.

[41] For more details, please refer to Angrist and Kolesár (2024). Rejection rates of conventional t-tests as a function of $E[F]$ and ρ are shown in their contour plot in Figure 1 (Panel B).

Table 3: First-Stage Estimates

	(1) FFF event	(2) FFF strikers per 1,000 inhabitants
FFF day precipitation (mm)	-0.030***	-1.336***
	(0.008)	(0.497)
Observations	295,336	288,648
F-stat	77.70	14.14
F-stat of the excluded instrument	14.62	7.236
Province FE	YES	YES
Time FE	YES	YES
Province linear time-trend	YES	YES
Probability of rain	YES	YES
Municipality characteristics	YES	YES

Notes: This table presents estimates of the first-stage IV model Equation (1) using panel data at municipality-year-month level. Column (1) reports results considering a treatment dummy for the FFF event as the endogenous variable. Column (2) examines results using the number of FFF strikers per 1,000 inhabitants as an alternative endogenous treatment. In column (2), the number of observations is net of treated municipalities with missing information on the number of strikers. In both columns, the endogenous variable (i.e., FFF event or FFF strikers per 1,000 inhabitants) is instrumented by rainfall (mm) on March 15, 2019, the date of the first FFF event. The regression controls for province fixed effects, year-month fixed effects, a province linear time trend, and a set of predetermined characteristics of the municipality, including: dummy variables corresponding to the deciles of the historical rain probability distribution (1980-2018), the share of votes for green parties, the share of recycled waste, the per capita number of vehicles, the share of work trips within the municipality, the share of cars, the per capita number of taxpayers, the Gini index, the resident population, the per capita number of public high schools, and a set of dummies for each decile of the population aged 18 years, all of which were measured in 2018. Estimates are weighted by the population of each municipality, with standard errors clustered at municipality level. *** p<0.01, ** p<0.05, * p<0.1.

Table 4 presents estimates of the second-stage IV model Equation (3).[42] Panel A displays estimates using the FFF treatment dummy, while Panel B presents the results obtained using the per capita number of FFF strikers as a treatment variable. 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. In column (1), we note a reduction in the number of cars purchased per 1,000 inhabitants, equivalent to half of the SD. In column (2), we also observe a reduction in the total CO_2 per car (i.e., the average CO_2 of cars purchased). This implies that the cars purchased in the months following the FFF event of March 2019 exhibit an average level of technical CO_2 emissions reduced by one-fourth of the SD when compared to counterfactual municipalities (Panel A). The observed reduction in both the number of cars purchased and in their average

[42] Appendix Tables A.2 and A.3 report the corresponding GLS and the reduced-form estimates, respectively.

CO2 should also translate into a reduction in overall CO2 emissions. However, the extent of this overall reduction could potentially depend on the mileage driven by individuals exposed to FFF, which we cannot directly observe. These individuals might purchase smaller cars with lower emissions per kilometer but could drive more than before, thereby offsetting some of the benefits. Nonetheless, we do not have any evidence of a change in the driving habits of Italians, as the average distance driven per vehicle remains at around 10,700 km per year (UNRAE, 2022).

Table 4: IV Baseline Results

	(1) Number of cars per 1,000 inhabitants	(2) Tot. CO2 per car	(3) Share low CO2 (Quartile 1)	(4) Share high CO2 (Quartile 4)
Panel A: FFF event	-1.957***	-9.002**	0.072***	-0.088***
	(0.690)	(3.519)	(0.028)	(0.033)
Observations	295,336	295,336	295,336	295,336
F-stat of the excl. instrument	14.62	14.62	14.62	14.62
$\|\hat{\rho}\|$	0.568	0.645	0.620	0.630
Avg. outcome	4.530	127.7	0.235	0.251
Outcome SD	3.849	34.14	0.192	0.204
Panel B: FFF strikers per capita	-67.231**	-196.522**	1.913**	-2.332**
	(29.200)	(100.216)	(0.900)	(1.107)
Observations	288,648	288,648	288,648	288,648
F-stat of the excl. instrument	7.236	7.236	7.236	7.236
$\|\hat{\rho}\|$	0.893	0.796	0.838	0.855
Avg. outcome	4.535	127.6	0.234	0.251
Outcome SD	3.888	34.45	0.194	0.206
Province FE	YES	YES	YES	YES
Year-month FE	YES	YES	YES	YES
Province linear time trend	YES	YES	YES	YES
Probability of rain	YES	YES	YES	YES
Municipality characteristics	YES	YES	YES	YES

Notes: This table presents estimates of the second-stage IV model Equation (3) using panel data at municipality-year-month level. Tables A.2 and A.3 report the corresponding GLS and reduced-form estimates, respectively. Panel A shows results considering a treatment dummy for the FFF event as the endogenous variable. Panel B examines results using the number of FFF strikers per capita as an alternative endogenous treatment. In Panel B, the number of observations is net of treated municipalities with missing information on the number of strikers. In both panels, the endogenous variable (i.e., FFF event or FFF strikers per capita) is instrumented by rainfall (mm) on March 15, 2019, the date of the first FFF event. The regression controls for province fixed effects, year-month fixed effects, a province linear time trend, and a set of predetermined characteristics of the municipality, including: dummy variables corresponding to the deciles of the historical rain probability distribution (1980-2018), the share of votes for green parties, the share of recycled waste, the per capita number of vehicles, the share of work trips within the municipality, the share of cars, the per capita number of taxpayers, the Gini index, the resident population, the per capita number of public high schools, and a set of dummies for each decile of the population aged 18 years, all of which were measured in 2018. Column (1) reports results for the number of cars purchased per 1,000 inhabitants. Column (2) shows results for the total CO2 emissions per car purchased. Columns (3) and (4) present results for the share of cars purchased belonging to the first and fourth quartiles of the CO2 distribution, respectively. The table reports the estimated degree of endogeneity ($\hat{\rho}$) according to Angrist and Kolesár (2024) as described in the Equation (5): as long as $|\hat{\rho}| < 0.747$, the 95% confidence interval coverage is distorted by no more than 5% for any population F for the first stage. Alternatively, for any $E[F] \geq 7.01$, rejection rates stay below 10% regardless of the degree of endogeneity. This proves that the inference strategy is reliable. Estimates are weighted by the population of each municipality, with standard errors clustered at municipality level. *** p<0.01, ** p<0.05, * p<0.1.

The average CO_2 reduction displayed in column (2) could be driven by a change to a type of car that emits less CO_2. For this reason, in columns (3) and (4), we present results for the share of cars purchased belonging to the first and fourth quartiles of the CO_2 emissions distribution (i.e., low and high CO_2), respectively.[43] 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% of the SD, while the share of high-emission cars decreases by 43% of the SD. Finally, when examining Panel B, we observe that these effects increase in magnitude as the number of strikers per capita rises.[44]

In Table A.5 of the Appendix, we replicate our baseline analysis using data on new automobile purchases. The results appear consistent with those obtained for used cars shown in Table 4, although they are noisier and less precise. This is likely due to the measurement error problem discussed in Section 2.2.

4.3 Placebo Analyses and Robustness Checks

In this section, we present the placebo analyses conducted to validate the robustness of our instrumental variable approach. Cooperman (2017) and Lind (2019) have highlighted the risk that studies using rainfall as an instrument might produce results driven by spurious correlations, due to the potential strong spatial auto-correlation of rainfall, thus leading to an invalid causal inference.

[43]We did not find any statistically significant effect on the share of cars belonging to the second and third quartiles of the CO_2 emissions distribution, with coefficients close to zero in magnitude. Therefore, in the remaining analyses, we focus only on the first and fourth quartiles. However, for transparency, results for the second and third quartiles are displayed in Appendix Table A.4.

[44]Tables A.6 and A.7 in the Appendix present results for both the first and second stages, using a panel with just two periods (pre- and post-FFF). In accordance with this data structure, the model specification excludes year-month fixed effects and the province linear time trend, including instead a dummy variable for the post-treatment period. The results of this analysis are consistent with those in Tables 3 and 4, providing evidence that our findings are not driven by the data-generating process used to create the monthly panel. However, we believe that the monthly panel structure is the most appropriate choice for this study. It enables optimal use of the automobile-related data, descriptive investigation of the dynamics of the effect (Figure 2), and employment of a model specification that controls for idiosyncratic changes in economic or weather conditions at province-year-month level.

We have already shown the results of a Moran's I test in Section 2, revealing that in our empirical context the spatial auto-correlation of rainfall is statistically significant but negligible in magnitude, regardless of the distance matrix adopted. Nonetheless, to eliminate any lingering concerns, we performed two different placebo tests to show that our first-stage effects are not driven by spurious spatial correlations in the rainfall data.

In the first of these tests, we consider all rainy days from 2016 to 2018 and conduct an analysis where we estimate 1,000 placebo first stages. We randomly and fictitiously assign a rainy day from 2016 to 2018 as if it were the rainfall on the actual FFF event day (March 15, 2019). In a second placebo exercise, we perform estimates based on 1,000 cross-sectional random reshuffles of the treatment and the rainfall for the FFF day across municipalities.

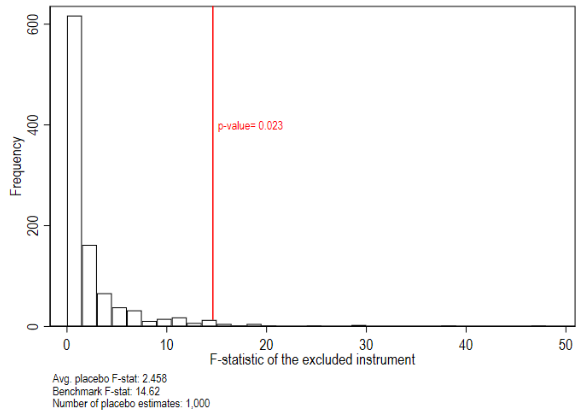
We present these results for the dichotomous treatment variable in Figure 3. Panel (a) shows the first exercise and Panel (b) the second. Specifically, the two histograms depict the distribution of the F-statistics of the excluded instrument for these 1,000 placebo estimates. The p-value is calculated as the fraction of F-statistics that are greater than the actual F-statistic, represented by the red vertical line.

In both panels, the p-value is statistically significant, thus indicating that our true first stage is unlikely to be driven by spurious correlation. Otherwise, the placebo exercises would have shown a large number of statistically significant first-stage estimates, similar to those discussed in Lind (2019). In particular, Figure 3 reports that 97.7% to 99.7% of the placebo estimates show an F-statistic of the excluded instrument lower than the actual value, with average placebo F-statistic equal to 2.458 in Panel (a) or 1.96 for the second placebo in Panel (b).[45]

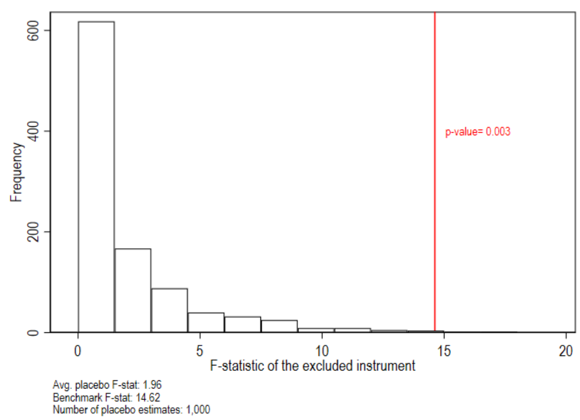
[45] Figure A.2 in the Appendix replicates these exercises using the number of FFF strikers per capita as the endogenous treatment variable. In this case also, the validity of our first stage is confirmed, albeit with slightly less precision compared to the dichotomous variable, for the reasons already discussed in Section 4.2.

Figure 3: Placebo Analyses of the First-Stage – FFF event

(a) Random Assignment of Rainy Days from 2016-2018



(b) Random Reshuffling of Treatment and Precipitation



Notes: This figure plots the distribution of 1,000 placebo estimates of Equation (1), using the FFF event dummy as endogenous variable. In Panel (a), we estimate placebos by randomly and fictitiously attributing the precipitation drawn from years 2016-2018 to the FFF event day. In Panel (b), we randomly reshuffle the actual treatment status (FFF event dummy) and precipitation. In both panels, the p-value is calculated as the fraction of placebo F-stat for the excluded instrument that is greater than the actual first-stage F-statistic, which is shown as a red vertical line. Below the graph on the left, we report the average placebo F-stat, the benchmark F-stat, and the number of placebo estimates.

