MASTER THESIS

PARIS SCHOOL OF ECONOMICS

Natural Disasters, Pollution Peaks and Vote for Green Parties: Do Salient Events Affect Environmental Concerns?

Author

THOMAS BEZY

Under the supervision of

LUCAS CHANCEL and THOMAS PIKETTY

Referee

KATHELINE SCHUBERT

2021-06-29

Abstract

I consider the effect of natural disasters and PM_{10} pollution peaks on the share of votes received by green parties. Natural disasters such as floods and droughts can reduce the psychological distance to climate change and affect perceptions. In the case of pollution peaks, the impact of pollution on health can motivate citizens to change their vote in favor of green parties. The elections scales I consider are Regional, Legislative and European, in France from 2002 to 2019. I study and discuss the effect of standard determinants of the vote for green parties (education, income, age, density and pollution) before adding the effect of the salient events described above. I find a positive and significant effect for floods and pollution peaks for Regional elections only, suggesting that these events have an impact at a local level but do not change views on climate change as a global issue. On the other hand, drought-related disasters appear to have a positive and significant effect for all types of elections, which could mean that droughts and high temperatures are more likely to affect perceptions in the long run. The aggregate effect on green voting is around 1% for all types of disasters. Concerning pollution peaks, I find that they account for about 2.4% of green votes.

Keywords: Air Pollution, Natural Disasters, Political Economy, Voting Behavior

JEL Codes: D72, D91, Q53, Q54

Acknowledgements

I would like to thank particularly my supervisor Lucas Chancel and co-supervisor Thomas Piketty for their continuous support and very helpful comments. I also thank Katheline Schubert for being my referee and for her advice.

I am grateful to Ekatherina Zhuravskaya who helped designing this subject at the beginning of the year and for her very insightful comments during seminar sessions. I also would like to thank Katrin Millock, Laurent Gobillon, Simon Persico and Florent Gougou for sharing their opinion and ideas about this topic. These discussions have helped me a lot in framing this project.

I would like to address a big thank to Pascale Champalaune for the time she took to discuss this project and for the data she gave me on $PM_{2.5}$ pollution levels. This study would have been very different without this contribution!

I also thank the ten ASQAAs who accepted to gather and share their data on pollution levels starting from 2000. Many thanks to Pablo Campargue-Rodriguez and Yann Channac Mongredien who took time to answer my questions and helped me to better understand the processes used by measuring stations.

Finally, on a more personal note, I would like to thank my friends Romaine and Venance who supported and helped me throughout this year of pandemic. Our discussions have been essential to help me designing and developing this project.

Contents

1 Introduction

The Alex storm in the *vallée de Roya* the 2nd of October, 2020 in the South East of France caused the death of 9 people, the degradation of 35km of roads, the collapse of 10 bridges and the destruction of around 200 buildings[1]. As climate change is very likely to increase the occurrence and the severity of these extreme weather events (Huntingford et al., 2014), dealing with their physical consequences will certainly become a major issue.

However, natural disasters do not affect only buildings, they also have a psychological cost. In this paper, I will investigate whether these psychological consequences can affect perceptions on climate change issues by studying the evolution of voting outcomes for green parties in areas that are affected by such events. Psychological distance between individuals and environmental risks can indeed make climate change a more concrete threat (Jones, Hine & Marks, 2017). Moreover I will consider the effect of pollution peaks that could also have the role of salient events affecting perceptions.

To produce this study, I gathered data on natural disasters, socio-professional characteristics and Regional, Legislative and European elections in France from 2002 to 2019. After collecting and harmonizing data from 10 French regions, I also took into account the effect of pollution peaks. Thanks to a dataset built by Pascale Champalaune[2] based on data from the Atmospheric Composition Analysis Group (ACAG), I also incorporated a measure of the average annual $PM_{2.5}$ particules concentration into my econometric models. All dataframes provide information at the level of the municipality, which enables me to have data at a precise level.

The main contributions of this study are the following. First, I provide an analysis of the determinants of the vote for green parties in France. Secondly, I cover the effect of a large panel of salient events: floods, earthquakes, drought-related disasters and PM_{10} pollution peaks. To my knowledge, the effect of pollution peaks on green voting is not documented in the literature. Finally, using the vote for green parties as my outcome variable enables me to examine whether the psychological implications of these salient events have concrete consequences, whereas an analysis based on surveys is not sufficient to know whether survey answers translate in concrete actions.