Furthermore, we provide several robustness analyses to check the sensitivity of our baseline results. First, in Table 5, we exclude control variables referring to municipality characteristics (i.e., the matrix X_m described in Section 3) from our IV analysis. Results are slightly less precise compared to our baseline estimates but are robust both qualitatively and quantitatively, providing evidence that the baseline results are not driven by the chosen set of municipality characteristics.

Table 5: IV Robustness Check (1) - Excluding Municipality Characteristics

	(1) Number of cars per 1,000 inhabitants	(2) Tot. CO2 per car	(3) Share Low CO2 (Quartile 1)	(4) Share High CO2 (Quartile 4)
Panel A: FFF event	-1.338**	-8.826**	0.093***	-0.118***
	(0.536)	(3.453)	(0.030)	(0.038)
Observations	295,336	295,336	295,336	295,336
F-stat of the excl. instrument	12.75	12.75	12.75	12.75
$\lvert\hat{\rho}\rvert$	0.555	0.688	0.745	0.746
Avg. outcome	4.530	127.7	0.235	0.251
Outcome SD	3.849	34.14	0.192	0.204
Panel B: FFF strikers per capita	-32.803**	-227.498*	2.590**	-3.283**
	(15.738)	(117.446)	(1.151)	(1.514)
Observations	288,648	288,648	288,648	288,648
F-stat of the excl. instrument	6.428	6.428	6.428	6.428
$\lvert\hat{\rho}\rvert$	0.687	0.839	0.892	0.900
Avg. outcome	4.535	127.6	0.234	0.251
Outcome SD	3.888	34.45	0.194	0.206
Province FE	YES	YES	YES	YES
Year-month FE	YES	YES	YES	YES
Province linear time trend	YES	YES	YES	YES
Probability of rain	NO	NO	NO	NO
Municipality characteristics	NO	NO	NO	NO

Notes: This table presents estimates of the second-stage IV model Equation (3) using panel data at municipality-year-month level, and without including controls for municipality characteristics. Panel A shows results considering a treatment dummy for the FFF event as the endogenous variable. Panel B examines results using the number of FFF strikers per capita as an alternative endogenous treatment. In Panel B, the number of observations is net of treated municipalities with missing information on the number of strikers. In both panels, the endogenous variable (i.e., FFF event or FFF strikers per capita) is instrumented by rainfall (mm) on March 15, 2019, the date of the first FFF event. The regression controls for province fixed effects, year-month fixed effects, and a provincial linear time trend. Column (1) reports results for the number of cars purchased per 1,000 inhabitants. Column (2) shows results for the total CO2 emissions per car purchased. Columns (3) and (4) present results for the share of cars purchased belonging to the first and fourth quartiles of the CO2 distribution, respectively. The table reports the estimated degree of endogeneity ($\hat{\rho}$) according to Angrist and Kolesár (2024) as described in the Equation (5): as long as $|\hat{\rho}| < 0.747$, the 95% confidence interval coverage is distorted by no more than 5% for any population F for the first stage. Alternatively, for any $E[F] \geq 7.01$, rejection rates stay below 10% regardless of the degree of endogeneity. In Panel B, the F-statistic of the excluded instrument is 6.428, and $|\hat{\rho}| > 0.747$. However, according to Angrist and Kolesár (2024), this is valid as long as $|\hat{\rho}| \leq 0.95$. This proves that the inference strategy is reliable. Estimates are weighted by the population of each municipality, with standard errors clustered at municipality level. *** p<0.01, ** p<0.05, * p<0.1.

Second, in Table 6, we employ an alternative IV, a dummy variable taking a value of one when rainfall exceeds 0.1 inches (Madestam *et al.*, 2013). In this case also, the results remain robust even though the binary instrument is weaker compared to the continuous measure of rainfall used in the baseline analysis, likely because it does not exploit the full variation in rainfall. This also results in weaker statistical significance for the average CO2 of cars purchased. However, the causal inference is still reliable according to Angrist and Kolesár (2024).

Table 6: IV Robustness Check (2) - Alternative Instrument

	(1) Number of cars per 1,000 inhabitants	(2) Tot. CO2 per car	(3) Share Low CO2 (Quartile 1)	(4) Share High CO2 (Quartile 4)
Panel A: FFF event	-1.761**	-7.190+	0.090**	-0.096**
	(0.817)	(4.382)	(0.036)	(0.039)
Observations	295,336	295,336	295,336	295,336
F-stat of the excl. instrument	7.171	7.171	7.171	7.171
$\lvert\hat{\rho}\rvert$	0.656	0.461	0.696	0.721
Avg. outcome	4.530	127.7	0.235	0.251
Outcome SD	3.849	34.14	0.192	0.204
Panel B: FFF strikers per capita	-36.184+	-218.843+	2.450**	-3.005**
	(22.984)	(148.271)	(1.202)	(1.396)
Observations	288,648	288,648	288,648	288,648
F-stat of the excl. instrument	7.656	7.656	7.656	7.656
$\lvert\hat{\rho}\rvert$	0.521	0.556	0.705	0.773
Avg. outcome	4.535	127.6	0.234	0.251
Outcome SD	3.888	34.45	0.194	0.206
Province FE	YES	YES	YES	YES
Year-month FE	YES	YES	YES	YES
Province linear time trend	YES	YES	YES	YES
Probability of rain	YES	YES	YES	YES
Municipality characteristics	YES	YES	YES	YES

Notes: This table presents estimates of the second-stage IV model Equation (3) using panel data at municipality-year-month level. Panel A shows results considering a treatment dummy for the FFF event as the endogenous variable. Panel B examines results using the number of FFF strikers per capita as an alternative endogenous treatment. In Panel B, the number of observations is net of treated municipalities with missing information on the number of strikers. In both panels, the endogenous variable (i.e., FFF event or FFF strikers per capita) is instrumented by a rain dummy that takes a value of one if a municipality experienced precipitation greater than 0.01 inches (2.54 mm) on March 15, 2019, the date of the first FFF event. The regression controls for province fixed effects, year-month fixed effects, a province linear time trend, and a set of predetermined characteristics of the municipality, including: dummy variables corresponding to the deciles of the historical rain probability distribution (1980-2018), the share of votes for green parties, the share of recycled waste, the per capita number of vehicles, the share of work trips within the municipality, the share of cars, the per capita number of taxpayers, the Gini index, the resident population, the per capita number of public high schools, and a set of dummies for each decile of the population aged 18 years, all of which were measured in 2018. Column (1) reports results for the number of cars purchased per 1,000 inhabitants. Column (2) shows results for the total CO2 emissions per car purchased. Columns (3) and (4) present results for the share of cars purchased belonging to the first and fourth quartiles of the CO2 distribution, respectively. The table reports the estimated degree of endogeneity ($\hat{\rho}$) according to Angrist and Kolesár (2024) as described in the Equation (5): as long as $|\hat{\rho}| < 0.747$, the 95% confidence interval coverage is distorted by no more than 5% for any population F for the first stage. Alternatively, for any $E[F] \geq 7.01$, rejection rates stay below 10% regardless of the degree of endogeneity. This proves that the inference strategy is reliable. Estimates are weighted by the population of each municipality, with standard errors clustered at municipality level. *** p<0.01, ** p<0.05, * p<0.1. + p<0.15

Third, in Table 7, we test the sensitivity of our results using an alternative control group in which we exclude control municipalities belonging to the same Local Labor System (LLS) as a treated municipality.[46] This exercise allows us to test for potential

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

bias introduced by spillover effects because people living in a control municipality may potentially participate in an FFF event hosted by a neighboring municipality, which could introduce a downward bias in our estimates. We find qualitatively robust results with a reduced magnitude.

Table 7: IV Robustness Check (3) - Alternative Control Group

	(1) Number of cars per 1,000 inhabitants	(2) Tot. CO2 per car	(3) Share Low CO2 (Quartile 1)	(4) Share High CO2 (Quartile 4)
Panel A: FFF event	-1.082***	-5.711***	0.031**	-0.054***
	(0.336)	(2.089)	(0.015)	(0.019)
Observations	156,066	156,066	156,066	156,066
F-stat of the excl. instrument	37.30	37.30	37.30	37.30
$\lvert\hat{\rho}\rvert$	0.249	0.391	0.263	0.359
Avg. outcome	4.375	127.6	0.232	0.254
Outcome SD	2.714	34.84	0.198	0.212
Panel B: FFF strikers per capita	-51.045***	-138.212*	1.159**	-1.958**
	(19.014)	(78.383)	(0.576)	(0.838)
Observations	149,378	149,378	149,378	149,378
F-stat of the excl. instrument	11.21	11.21	11.21	11.21
$\lvert\hat{\rho}\rvert$	0.827	0.640	0.629	0.750
Avg. outcome	4.377	127.3	0.231	0.254
Outcome SD	2.760	35.47	0.202	0.216
Province FE	YES	YES	YES	YES
Year-month FE	YES	YES	YES	YES
Province linear time trend	YES	YES	YES	YES
Probability of rain	YES	YES	YES	YES
Municipality characteristics	YES	YES	YES	YES

Notes: This table presents estimates of the second-stage IV model Equation (3) using panel data at municipality-year-month level. In this analysis, control municipalities that belong to the same Local Labor System (LLS) as a treated municipality are excluded. Panel A shows results considering a treatment dummy for the FFF event as the endogenous variable. Panel B examines results using the number of FFF strikers per capita as an alternative endogenous treatment. In Panel B, the number of observations is net of treated municipalities with missing information on the number of strikers. In both panels, the endogenous variable (i.e., FFF event or FFF strikers per capita) is instrumented by rainfall (mm) on March 15, 2019, the date of the first FFF event. The regression controls for province fixed effects, year-month fixed effects, a province linear time trend, and a set of predetermined characteristics of the municipality, including: dummy variables corresponding to the deciles of the historical rain probability distribution (1980-2018), the share of votes for green parties, the share of recycled waste, the per capita number of vehicles, the share of work trips within the municipality, the share of cars, the per capita number of taxpayers, the Gini index, the resident population, the per capita number of public high schools, and a set of dummies for each decile of the population aged 18 years, all of which were measured in 2018. Column (1) reports results for the number of cars purchased per 1,000 inhabitants. Column (2) shows results for the total CO2 emissions per car purchased. Columns (3) and (4) present results for the share of cars purchased belonging to the first and fourth quartiles of the CO2 distribution, respectively. The table reports the estimated degree of endogeneity ($\hat{\rho}$) according to Angrist and Kolesár (2024) as described in the Equation (5): as long as $|\hat{\rho}| < 0.747$, the 95% confidence interval coverage is distorted by no more than 5% for any population F for the first stage. Alternatively, for any $E[F] \geq 7.01$, rejection rates stay below 10% regardless of the degree of endogeneity. This proves that the inference strategy is reliable. Estimates are weighted by the population of each municipality, with standard errors clustered at municipality level. *** p<0.01, ** p<0.05, * p<0.1.

In Table A.8 of the Appendix, we present the results of an additional robustness check in which we remove from the control group the "never-taker" municipalities, namely those that did not participate in the FFF event despite the absence of precipitation. As shown in Figure 1, these municipalities represent a significant portion of the total sample. The results remain robust even when these municipalities are excluded, although—as expected—the magnitude of the effect decreases.

Finally, given the positive spatial correlation of rainfall (see Figure 1), in Table 8 we cluster standard errors on LLSs in order to allow for some spatial auto-correlation in the errors.

Table 8: IV Robustness Check (4) - Alternative Clustering

	(1) Number of cars per 1,000 inhabitants	(2) Tot. CO2 per car	(3) Share Low CO2 (Quartile 1)	(4) Share High CO2 (Quartile 4)
Panel A: FFF event	-1.957***	-9.002**	0.072**	-0.088**
	(0.627)	(3.771)	(0.029)	(0.036)
Observations	295,336	295,336	295,336	
F-stat of the excl. instrument	16.02	16.02	16.02	16.02
$\lvert\hat{\rho}\rvert$	0.427	0.567	-0.510	0.482
Avg. outcome 4.530	127.7	0.235	0.251	
Outcome SD	3.849	34.14	0.192	0.204
Panel B: FFF strikers per capita	-67.231***	-196.522**	1.913**	-2.332**
	(24.213)	(95.900)	(0.828)	(1.062)
Observations	288,648	288,648	288,648	288,648
F-stat of the excl. instrument	10.45	10.45	10.45	10.45
$\lvert\hat{\rho}\rvert$	0.822	0.679	-0.728	0.731
Avg. outcome	4.535	127.6	0.234	0.251
Outcome SD	3.888	34.45	0.194	0.206
Province FE	YES	YES	YES	YES
Year-month FE	YES	YES	YES	YES
Province linear time trend	YES	YES	YES	YES
Probability of rain	YES	YES	YES	YES
Municipality characteristics	YES	YES	YES	YES

Notes: This table presents estimates of the second-stage IV model Equation (3) using panel data at municipality-year-month level. Panel A shows results considering a treatment dummy for the FFF event as the endogenous variable. Panel B examines results using the number of FFF strikers per capita as an alternative endogenous treatment. In Panel B, the number of observations is net of treated municipalities with missing information on the number of strikers. In both panels, the endogenous variable (i.e., FFF event or FFF strikers per capita) is instrumented by rainfall (mm) on March 15, 2019, the date of the first FFF event. The regression controls for province fixed effects, year-month fixed effects, a province linear time trend, and a set of predetermined characteristics of the municipality, including: dummy variables corresponding to the deciles of the historical rain probability distribution (1980-2018), the share of votes for green parties, the share of recycled waste, the per capita number of vehicles, the share of work trips within the municipality, the share of cars, the per capita number of taxpayers, the Gini index, the resident population, the per capita number of public high schools, and a set of dummies for each decile of the population aged 18 years, all of which were measured in 2018. Column (1) reports results for the number of cars purchased per 1,000 inhabitants. Column (2) shows results for the total CO2 emissions per car purchased. Columns (3) and (4) present results for the share of cars purchased belonging to the first and fourth quartiles of the CO2 distribution, respectively. The table reports the estimated degree of endogeneity ($\hat{\rho}$) according to Angrist and Kolesár (2024) as described in the Equation (5): as long as $|\hat{\rho}| < 0.747$, the 95% confidence interval coverage is distorted by no more than 5% for any population F for the first stage. Alternatively, for any $E[F] \geq 7.01$, rejection rates stay below 10% regardless of the degree of endogeneity. This proves that the inference strategy is reliable. Estimates are weighted by the population of each municipality, with standard errors clustered at local labor system (LLS) level. *** p<0.01, ** p<0.05, * p<0.1.

To further check the robustness of our results, in the Appendix Table A.9, we estimate our first-stage using different clustering measures. Specifically, column (1) shows our baseline, where we cluster at municipal level; in column (2), we cluster based on Local Labor Systems (LLSs); in column (3), at provincial level; and in column (4), at regional level.[47] First-stage estimates remain highly significant across all clustering dimensions.[48] This indicates that even when allowing for greater spatial correlation in the errors, the first-stage remains robust, with our adopted clustering level being the more conservative option.[49]

5 Mechanism and Heterogeneous Effects

5.1 Mechanism

In interpreting the findings of Table 4, a key issue is whether the observed effects are mediated by social norms—with consumers realizing that their community now favors greener behavior (Carattini *et al.*, 2019)—or whether FFF-related political pressure provides a signal to citizens that future policy tightening is imminent, thus prompting consumers to adjust their choices in favor of cars that are less subject to restrictive regulations. Given the scope of FFF, both channels are plausible, and we attempt to provide empirical evidence for each mechanism.[50]

[47]Since Italy has 20 regions, we employ wild cluster bootstrap (WCB) inference with replacement (1,000 replications) in line with Cameron *et al.* (2008), and calculate the wild-bootstrapped standard error from the resulting confidence intervals.

[48]We also implement an additional robustness check by augmenting the model specification (1) with an explicit control for potential spatial auto-correlation in the instrument. Specifically, we include an interaction term between the instrument (rainfall) and the binary distance matrix G used for computing Moran's I test, as described in Section 2. According to Anselin (2002), this model specification can be estimated using a GLS estimator when G is exogenous, which is the case here, as it accounts for the distance between municipalities. Our first-stage results remain negative and statistically significant at conventional levels, with magnitudes largely unchanged, even when controlling for spatial auto-correlation between municipalities.

[49]Regarding the use of the alternative endogenous treatment variable (i.e., FFF strikers per capita), the F-statistics are in some cases slightly weaker for the reasons already described in Sections 2 and 4.

[50]The primary goals of FFF are to promote green behavior and to exert political pressure to tackle the climate change issue caused by high levels of CO2 emissions polluting the atmosphere. See: https://fridaysforfuture.org/what-we-do/who-we-are/.

First, to test whether the FFF event changed the pro-environmental attitudes of local communities hosting the event, we used data on volunteer associations from Pulejo (2023), which includes 26,796 associations active before March 2020 across municipalities in 16 Italian regions.[51] These data report both the date of registration and any date of cancellation, as well as the primary purpose of the association (e.g., environmental, cultural, health). We use information on both registration and cancellation dates to create the following outcome variables at municipality-year-month level from January 2017 to February 2020: the number of active volunteer associations per 1,000 inhabitants, the number of active environmental associations per 1,000 inhabitants, and the share of active environmental associations.[52] Therefore, the measurement of the number of active associations each month can be influenced by both new openings and cancellations. In Table 9, we show the corresponding results of Equation (3).[53]

We do not find any statistically significant effect. These results provide evidence that FFF did not induce a sharp change in the pro-environmental attitudes of local communities.[54] Despite this, to examine consumption choices, in Table 10 we present results on the shares for cars purchased based on different types of engine. In column (1) of Table 4, we noticed a reduction in the number of cars purchased per 1,000 inhabitants, equivalent to half of the SD. This suggests there may be an individual mechanism driven by a greater awareness of social norms, even though we cannot observe whether individuals who decide not to purchase a used car opt for an alternative green transportation option (e.g., bycicles, new electric car, public transport, etc). However, where

[51]For more details about the data collection, please refer to Pulejo (2023). Data on volunteer associations are missing for the following Italian regions: Lazio, Apulia, Sardinia, and Veneto. This is because these regions do not report the registration dates for volunteer associations active within their territories.

[52]We consider "environmental" associations to be exclusively those with an explicit and unique environmental scope.

[53]In Appendix.2, we also investigate whether multiple exposures to FFF events affect these outcomes.

[54]We replicate the analysis shown in Table 4 using the same sample as the estimation shown in Table 9, and the results are robust and qualitatively similar to our baseline findings. This alleviates any concerns that the lack of statistical significance shown in Table 9 might be linked to the use of a different sample of municipalities. These results are available upon request from the authors.

Table 9: Mechanism - Volunteer Associations (IV)

	(1) Number of active volunteer associations (per 1,000 inhabitants)	(2) Number of active environmental volunteer associations (per 1,000 inhabitants)	(3) Share of active environmental volunteer associations
Panel A: FFF event	0.019	-0.020	-0.019
	(0.170)	(0.018)	(0.027)
Observations	236,664	236,664	236,664
F-stat of the excl. instrument	12.81	12.81	12.81
$\lvert\hat{\rho}\rvert$	0.286	0.311	0.194
Avg. outcome	0.690	0.018	0.019
Outcome SD	1.089	0.139	0.096
Panel B: FFF strikers per capita	6.646	-0.325	-0.479
	(4.478)	(0.426)	(0.684)
Observations	231,344	231,344	231,344
F-stat of the excl. instrument	4.640	4.640	4.640
$\lvert\hat{\rho}\rvert$	0.499	0.343	0.433
Avg. outcome	0.687	0.018	0.019
Outcome SD	1.097	0.140	0.097
Province FE	YES	YES	YES
Year-month FE	YES	YES	YES
Province linear time trend	YES	YES	YES
Probability of rain	YES	YES	YES
Municipality characteristics	YES	YES	YES

Notes: This table presents estimates of the second-stage IV model Equation (3) using panel data at municipality-year-month level. Panel A shows results considering a treatment dummy for the FFF event as the endogenous variable. Panel B examines results using the number of FFF strikers per capita as an alternative endogenous treatment. In Panel B, the number of observations is net of treated municipalities with missing information on the number of strikers. In both panels, the endogenous variable (i.e., FFF event or FFF strikers per capita) is instrumented by rainfall (mm) on March 15, 2019, the date of the first FFF event. The regression controls for province fixed effects, year-month fixed effects, a province linear time trend, and a set of predetermined characteristics of the municipality, including: dummy variables corresponding to the deciles of the historical rain probability distribution (1980-2018), the share of votes for green parties, the share of recycled waste, the per capita number of vehicles, the share of work trips within the municipality, the share of cars, the per capita number of taxpayers, the Gini index, the resident population, the per capita number of public high schools, and a set of dummies for each decile of the population aged 18 years, all of which were measured in 2018. Column (1) reports results for the total number of active volunteer associations per thousand inhabitants. Column (2) presents results for the total number of active environmental volunteer associations per thousand inhabitants. Column (3) displays results for the share of active environmental volunteer associations. Data on volunteer associations are missing for the following Italian regions: Lazio, Apulia, Sardinia, and Veneto. The table reports the estimated degree of endogeneity ($\hat{\rho}$) according to Angrist and Kolesár (2024) as described in the Equation (5): as long as $|\hat{\rho}| < 0.747$, the 95% confidence interval coverage is distorted by no more than 5% for any population F for the first stage. Alternatively, for any $E[F] \geq 7.01$, rejection rates stay below 10% regardless of the degree of endogeneity. This proves that the inference strategy is reliable. Estimates are weighted by the population of each municipality, with standard errors clustered at municipality level. *** p<0.01, ** p<0.05, * p<0.1.

a used car has been purchased, in column (1) of Table 10, we do not observe particularly significant effects on the choice of electric cars (the greener option), but we do find substitution effects between goods potentially subject to different traffic restrictions (columns (2) to (5)), which lead us to explore an alternative potential driver of these effects.

Second, we test for potential rationale-driven consumer responses triggered by climate protests in their areas of residence. We investigated consumers' reactions to the political pressure exerted by FFF by examining the substitution effect occurring in the second-hand car market between different engine types according to European Emis-

Table 10: Mechanism - Engine Types (IV)

	(1) Share Electric	(2) Share Petrol	(3) Share Mixed-Petrol	(4) Share Diesel	(5) Share Gas
Panel A: FFF event	0.004	0.066**	0.007	-0.090**	0.005***
	(0.002)	(0.031)	(0.007)	(0.036)	(0.001)
Observations	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
$\lvert\hat{\rho}\rvert$	0.376	0.451	0.327	0.590	0.801
Avg. outcome	0.004	0.342	0.049	0.547	0.002
Outcome SD	0.025	0.231	0.093	0.259	0.018
Panel B: FFF strikers per capita	0.075	1.682*	0.121	-1.886*	0.118**
	(0.057)	(0.951)	(0.164)	(1.008)	(0.047)
Observations	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
$\lvert\hat{\rho}\rvert$	0.547	0.752	0.343	0.759	0.916
Avg. outcome	0.004	0.341	0.049	0.547	0.002
Outcome SD	0.025	0.233	0.094	0.261	0.018
Province FE	YES	YES	YES	YES	YES
Year-month FE	YES	YES	YES	YES	YES
Province linear time trend	YES	YES	YES	YES	YES
Probability of rain	YES	YES	YES	YES	YES
Municipality characteristics	YES	YES	YES	YES	YES

Notes: This table presents estimates of the second-stage IV model Equation (3) using panel data at municipality-year-month level. Panel A reports results considering a treatment dummy for the FFF event as the endogenous variable. Panel B examines results using the number of FFF strikers per capita as an alternative endogenous treatment. In Panel B, the number of observations is net of treated municipalities with missing information on the number of strikers. In both panels, the endogenous variable (i.e., FFF event or FFF strikers per capita) is instrumented by rainfall (mm) on March 15, 2019, the date of the first FFF event. The regression controls for province fixed effects, year-month fixed effects, a province linear time trend, and a set of predetermined characteristics of the municipality, including: dummy variables corresponding to the deciles of the historical rain probability distribution (1980-2018), the share of votes for green parties, the share of recycled waste, the per capita number of vehicles, the share of work trips within the municipality, the share of cars, the per capita number of taxpayers, the Gini index, the resident population, the per capita number of public high schools, and a set of dummies for each decile of the population aged 18 years, all of which were measured in 2018. Columns (1) to (5) present results for the share of cars purchased with the following engine types: electric, petrol, mixed-petrol, diesel, and gas (e.g., methane or LPG). The electric category also includes full-hybrid and mild-hybrid electric cars, which are not classified under the mixed-petrol category. The table reports the estimated degree of endogeneity ($\hat{\rho}$) according to Angrist and Kolesár (2024) as described in the Equation (5): as long as $\lvert\hat{\rho}\rvert < 0.747$, the 95% confidence interval coverage is distorted by no more than 5% for any population F for the first stage. Alternatively, for any $E[F] \geq 7.01$, rejection rates stay below 10% regardless of the degree of endogeneity. This proves that the inference strategy is reliable. Estimates are weighted by the population of each municipality, with standard errors clustered at municipality level. *** p<0.01, ** p<0.05, * p<0.1.

sion Standards (EES).[55] These are currently the main indicators used for local policy targeting, such as limited traffic areas or the blocking of vehicular traffic for specific types of vehicles based on their emissions.[56]

[55] These are typically referred to as Euro 1, Euro 2, Euro 3, Euro 4, Euro 5, and Euro 6. These classes are defined at European level and label automobiles based on their year of registration and their CO2 emissions. Specifically, E1 labels cars registered from 1993 to 1996, E2 those from 1997 to 2000, E3 those from 2001 to 2005, E4 those from 2006 to 2010, E5 those from 2011 to 2014, and E6 those registered from 2015 onwards.

[56] Limited traffic areas function through mechanisms where a magnetic loop placed under the road surface detects vehicles in transit, while a camera captures the license plate number and transmits the data to a central system. This system quickly determines whether the vehicle is authorized. Regarding the blocking of vehicular traffic, when certain concentrations of pollutants in the atmosphere are reached, measures are taken to temporarily block the circulation of more polluting vehicles to allow the re-establishment of acceptable concentration limits. These policies usually define the EES class and the engine type of vehicles for which circulation is limited, as well as the area where the restriction applies.

In Table 10, we find that FFF events 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 minimal) rise in gas-powered cars. These findings provide robust evidence of a substitution effect taking place between diesel and petrol cars as an 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 environment-related traffic restrictions. This implication is further reinforced by empirical evidence showing that there are no strong and significant results for electric cars—an outcome we would expect to see if FFF had influenced consumer behavior through social norms, leading them to opt for purely green products.

To further investigate this mechanism, Table 11 presents our results on car transactions categorized by EES. Specifically, Panel A reports transactions relating to petrol cars, while Panel B reports those for diesel cars. We observe a sharp decrease in the number of diesel cars per 1,000 inhabitants in almost all EES classes, with a significant reduction even in class E6, which is the least polluting among diesel cars but has a higher likelihood of being targeted by traffic limitations than its petrol counterpart.[57] When examining petrol cars, we observe the reduction only for EES classes E4 and E5.

Overall, these results lead to an increase in the share of E6 petrol cars and a decline in the share of both E5 and E4 diesel cars, as demonstrated in Figure 4. 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.

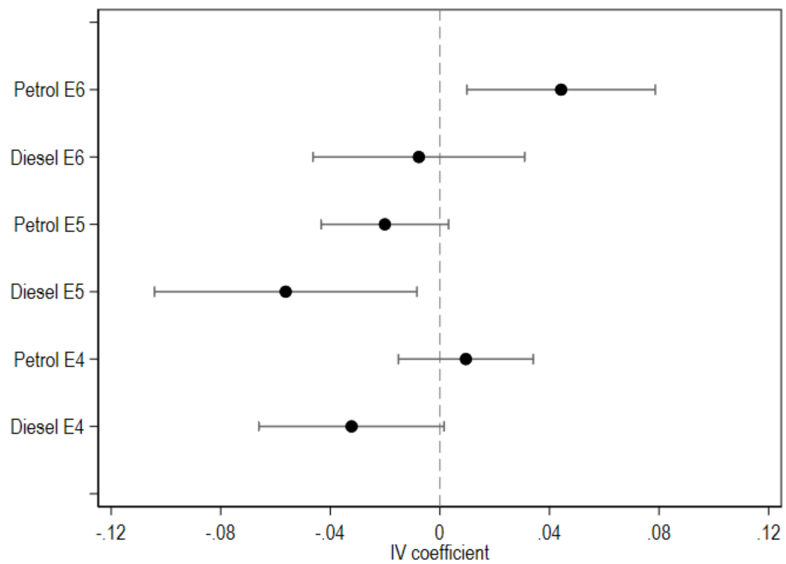
[57]Generally, we do not observe any significant effect on classes E1 to E3, as the market share of these vehicles is smaller and they often represent cars that may have special permission to circulate due to their historical significance. For more details (in Italian), see: https://web.aci.it/auto-storiche-e-turismo/i-veicoli-storici-la-normativa-di-riferimento/.

Table 11: Mechanism - EES Classes (IV)

Outcome: Number of cars per 1,000 inhabitants for each EES class	(1) Class E1	(2) Class E2	(3) Class E3	(4) Class E4	(5) Class E5	(6) Class E6
Panel A: Petrol cars						
FFF event	0.000	-0.017	-0.097	-0.143*	-0.211***	0.059
	(0.000)	(0.025)	(0.067)	(0.079)	(0.070)	(0.066)
$\lvert\hat{\rho}\rvert$	0.138	0.187	0.267	0.372	0.573	0.342
Avg. outcome	0.000	0.133	0.491	0.386	0.318	0.311
Outcome SD	0.004	0.388	0.798	0.790	0.624	0.571
Panel B: Diesel cars						
FFF event	-0.000	-0.016	-0.175*	-0.434**	-0.546***	-0.292**
	(0.000)	(0.015)	(0.099)	(0.169)	(0.206)	(0.114)
$\lvert\hat{\rho}\rvert$	0.108	0.250	0.303	0.534	0.616	0.521
Avg. outcome	0.000	0.041	0.529	0.642	0.803	0.609
Outcome SD	0.001	0.218	0.893	1.160	1.049	0.819
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
Year-month FE	YES	YES	YES	YES	YES	YES
Province linear time trend	YES	YES	YES	YES	YES	YES
Probability of rain	YES	YES	YES	YES	YES	YES
Municipality characteristics	YES	YES	YES	YES	YES	YES

Notes: This table presents estimates of the second-stage IV model Equation (3) using panel data at municipality-year-month level. In both panels, the endogenous treatment variable is a dummy for the FFF event and it is instrumented by rainfall (mm) on March 15, 2019, the date of the first FFF event. The regression controls for province fixed effects, year-month fixed effects, a province linear time trend, and a set of predetermined characteristics of the municipality, including: dummy variables corresponding to the deciles of the historical rain probability distribution (1980-2018), the share of votes for green parties, the share of recycled waste, the per capita number of vehicles, the share of work trips within the municipality, the share of cars, the per capita number of taxpayers, the Gini index, the resident population, the per capita number of public high schools, and a set of dummies for each decile of the population aged 18 years, all of which were measured in 2018. Panel A, columns (1) to (6), reports results for the total per capita number of petrol cars purchased belonging to each of the six emission classes defined by the European Emission Standards (EES). Panel B displays the corresponding results for diesel cars. The table reports the estimated degree of endogeneity ($\hat{\rho}$) according to Angrist and Kolesár (2024) as described in the Equation (5): as long as $|\hat{\rho}| < 0.747$, the 95% confidence interval coverage is distorted by no more than 5% for any population F for the first stage. Alternatively, for any $E[F] \geq 7.01$, rejection rates stay below 10% regardless of the degree of endogeneity. This proves that the inference strategy is reliable. Estimates are weighted by the population of each municipality, with standard errors clustered at municipality level. *** p<0.01, ** p<0.05, * p<0.1.

Figure 4: Mechanism - EES Classes (IV) - Shares



Notes: This figure shows estimates of the second-stage IV model Equation (3) using panel data at municipality-year-month level, where different outcomes are displayed on the vertical axis of each graph. Outcome variables measure the share of petrol/diesel cars purchased for each emission class in the range E4-E6 as defined by the European Emission Standards (EES). The endogenous treatment variable, a dummy for the FFF event, is instrumented by rainfall (mm) on March 15, 2019, the date of the first FFF event. The regression controls for province fixed effects, year-month fixed effects, a province linear time trend, and a set of predetermined characteristics of the municipality, including: dummy variables corresponding to the deciles of the historical rain probability distribution (1980-2018), the share of votes for green parties, the share of recycled waste, the per capita number of vehicles, the share of work trips within the municipality, the share of cars, the per capita number of taxpayers, the Gini index, the resident population, the per capita number of public high schools, and a set of dummies for each decile of the population aged 18 years, all of which were measured in 2018. Estimates are weighted by the population of each municipality and 95% confidence intervals are obtained after clustering the standard errors at municipality level.

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 serious mobility limitations, consumers seem to react by switching to safer options, in particular cars that are prospectively less subject to severe traffic restrictions, rather than completely transitioning to the greenest electric cars.

5.2 Heterogeneity Analysis

Figure 5 presents the results of the heterogeneity analysis by age classes. Here, we divided consumers into ten different age groups, reported on the vertical axis of each graph, and examined their consumption choices. Specifically, Panel (a) reports results for the number of cars purchased per 1,000 inhabitants, while Panel (b) shows results for the total CO2 per car. Panels (c) and (d) display results for the share of cars purchased belonging to the first and fourth quartiles of the CO2 distribution, respectively. We find that the reductions in the number of cars and in their average CO2 are primarily driven by individuals younger than 30 years, with the strongest effect observed in the 18-25 year age group, who are likely to be closer to the FFF movement and more concerned about climate change. Moreover, we observe a sharp reduction in the number of automobiles for individuals aged 51-55 years, who also show the largest decrease in the share of high-emission cars (Panel (d)).[58] When we examine the share of low-emission cars in Panel (c), the results appear to be driven primarily by individuals aged 26-45 years, while those aged 18-25 do not show significant changes in the share of high-/low-emission cars—a result that contrasts with the findings in Panel (b) for the same age group.

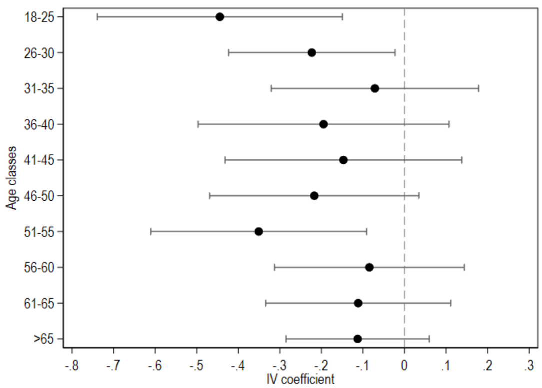
For this reason, to further explore the behavior of individuals aged 18-28, we replicate the analysis by engine types for this age group in Table 12. We find that, when buying a car, diesel vehicles are disregarded, as evinced by the sharp drop in the share of these types of cars (column (4)), which are perceived as more polluting. However, we do not observe clear substitution patterns between vehicles potentially subject to different regulations. All in all, these findings provide evidence that individuals aged 18-25 are induced by FFF to adopt pro-environmental behaviors that might not be directly connected to the anticipation of tighter regulations but are probably more related to

[58]Fabel *et al.* (2022) argue that children influenced by FFF were able to influence the political behavior of their parents in favor of green parties. Unfortunately, our data do not allow us to investigate this potential inter-generational transmission directly. We can only speculate that individuals aged 51-55 may have children who are close in age to the FFF movement, given that the average age for having a first child in Italy ranges from 28 to 32 years; see: https://www.istat.it/demografiadelleuropa/bloc-2b.html?lang=it.

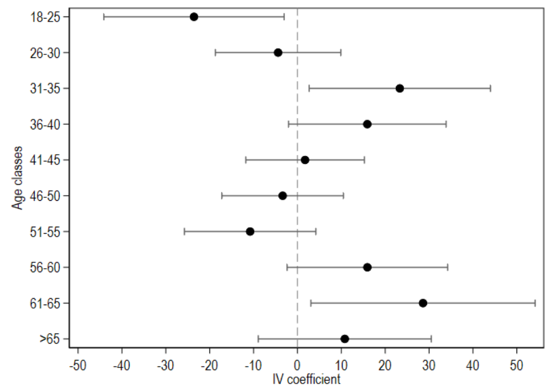
the impact of FFF on consumers through social norms.

Figure 5: Heterogeneity - Age Classes

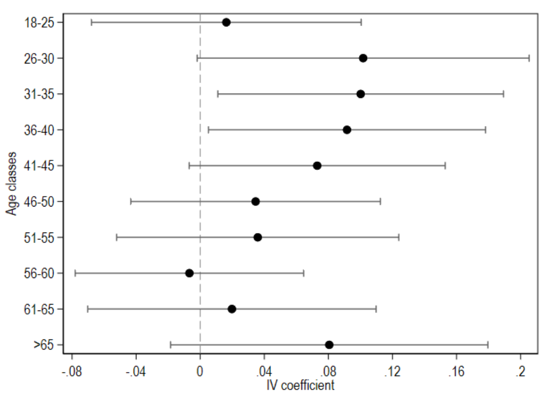
(a) Number of cars per 1,000 inhabitants



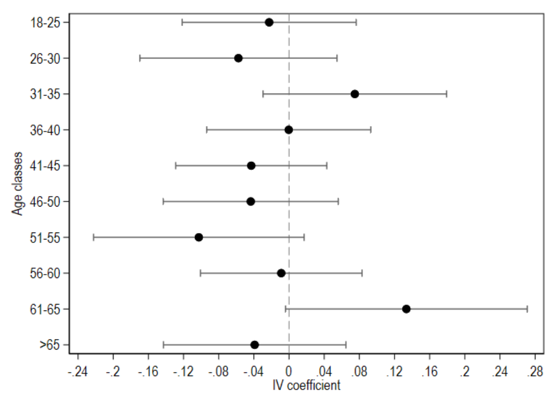
(b) Tot. CO2 per car



(c) Share of low-CO2 cars (Q1)



(d) Share of high-CO2 cars (Q4)



Notes: This figure shows estimates of the second-stage IV model Equation (3) using panel data at municipality-year-month level, where the outcome is measured separately for each age class, which are displayed on the vertical axis of each graph. In all the panels, the endogenous treatment variable, a dummy for the FFF event, is instrumented by rainfall (mm) on March 15, 2019, the date of the first FFF event. The regression controls for province fixed effects, year-month fixed effects, a province linear time trend, and a set of predetermined characteristics of the municipality, including: dummy variables corresponding to the deciles of the historical rain probability distribution (1980-2018), the share of votes for green parties, the share of recycled waste, the per capita number of vehicles, the share of work trips within the municipality, the share of cars, the per capita number of taxpayers, the Gini index, the resident population, the per capita number of public high schools, and a set of dummies for each decile of the population aged 18 years, all of which were measured in 2018. Panel (a) reports results for the number of cars purchased per 1,000 inhabitants, while Panel (b) shows results for the total CO2 per car. Panels (c) and (d) display results for the share of cars purchased belonging to the first and fourth quartiles of the CO2 distribution, respectively. Estimates are weighted by the population of each municipality and 95% confidence intervals are obtained after clustering the standard errors at municipality level.

Table 12: Engine Types (IV) - by Age Class 18-25

	(1) Share Electric	(2) Share Petrol	(3) Share Mixed-Petrol	(4) Share Diesel	(5) Share Gas
Panel A: FFF event	0.006	0.051	-0.006	-0.214***	0.001
	(0.004)	(0.055)	(0.013)	(0.083)	(0.002)
Observations	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
$\lvert\hat{\rho}\rvert$	0.340	0.207	0.151	0.626	0.213
Avg. outcome	0.001	0.216	0.028	0.253	0.001
Outcome SD	0.027	0.352	0.127	0.379	0.020
Panel B: FFF strikers per capita	0.107	0.625	-0.093	-4.505**	0.040
	(0.099)	(1.275)	(0.310)	(2.141)	(0.039)
Observations	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
$\lvert\hat{\rho}\rvert$	0.317	0.318	0.512	0.732	0.506
Avg. outcome	0.001	0.212	0.027	0.250	0.001
Outcome SD	0.027	0.353	0.127	0.379	0.020
Province FE	YES	YES	YES	YES	YES
Year-month FE	YES	YES	YES	YES	YES
Province linear time trend	YES	YES	YES	YES	YES
Probability of rain	YES	YES	YES	YES	YES
Municipality characteristics	YES	YES	YES	YES	YES

Notes: This table presents estimates of the second-stage IV model Equation (3) using panel data at municipality-year-month level. Panel A reports results considering a treatment dummy for the FFF event as the endogenous variable. Panel B examines results using the number of FFF strikers per capita as an alternative endogenous treatment. In Panel B, the number of observations is net of treated municipalities with missing information on the number of strikers. In both panels, the endogenous variable (i.e., FFF event or FFF strikers per capita) is instrumented by rainfall (mm) on March 15, 2019, the date of the first FFF event. The regression controls for province fixed effects, year-month fixed effects, a province linear time trend, and a set of predetermined characteristics of the municipality, including: dummy variables corresponding to the deciles of the historical rain probability distribution (1980-2018), the share of votes for green parties, the share of recycled waste, the per capita number of vehicles, the share of work trips within the municipality, the share of cars, the per capita number of taxpayers, the Gini index, the resident population, the per capita number of public high schools, and a set of dummies for each decile of the population aged 18 years, all of which were measured in 2018. Columns (1) to (5) present results for the share of cars purchased with the following engine types: electric, petrol, mixed-petrol, diesel, and gas (e.g., methane or LPG). The electric category also includes full-hybrid and mild-hybrid electric cars, which are not classified under the mixed-petrol category. All the outcomes are measured for car buyers aged 18-25 years. The table reports the estimated degree of endogeneity ($\hat{\rho}$) according to Angrist and Kolesár (2024) as described in the Equation (5): as long as $|\hat{\rho}| < 0.747$, the 95% confidence interval coverage is distorted by no more than 5% for any population F for the first stage. Alternatively, for any $E[F] \geq 7.01$, rejection rates stay below 10% regardless of the degree of endogeneity. This proves that the inference strategy is reliable. Estimates are weighted by the population of each municipality, with standard errors clustered at municipality level. *** p<0.01, ** p<0.05, * p<0.1, + p<0.15.

Finally, in Appendix Table A.10, we analyze heterogeneous effects between males and females. We find results that are similar qualitatively but more intense for females if compared to the sample average and SD, as has also been observed in other studies (Laroche *et al.*, 2001; Brough *et al.*, 2016).

6 Concluding Remarks

This paper studies the consumption effects of climate activism, with a specific focus on FFF, which has recently boosted global climate protests. While environmental concerns have increasingly dominated the public debate, the impact of such movements on consumers' choices remains understudied. We estimate the effects of FFF by employing an instrumental variable approach based on precipitation levels on the day of the first climate strike to establish causality.

Our findings reveal a significant impact of FFF on consumer choices. In particular, we observe a reduction in the number of cars purchased per 1,000 inhabitants as well as in their average CO2 emissions, associated with a rise in the share of low-emission vehicles and a fall in high-emission ones.

Our investigation highlights how the observed shifts in consumption patterns are potentially driven by two alternative mechanisms. On the one hand, by shaping social norms, FFF events might promote greener purchasing behaviors. On the other hand, the political pressure exerted by the FFF movement may have induced consumers to rationally anticipate stricter future environmental regulations. Empirical evidence suggests that the latter mechanism is generally more pronounced than the former. However, the first channel seems likely to be at work among individuals aged 18-25, who are potentially more involved in the FFF movement.

These results offer useful insights into the interplay between climate activism, consumer decisions, and environmental policy. Moreover, they could be confirmed for similar European second-hand automobile markets, and our methodology can, in principle, be applied to many other countries. This is because it focuses on global FFF strikes that occurred concurrently worldwide. Overall, these findings hold significance for policymakers aiming to promote environmentally sustainable consumption, locally and globally.

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Appendix

Appendix.1 Additional Tables and Figures

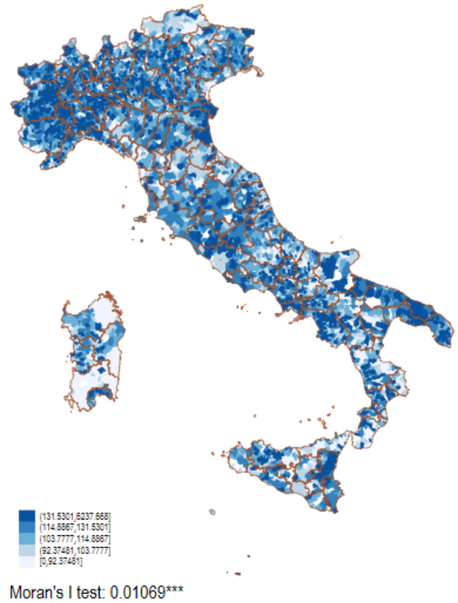
Table A.1: Summary Statistics - Car Data

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)
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)
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)
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)
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)
Observations: 2,408,519		

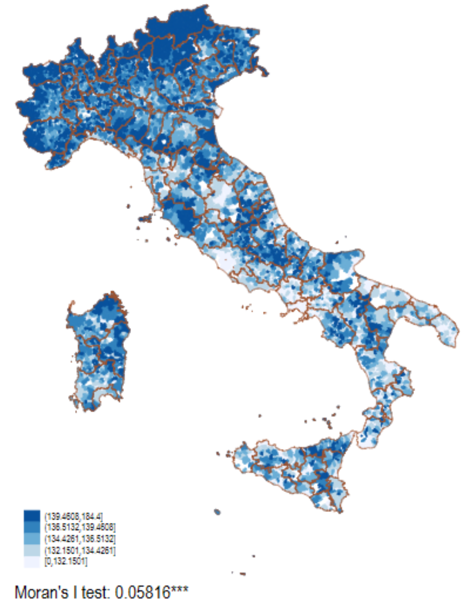
Notes: The table reports summary statistics for car microdata based on car sales occurring between January 2017 and February 2020 in Italy. Summary statistics refer only to the municipalities (treated and controls) included in the panel for analysis shown in Table 1 (i.e., 7,772 municipalities out of 7,904 municipalities in Italy). Panel 1 reports summary statistics for the entire sample, while Panels 2 to 5 display summary statistics for each quartile of the CO2 emission distribution.

Figure A.1: Maps of Baseline Outcomes in the pre-FFF Period

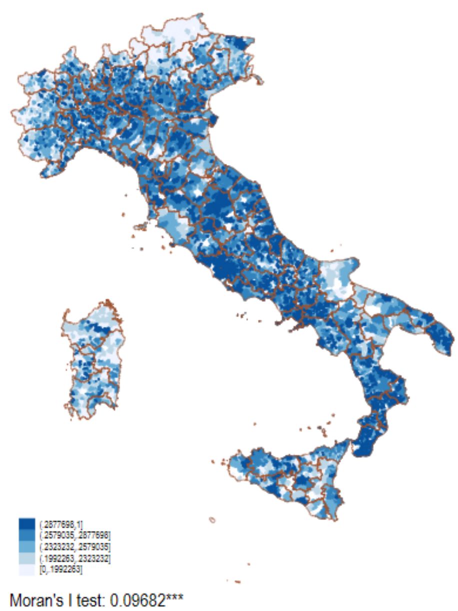
(a) Number of cars per 1,000 inhabitants



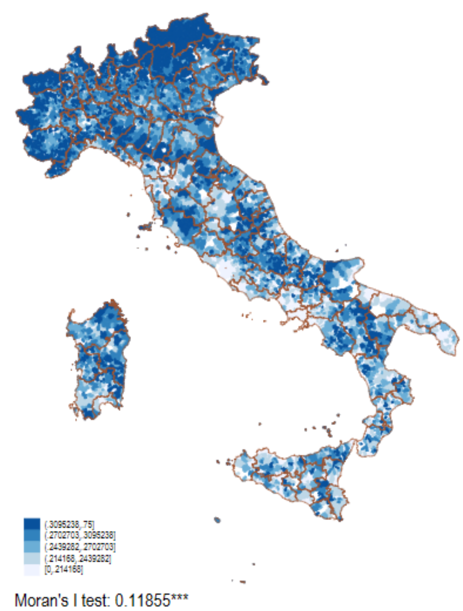
(b) Tot. CO2 per car



(c) Share of low-CO2 cars (Q1)



(d) Share of high-CO2 cars (Q4)



Notes: This figure depicts the geographical distribution of baseline outcomes measured before the FFF event of March 15, 2019. Specifically, variables are measured in the period from January 2017 to February 2019. Panel (a) shows the number of cars purchased per 1,000 inhabitants, while Panel (b) reports the total CO2 per car. Panels (c) and (d) display the share of cars purchased belonging to the first and fourth quartiles of the CO2 distribution, respectively. Finally, at the bottom of the graph on the left, we also report the results of the univariate Moran's I test with a binary spatial weights matrix to ensure that each municipality is connected to at least one other municipality. Two municipalities are defined as close if the distance between them is no more than 145.2 km. *** p<0.01, ** p<0.05, * p<0.1

Table A.2: GLS Estimates – Baseline Results

	(1) Number of cars per 1,000 inhabitants	(2) Tot. CO2 per car	(3) Share low CO2 (Quartile 1)	(4) Share high CO2 (Quartile 4)
Panel A: FFF event	-0.176***	-0.686**	0.006***	-0.006***
	(0.033)	(0.312)	(0.001)	(0.001)
Observations	295,336	295,336	295,336	295,336
F-stat	27.75	5.926	9.237	12.73
Avg. outcome	4.530	127.7	0.235	0.251
Outcome SD	3.849	34.14	0.192	0.204
Panel B: FFF strikers per capita	0.281	2.147	-0.038*	0.045*
	(0.690)	(1.678)	(0.022)	(0.027)
Observations	288,648	288,648	288,648	288,648
F-stat	23.76	6.188	9.788	11.09
Avg. outcome	4.535	127.6	0.234	0.251
Outcome SD	3.888	34.45	0.194	0.206
Province FE	YES	YES	YES	YES
Year-month FE	YES	YES	YES	YES
Province linear time trend	YES	YES	YES	YES
Probability of rain	YES	YES	YES	YES
Municipality characteristics	YES	YES	YES	YES

Notes: This table presents the generalized least square (GLS) estimates relating to the IV analysis shown in Table 4, using panel data at municipality-year-month level. Panel A reports results considering a treatment dummy for the FFF event as the endogenous variable. Panel B examines results using the number of FFF strikers per capita as an alternative endogenous treatment. In Panel B, the number of observations is net of treated municipalities with missing information on the number of strikers. The regression controls for province fixed effects, year-month fixed effects, a province linear time trend, and a set of predetermined characteristics of the municipality, including: dummy variables corresponding to the deciles of the historical rain probability distribution (1980-2018), the share of votes for green parties, the share of recycled waste, the per capita number of vehicles, the share of work trips within the municipality, the share of cars, the per capita number of taxpayers, the Gini index, the resident population, the per capita number of public high schools, and a set of dummies for each decile of the population aged 18 years, all of which were measured in 2018. Column (1) reports results for the number of cars purchased per 1,000 inhabitants. Column (2) shows results for the total CO2 emissions per car purchased. Columns (3) and (4) present results for the share of cars purchased belonging to the first and fourth quartiles of the CO2 distribution, respectively. Estimates are weighted by the population of each municipality, with standard errors clustered at municipality level. *** p<0.01, ** p<0.05, * p<0.1.

Table A.3: Reduced-Form Estimates – Baseline Results

	(1) Number of cars per 1,000 inhabitants	(2) Tot. CO2 per car	(3) Share low CO2 (Quartile 1)	(4) Share high CO2 (Quartile 4)
FFF event precipitation (mm)	0.059***	0.273***	-0.002***	0.003***
	(0.018)	(0.082)	(0.001)	(0.001)
Observations	295,336	295,336	295,336	295,336
F-stat	27.49	6.248	9.088	10.61
Avg. outcome	4.530	127.7	0.235	0.251
Outcome SD	3.849	34.14	0.192	0.204
Province FE	YES	YES	YES	YES
Year-month FE	YES	YES	YES	YES
Province linear time trend	YES	YES	YES	YES
Probability of rain	YES	YES	YES	YES
Municipality characteristics	YES	YES	YES	YES

Notes: This table presents estimates of the reduced-form IV model Equation (2) using panel data at municipality-year-month level. Outcomes are regressed on the rainfall (mm) instrument, measured on March 15, 2019, the date of the first FFF event. The regression controls for province fixed effects, year-month fixed effects, a province linear time trend, and a set of predetermined characteristics of the municipality, including: dummy variables corresponding to the deciles of the historical rain probability distribution (1980-2018), the share of votes for green parties, the share of recycled waste, the per capita number of vehicles, the share of work trips within the municipality, the share of cars, the per capita number of taxpayers, the Gini index, the resident population, the per capita number of public high schools, and a set of dummies for each decile of the population aged 18 years, all of which were measured in 2018. Column (1) reports results for number of cars purchased per 1,000 inhabitants. Column (2) shows results for the total CO2 emissions per car purchased. Columns (3) and (4) present results for the share of cars purchased belonging to the first and fourth quartiles of the CO2 distribution, respectively. Estimates are weighted by the population of each municipality, with standard errors clustered at municipality level. The results are qualitatively and quantitatively similar when estimates are calculated based on the number of observations, excluding those with missing information on strikers (see Table 4, Panel B). These results are available upon request from the authors. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.4: IV Results – Share Emission Mid-quartiles

	(1) Share mid-low CO2 (Quartile 2)	(2) Share mid-high CO2 (Quartile 3)
Panel A: FFF event	0.012	-0.004
	(0.017)	(0.016)
Observations	295,336	295,336
F-stat of the excl. instrument	14.62	14.62
$\lvert\hat{\rho}\rvert$	0.135	0.106
Avg. outcome	0.225	0.233
Outcome SD	0.188	0.190
Panel B: FFF strikers per capita	0.602	-0.071
	(0.473)	(0.394)
Observations	288,648	288,648
F-stat of the excl. instrument	7.236	7.236
$\lvert\hat{\rho}\rvert$	0.562	1.230
Avg. outcome	0.225	0.232
Outcome SD	0.190	0.192
Province FE	YES	YES
Year-month FE	YES	YES
Province linear time trend	YES	YES
Probability of rain	YES	YES
Municipality characteristics	YES	YES

Notes: This table presents estimates of the second-stage IV model Equation (3) using panel data at municipality-year-month level. Panel A shows results considering a treatment dummy for the FFF event as the endogenous variable. Panel B examines results using the number of FFF strikers per capita as an alternative endogenous treatment. In Panel B, the number of observations is net of treated municipalities with missing information on the number of strikers. In both panels, the endogenous variable (i.e., FFF event or FFF strikers per capita) is instrumented by rainfall (mm) on March 15, 2019, the date of the first FFF event. The regression controls for province fixed effects, year-month fixed effects, a province linear time trend, and a set of predetermined characteristics of the municipality, including: dummy variables corresponding to the deciles of the historical rain probability distribution (1980-2018), the share of votes for green parties, the share of recycled waste, the per capita number of vehicles, the share of work trips within the municipality, the share of cars, the per capita number of taxpayers, the Gini index, the resident population, the per capita number of public high schools, and a set of dummies for each decile of the population aged 18 years, all of which were measured in 2018. Columns (1) and (2) present results for the share of cars purchased belonging to the second and third quartiles of the CO2 distribution, respectively. The table reports the estimated degree of endogeneity ($\hat{\rho}$) according to Angrist and Kolesár (2024) as described in the Equation (5): as long as $|\hat{\rho}| < 0.747$, the 95% confidence interval coverage is distorted by no more than 5% for any population F for the first stage. Alternatively, for any $E[F] \geq 7.01$, rejection rates stay below 10% regardless of the degree of endogeneity. This proves that the inference strategy is reliable. Estimates are weighted by the population of each municipality, with standard errors clustered at municipality level. *** p<0.01, ** p<0.05, * p<0.1.

Table A.5: IV Baseline Results – New Cars

	(1) Number of cars per 1,000 inhabitants	(2) Tot. CO2 per car	(3) Share low CO2 (Quartile 1)	(4) Share high CO2 (Quartile 4)
Panel A: FFF event	0.041	-8.173	0.079**	-0.134**
	(0.165)	(9.901)	(0.041)	(0.057)
Observations	295,336	295,336	295,336	295,336
F-stat of the excl. instrument	14.62	14.62	14.62	14.62
$\lvert\hat{\rho}\rvert$	0.247	0.140	0.386	0.487
Avg. outcome	0.901	70.70	0.158	0.145
Outcome SD	1.255	59.93	0.261	0.254
Panel B: FFF strikers per capita	-1.406	-269.320	1.725+	-2.988**
	(3.681)	(220.223)	(1.050)	(1.459)
Observations	288,648	288,648	288,648	288,648
F-stat of the excl. instrument	7.236	7.236	7.236	7.236
$\lvert\hat{\rho}\rvert$	0.029	0.198	0.580	0.640
Avg. outcome	0.90	69.99	0.156	0.143
Outcome SD	1.26	60.06	0.262	0.255
Province FE	YES	YES	YES	YES
Year-month FE	YES	YES	YES	YES
Province linear time trend	YES	YES	YES	YES
Probability of rain	YES	YES	YES	YES
Municipality characteristics	YES	YES	YES	YES

Notes: This table presents estimates of the second-stage IV model Equation (3) using panel data at municipality-year-month level. Panel A shows results considering a treatment dummy for the FFF event as the endogenous variable. Panel B examines results using the number of FFF strikers per capita as an alternative endogenous treatment. In Panel B, the number of observations is net of treated municipalities with missing information on the number of strikers. In both panels, the endogenous variable (i.e., FFF event or FFF strikers per capita) is instrumented by rainfall (mm) on March 15, 2019, the date of the first FFF event. The regression controls for province fixed effects, year-month fixed effects, a province linear time trend, and a set of predetermined characteristics of the municipality, including: dummy variables corresponding to the deciles of the historical rain probability distribution (1980-2018), the share of votes for green parties, the share of recycled waste, the per capita number of vehicles, the share of work trips within the municipality, the share of cars, the per capita number of taxpayers, the Gini index, the resident population, the per capita number of public high schools, and a set of dummies for each decile of the population aged 18 years, all of which were measured in 2018. Column (1) reports results for the number of new cars purchased per 1,000 inhabitants. Column (2) shows results for the total CO2 emissions per new car. Columns (3) and (4) present results for the share of new cars purchased belonging to the first and fourth quartiles of the CO2 distribution, respectively. The table reports the estimated degree of endogeneity ($\hat{\rho}$) according to Angrist and Kolesár (2024) as described in the Equation (5): as long as $|\hat{\rho}| < 0.747$, the 95% confidence interval coverage is distorted by no more than 5% for any population F for the first stage. Alternatively, for any $E[F] \geq 7.01$, rejection rates stay below 10% regardless of the degree of endogeneity. This proves that the inference strategy is reliable. Estimates are weighted by the population of each municipality, with standard errors clustered at municipality level. *** p<0.01, ** p<0.05, * p<0.1. + p<0.15

Table A.6: First-Stage Estimates – Two-period Panel

	(1) FFF event	(2) FFF strikers per 1,000 inhabitants
FFF day precipitation (mm)	-0.035***	-1.460**
	(0.011)	(0.573)
Observations	15,544	15,192
F-stat	76.10	21.75
F-stat of the excluded instrument	10.93	6.490
Province FE	YES	YES
Time FE	YES	YES
Probability of rain	YES	YES
Municipality characteristics	YES	YES

Notes: This table presents estimates of the first-stage IV model equation using panel data for two time periods at municipality level. Column (1) reports results considering a treatment dummy for the FFF event as the endogenous variable. Column (2) examines results using the number of FFF strikers per 1,000 inhabitants as an alternative endogenous treatment. In column (2), the number of observations is net of treated municipalities with missing information on the number of strikers. In both columns, the endogenous variable (i.e., FFF event or FFF strikers) is instrumented by rainfall (mm) on March 15, 2019, the date of the first FFF event. The regression controls for province fixed effects, a post-FFF-period dummy, and a set of predetermined characteristics of the municipality, including: dummy variables corresponding to the deciles of the historical rain probability distribution (1980-2018), the share of votes for green parties, the share of recycled waste, the per capita number of vehicles, the share of work trips within the municipality, the share of cars, the per capita number of taxpayers, the Gini index, the resident population, the per capita number of public high schools, and a set of dummies for each decile of the population aged 18 years, all of which were measured in 2018. Estimates are weighted by the population of each municipality, with standard errors clustered at municipality level. *** p<0.01, ** p<0.05, * p<0.1.

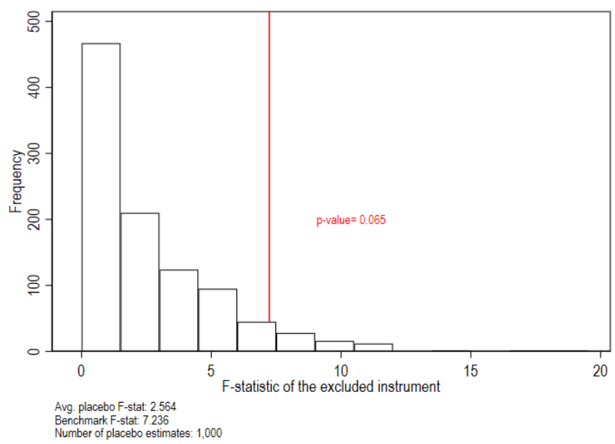
Table A.7: IV Baseline Results – Two-period Panel

	(1) Number of cars per 1,000 inhabitants	(2) Tot. CO2 per car	(3) Share low CO2 (Quartile 1)	(4) Share high CO2 (Quartile 4)
Panel A: FFF event	-31.619**	-5.967***	0.055**	-0.086***
	(15.039)	(2.070)	(0.023)	(0.030)
Observations	15,544	15,544	15,544	15,544
F-stat of the excl. instrument	10.93	10.93	10.93	10.93
$\lvert\hat{\rho}\rvert$	0.859	0.800	0.772	0.857
Avg. outcome	86.08	134.9	0.249	0.269
Outcome SD	68.84	7.346	0.068	0.079
Panel B: FFF strikers per capita	-995.782*	-157.352**	1.467**	-2.167**
	(508.510)	(68.877)	(0.696)	(0.947)
Observations	15,192	15,192	15,192	15,192
F-stat of the excl. instrument	6.915	6.915	6.915	6.915
$\lvert\hat{\rho}\rvert$	0.947	0.910	0.877	0.930
Avg. outcome	86.16	135	0.249	0.269
Outcome SD	69.44	7.409	0.069	0.080
Province FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Probability of rain	YES	YES	YES	YES
Municipality characteristics	YES	YES	YES	YES

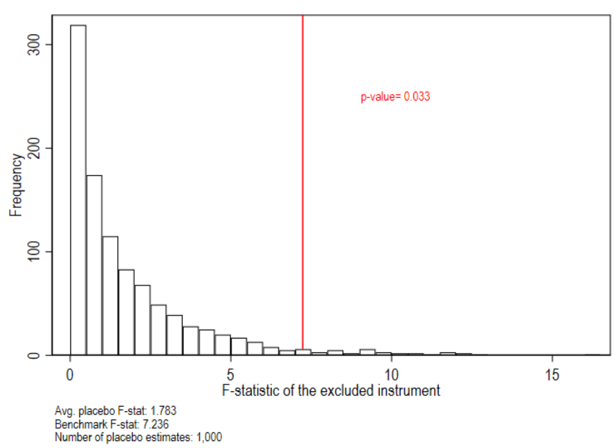
Notes: This table presents estimates of the second-stage IV model equation using panel data for two time periods at municipality level. Panel A shows results considering a treatment dummy for the FFF event as the endogenous variable. Panel B examines results using the number of FFF strikers per capita as an alternative endogenous treatment. In Panel B, the number of observations is net of treated municipalities with missing information on the number of strikers. In both panels, the endogenous variable (i.e., FFF event or FFF strikers per capita) is instrumented by rainfall (mm) on March 15, 2019, the date of the first FFF event. The regression controls for province fixed effects, a post-FFF-period dummy, and a set of predetermined characteristics of the municipality, including: dummy variables corresponding to the deciles of the historical rain probability distribution (1980-2018), the share of votes for green parties, the share of recycled waste, the per capita number of vehicles, the share of work trips within the municipality, the share of cars, the per capita number of taxpayers, the Gini index, the resident population, the per capita number of public high schools, and a set of dummies for each decile of the population aged 18 years, all of which were measured in 2018. Column (1) reports results for the number of cars purchased per 1,000 inhabitants. Column (2) shows results for the total CO2 emissions per car. Columns (3) and (4) present results for the share of cars purchased belonging to the first and fourth quartiles of the CO2 distribution, respectively. The table reports the estimated degree of endogeneity ($\hat{\rho}$) according to Angrist and Kolesár (2024) as described in the Equation (5): as long as $|\hat{\rho}| < 0.747$, the 95% confidence interval coverage is distorted by no more than 5% for any population F for the first stage. Alternatively, for any $E[F] \geq 7.01$, rejection rates stay below 10% regardless of the degree of endogeneity. In Panel B, the F-statistic of the excluded instrument is 6.428, and $|\hat{\rho}| > 0.747$; however, according to Angrist and Kolesár (2024), this is valid as long as $|\hat{\rho}| \leq 0.95$. This proves that the inference strategy is reliable. Estimates are weighted by the population of each municipality, with standard errors clustered at municipality level. *** p<0.01, ** p<0.05, * p<0.1. + p<0.15

Figure A.2: Placebo Analyses of the First-Stage – FFF strikers

(a) Random Assignment of Rainy Days from 2016-2018



(b) Random Reshuffling of Treatment and Precipitation



Notes: This figure plots the distribution of 1,000 placebo estimates of Equation (1) using the number of FFF strikers per capita as endogenous variable. In Panel (a), we estimate placebos by randomly and fictitiously attributing the precipitation values drawn from years 2016-2018 to the FFF event day. In Panel (b), we randomly reshuffle the actual treatment status (FFF strikers) and precipitation. In both panels, the p-value is calculated as the fraction of placebo F-stat of the excluded instrument greater than the actual first-stage F-statistic that is shown as a red vertical line. Below the graph on the left, we report the average placebo F-stat, the benchmark F-stat, and the number of placebo estimates.

Table A.8: IV Robustness Check (5) – Removing Never-Takers

	(1) Number of cars per 1,000 inhabitants	(2) Tot. CO2 per car	(3) Share low CO2 (Quartile 1)	(4) Share high CO2 (Quartile 4)
Panel A: FFF event	-0.577***	-3.248***	0.021***	-0.027***
	(0.158)	(0.985)	(0.008)	(0.009)
Observations	84,854	84,854	84,854	84,854
F-stat of the excl. instrument	121.7	121.7	121.7	121.7
$\lvert\hat{\rho}\rvert$	0.256	0.225	-0.218	0.246
Avg. outcome	4.418	128.6	0.217	0.271
Outcome SD	2.824	36.71	0.195	0.222
Panel B: FFF strikers per capita	-11.816**	-84.612**	0.763**	-0.967**
	(5.129)	(37.451)	(0.311)	(0.385)
Observations	78,166	78,166	78,166	78,166
F-stat of the excl. instrument	12.74	12.74	12.74	12.74
$\lvert\hat{\rho}\rvert$	0.487	0.646	-0.683	0.728
Avg. outcome	4.425	128.2	0.213	0.272
Outcome SD	2.918	38	0.201	0.229
Province FE	YES	YES	YES	YES
Year-month FE	YES	YES	YES	YES
Province linear time trend	YES	YES	YES	YES
Probability of rain	YES	YES	YES	YES
Municipality characteristics	YES	YES	YES	YES

Notes: This table presents estimates of the second-stage IV model Equation (3) using panel data at municipality-year-month level. Panel A shows results considering a treatment dummy for the FFF event as the endogenous variable. Panel B examines results using the number of FFF strikers per capita as an alternative endogenous treatment. In Panel B, the number of observations is net of treated municipalities with missing information on the number of strikers. In both panels, the endogenous variable (i.e., FFF event or FFF strikers per capita) is instrumented by rainfall (mm) on March 15, 2019, the date of the first FFF event. The regression controls for province fixed effects, year-month fixed effects, a province linear time trend, and a set of predetermined characteristics of the municipality, including: dummy variables corresponding to the deciles of the historical rain probability distribution (1980-2018), the share of votes for green parties, the share of recycled waste, the per capita number of vehicles, the share of work trips within the municipality, the share of cars, the per capita number of taxpayers, the Gini index, the resident population, the per capita number of public high schools, and a set of dummies for each decile of the population aged 18 years, all of which were measured in 2018. Column (1) reports results for the number of cars purchased per 1,000 inhabitants. Column (2) shows results for the total CO2 emissions per car purchased. Columns (3) and (4) present results for the share of cars purchased belonging to the first and fourth quartiles of the CO2 distribution, respectively. The table reports the estimated degree of endogeneity ($\hat{\rho}$) according to Angrist and Kolesár (2024) as described in the Equation (5): as long as $|\hat{\rho}| < 0.747$, the 95% confidence interval coverage is distorted by no more than 5% for any population F for the first stage. Alternatively, for any $E[F] \geq 7.01$, rejection rates stay below 10% regardless of the degree of endogeneity. This proves that the inference strategy is reliable. Estimates are weighted by the population of each municipality, with standard errors clustered at municipality level. *** p<0.01, ** p<0.05, * p<0.1.

Table A.9: Robustness Check – First-Stage with Alternative Clustering

	Clustered SE Level			
	Municipal (1)	LLS (2)	Province (3)	Region (4)
Panel A: FFF event	-0.030***	-0.030***	-0.030***	-0.030**
	(0.008)	(0.008)	(0.008)	(0.013)
Observations	295,336	295,336	295,336	295,336
F-stat of the excl. instrument	14.62	16.02	15.24	30.94
Panel B: FFF strikers per 1,000 inh.	-1.336***	-1.336***	-1.336**	-1.336**
	(0.497)	(0.413)	(0.645)	(0.890)
Observations	288,648	288,648	288,648	288,648
F-stat of the excl. instrument	7.236	10.45	4.287	6.732
Number of clusters	7,772	610	107	20
Province FE	YES	YES	YES	YES
Year-month FE	YES	YES	YES	YES
Province linear time trend	YES	YES	YES	YES
Probability of rain	YES	YES	YES	YES
Municipality characteristics	YES	YES	YES	YES

Notes: This table presents estimates of the first-stage IV model Equation (1) using panel data at municipality-year-month level. Panel A reports results considering a treatment dummy for the FFF event as the endogenous variable. Panel B examines results using the number of FFF strikers per 1,000 inhabitants as an alternative endogenous treatment. In Panel B, the number of observations is net of treated municipalities with missing information on the number of strikers. In both panels, the endogenous variable (i.e., FFF event or FFF strikers) is instrumented by rainfall (mm) on March 15, 2019, the date of the first FFF event. The regression controls for province fixed effects, year-month fixed effects, a province linear time trend, and a set of predetermined characteristics of the municipality, including: dummy variables corresponding to the deciles of the historical rain probability distribution (1980-2018), the share of votes for green parties, the share of recycled waste, the per capita number of vehicles, the share of work trips within the municipality, the share of cars, the per capita number of taxpayers, the Gini index, the resident population, the per capita number of public high schools, and a set of dummies for each decile of the population aged 18 years, all of which were measured in 2018. In each column, standard errors (SE) are clustered at a different level. In column (1), SE are clustered at municipality level (baseline). In column (2), SE are clustered at local labor system (LLS) level. In column (3), SE are clustered at provincial level, while column (4) reports wild cluster bootstrap SE at regional level, calculated from the confidence intervals obtained through wild cluster bootstrap inference with 1,000 replications (Panel A: p-value = 0.036, t = -5.56; Panel B: p-value = 0.044, t = -2.59). Estimates are weighted by the population of each municipality. *** p<0.01, ** p<0.05, * p<0.1.

Table A.10: IV Baseline – Heterogeneity by Gender

	(1) Number of cars per 1,000 inhabitants	(2) Tot. CO2 per car	(3) Share low CO2 (Quartile 1)	(4) Share high CO2 (Quartile 4)
Panel A: Females				
FFF event	-0.000**	-9.181**	0.086**	-0.061*
	(0.000)	(4.062)	(0.040)	(0.036)
$\lvert\hat{\rho}\rvert$	0.394	0.505	0.576	0.304
Avg. outcome	0.002	109.7	0.242	0.170
Outcome SD	0.001	50.29	0.264	0.231
Panel B: Males				
FFF event	-0.001***	-8.820**	0.055**	-0.096***
	(0.001)	(3.793)	(0.025)	(0.035)
$\lvert\hat{\rho}\rvert$	0.571	0.567	0.437	0.655
Avg. outcome	0.003	125.2	0.209	0.272
Outcome SD	0.004	42.80	0.212	0.242
Observations	295,336	295,336	295,336	295,336
F-stat of the excl. instrument	14.62	14.62	14.62	14.62
Province FE	YES	YES	YES	YES
Year-month FE	YES	YES	YES	YES
Province linear time trend	YES	YES	YES	YES
Probability of rain	YES	YES	YES	YES
Municipality characteristics	YES	YES	YES	YES

Notes: This table presents estimates of the second-stage IV model Equation (3) using panel data at municipality-year-month level. In both panels, the endogenous variable is a treatment dummy for the FFF event and is instrumented by rainfall (mm) on March 15, 2019, the date of the first FFF event. The regression controls for province fixed effects, year-month fixed effects, a province linear time trend, and a set of predetermined characteristics of the municipality, including: dummy variables corresponding to the deciles of the historical rain probability distribution (1980-2018), the share of votes for green parties, the share of recycled waste, the per capita number of vehicles, the share of work trips within the municipality, the share of cars, the per capita number of taxpayers, the Gini index, the resident population, the per capita number of public high schools, and a set of dummies for each decile of the population aged 18 years, all of which were measured in 2018. Column (1) reports results for the number of cars purchased per 1,000 inhabitants. Column (2) shows results for the total CO2 emissions per car purchased. Columns (3) and (4) present results for the share of cars purchased belonging to the first and fourth quartiles of the CO2 distribution, respectively. Panel A refers to these outcomes measured among females, while Panel B focuses on males. The table reports the estimated degree of endogeneity ($\hat{\rho}$) according to Angrist and Kolesár (2024) as described in the Equation (5): as long as $|\hat{\rho}| < 0.747$, the 95% confidence interval coverage is distorted by no more than 5% for any population F for the first stage. Alternatively, for any $E[F] \geq 7.01$, rejection rates stay below 10% regardless of the degree of endogeneity. This proves that the inference strategy is reliable. Estimates are weighted by the population of each municipality, with standard errors clustered at municipality level. *** p<0.01, ** p<0.05, * p<0.1.

Appendix.2 Multivalued Treatment Effect

In order to properly identify the multivalued treatment effect 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 period after the first FFF event.[59] Therefore, we estimate the following first-stage equation to estimate the multivalued treatment effect:

$$NFFF_{m,t} = \alpha_0^{MV} + \alpha_1^{MV} Rain_{m,t} + \delta_p + \delta_t + \sum_{e=1}^{5} \delta^e_{RP_{e,m}} + \gamma X_m + \xi_{m,t}^{MV} \tag{6}$$

In equation (6), we consider as an excluded instrument the rainfall of the first FFF event, which we consider alternatively either as a continuous measure or as a binary variable defined over the 0.1 inch threshold. We also include as a control the probability of rain related to each month of the subsequent events.[60] δ_p is the province fixed effect and δ_t is a binary variable taking a value of one for the post-treatment period. The matrix X_m includes control for municipality characteristics as described in Section 3. Finally, we estimate the second-stage equation to measure the causal relationship of interest:

$$Y_{m,t} = \beta_0^{MV} + \beta_1^{MV} \widehat{NFFF_{m,t}} + \delta_p + \delta_t + \sum_{e=1}^{5} \delta^e_{RP_{e,m}} + \gamma X_m + \varepsilon_{m,t}^{MV} \tag{7}$$

where the variable $Y_{m,t}$ measures different economic outcomes of interest. Table A.11 shows the corresponding result for our baseline outcomes: CO2 emissions per capita, and the share of low-/high-emission cars. We find that multiple exposure to FFF events further strengthens the baseline effects we have shown in Section 4. Table A.12 shows

[59]Implementing this analysis with a monthly panel would transform the treatment structure into a staggered one, since the treatment status of some municipalities could increase in intensity from one month to the next. This structure could prove problematic in the case of heterogeneous treatment effects (Callaway *et al.*, 2024).

[60]In the Equation (6), the probability of rain is considered for five months, since two of the six FFF strikes occurred in September.

estimates of the Equation (7) when using data about volunteer associations and we do not observe any statistically significant result.

Table A.11: IV Multivalued Treatment Effect – Share of Emissions

	(1) Number of cars per 1,000 inhabitants	(2) Tot. CO2 per car	(3) Share low CO2 (Quartile 1)	(4) Share high CO2 (Quartile 4)
Panel A: Precipitation (mm) IV				
Number of FFF events (exposure)	-6.763**	-0.962**	0.009**	-0.014***
	(3.055)	(0.385)	(0.004)	(0.005)
F-stat of the excluded instrument	10.10	10.10	10.10	10.10
$\lvert\hat{\rho}\rvert$	0.902	0.711	0.749	0.849
Panel B: Rain dummy IV				
Number of FFF events (exposure)	-6.963**	-0.834**	0.010**	-0.015***
	(3.316)	(0.340)	(0.005)	(0.005)
F-stat of the excluded instrument	7.838	7.838	7.838	7.838
$\lvert\hat{\rho}\rvert$	0.929	0.435	0.752	0.776
Observations	15,544	15,544	15,544	15,544
Avg. outcome	86.08	134.9	0.249	0.269
Outcome SD	68.84	7.346	0.068	0.079
Province FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Probability of rain	YES	YES	YES	YES
Municipality characteristics	YES	YES	YES	YES

Notes: This table presents estimates of the second-stage IV model Equation (7) using panel data on two time periods at municipality level. The endogenous treatment variable ($NFFF_{m,t}$) counts the number of FFF events hosted by the municipality m since March 15, 2019, the date of the first FFF event. Panel A shows results considering rainfall (mm) on March 15, 2019 as the exogenous instrumental variable. Panel B examines results using a binary instrumental variable that takes a value of one if a municipality experienced precipitation greater than 0.01 inches (2.54 mm) on the date of the first FFF event. The regression controls for province fixed effects, time fixed effects (namely a dummy variable for the post-treatment period), and a set of predetermined characteristics of the municipality, including: dummy variables corresponding to the deciles of the historical rain probability distribution (1980-2018) for each month of the FFF events, the share of votes for green parties, the share of recycled waste, the per capita number of vehicles, the share of work trips within the municipality, the share of cars, the per capita number of taxpayers, the Gini index, the resident population, the per capita number of public high schools, and a set of dummies for each decile of the population aged 18 years, all of which were measured in 2018. Column (1) reports results for the total per capita CO2 emissions from cars purchased. Columns (2) and (3) present results for the share of cars purchased belonging to the first and fourth quartiles of the CO2 distribution, respectively. The table reports the estimated degree of endogeneity ($\hat{\rho}$) according to Angrist and Kolesár (2024) as described in the Equation (5): as long as $|\hat{\rho}| < 0.747$, the 95% confidence interval coverage is distorted by no more than 5% for any population F for the first stage. Alternatively, for any $E[F] \geq 7.01$, rejection rates stay below 10% regardless of the degree of endogeneity. This proves that the inference strategy is reliable. Estimates are weighted by the population of each municipality, with standard errors clustered at municipality level. *** p<0.01, ** p<0.05, * p<0.1.

Table A.12: IV Multivalued Treatment Effect – Volunteer Associations

	(1) Number of active volunteer associations (per 1,000 inhabitants)	(2) Number of active environmental volunteer associations (per 1,000 inhabitants)	(3) Share of active environmental volunteer associations
Panel A: Precipitation (mm) IV			
Number of FFF events (exposure)	0.024	0.002	0.003
	(0.020)	(0.002)	(0.004)
F-stat of the excluded instrument	9.323	9.323	9.323
$\lvert\hat{\rho}\rvert$	0.224	0.261	0.245
Panel B: Rain dummy IV			
Number of FFF events (exposure)	0.042	0.002	0.006
	(0.029)	(0.004)	(0.006)
F-stat of the excluded instrument	6.338	6.338	6.338
$\lvert\hat{\rho}\rvert$	0.593	0.242	0.389
Observations	12,456	12,456	12,456
Avg. outcome	0.713	0.019	0.020
Outcome SD	1.099	0.141	0.098
Province FE	YES	YES	YES
Time FE	YES	YES	YES
Probability of rain	YES	YES	YES
Municipality characteristics	YES	YES	YES

Notes: This table presents estimates of the second-stage IV model Equation (7) using panel data on two time periods at municipality level. The endogenous treatment variable ($NFFF_{m,t}$) counts the number of FFF events hosted by the municipality m since March 15, 2019, the date of the first FFF event. Panel A shows results considering rainfall (mm) on March 15, 2019, as the exogenous instrumental variable. Panel B examines results using a binary instrumental variable that takes a value of one if a municipality experienced precipitation greater than 0.01 inches (2.54 mm) on the date of the first FFF event. The regression controls for province fixed effects, time fixed effects (namely a dummy variable for the post-treatment period), and a set of predetermined characteristics of the municipality, including: dummy variables corresponding to the deciles of the historical rain probability distribution (1980-2018) for each month of the FFF events, the share of votes for green parties, the share of recycled waste, the per capita number of vehicles, the share of work trips within the municipality, the share of cars, the per capita number of taxpayers, the Gini index, the resident population, the per capita number of public high schools, and a set of dummies for each decile of the population aged 18 years, all of which were measured in 2018. Column (1) reports results for the total number of active volunteer associations per thousand inhabitants. Column (2) presents results for the total number of active environmental volunteer associations per thousand inhabitants. Column (3) displays results for the share of active environmental volunteer associations. Data on volunteer associations are missing for the following Italian regions: Lazio, Apulia, Sardinia, and Veneto. The table reports the estimated degree of endogeneity ($\hat{\rho}$) according to Angrist and Kolesár (2024) as described in the Equation (5): as long as $|\hat{\rho}| < 0.747$, the 95% confidence interval coverage is distorted by no more than 5% for any population F for the first stage. Alternatively, for any $E[F] \geq 7.01$, rejection rates stay below 10% regardless of the degree of endogeneity. This proves that the inference strategy is reliable. Estimates are weighted by the population of each municipality, with standard errors clustered at municipality level. *** p<0.01, ** p<0.05, * p<0.1.

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