Results can be grouped into two main sets. First, I find a positive and significant effect for floods and pollution peaks on the vote for green parties, only for Regional elections. These results can be explained by a wish from citizens to avoid floods and pollution peaks in the future, but not by a deep change in their perceptions towards climate change issues. As Regional councils are responsible for landscape design and transportation issues, they are likely to take these local issues into consideration. However, National and European Parliaments operate at a larger scale, which could explain why I do not find any effect for these outcomes.

Secondly, I find a positive and significant effect of drought-related disasters that is robust to every election panel. It suggests that unlike floods and pollution peaks, drought-related disasters can affect perceptions. It could be explained by the fact that these disasters are correlated with very high temperatures, which makes more obvious the link with climate change. This type of result is consistent with Konisky, Hughes & Kaylor (2015) who argued that the effect of natural disasters on perceptions depends on the link that can be made with climate change. It is also consistent with a long-standing literature showing that experiencing high temperatures affects climate change beliefs (see section 2 for more details). I also show that building infrastructures could lower this effect.

In terms of magnitudes, I find consequent effects in the municipalities affected: for floods, PM_{10} pollution

[1] F. Grünewald, Rapport de l'évaluation de la réponse à la tempête Alex dans les Alpes-Maritimes, 2020

[2] Inequality in Exposure to Air Pollution in France: Measurement and Impact of a City-Level Public Policy, Master Thesis, PSE.

peaks (denoted by an alert threshold) and drought-related disasters[3], I observe an increase in green voting that ranges between 1.8% and 3.5% for each event that occurred since the last election[4]. It is equivalent to an increase in the proportion of individuals with a high school diploma of about 5 to 10 percentage points. However, natural disasters concern mostly low populated areas, which explains why their aggregate effect accounts for around 1% of the votes for green parties. Put differently, if all disasters since 2002 had not happened, the share of votes going to green parties would have decreased by around 1% for each type of event according to my model. In the particular case of pollution peaks[5] for Regional elections, I find an aggregate effect of 2.4%.

These insights are interesting from three points of view. First, they are informative about the concrete consequences of salient events such as natural disasters and pollution peaks. They show that the psychological mechanism described at the beginning of this section can have an impact on voting outcomes. Secondly, in terms of political science, they show how voting outcomes can evolve. It can indeed be relevant to know that the share of votes going to green parties is likely to increase with the number of natural disasters and pollution peaks when one wants to understand French politics. Finally, this work gives policy recommendations. As natural disasters will become more frequent, the risk of climate change is likely to become more concrete which will affect voting outcomes. This phenomenon should encourage politicians to implement greener policies and to build protection plans in order to overcome this effect. Concerning the specific case of pollution peaks, it shows that pollution can affect local voting outcomes, which could be a motivation for a non green incumbent to deal with these issues.

This paper is organized as follows. In section 2, I review the literature related to the effect of salient events on climate change perceptions. In section 3, I present the data I used for this study and show descriptive statistics. Section 4 is dedicated to the standard determinants of the vote for green parties. This step is necessary in order to contextualize the effects I will study in next parts. In section 5, I explain my empirical strategy. In section 6, I show the results for natural disasters and PM_{10} pollution peaks on green voting and provide robustness checks to assess their validity. In section 7, I present two extensions for my econometric model in order to better characterize the effects. Section 8 is dedicated to conclusions.

2 Literature Review

The link between the distance to an event and perceptions now constitutes a large body of literature in psychology. In particular, Liberman & Trope (2010) developed the Construal-Level Theory of Psychological Distance. The rationale of this theory is that distance to an event makes it more abstract. Within this framework, psychological distance is defined on several dimensions: temporal, spatial, social and hypothetical (hypothetical means that the event is so unlikely to happen that it creates a distance between it and individuals). A large number of psychologists built on this theory to understand how perceptions related to climate change can evolve (Linden, Maibach & Leiserowitz, 2015, Jones, Hine & Marks, 2017). Environmental issues are indeed good candidates for this approach since they can be perceived as temporally and spatially distant, especially from the point of view of developed countries that are likely to experience less consequences from climate change as compared with

[3]For floods and pollution peaks, I consider here coefficients from Regional elections only. For drought-related disasters, I consider coefficients from all elections.

[4]For pollution peaks, it is for each event that occurred up to 2 years before the election.

[5]For the recommendation threshold

developing countries (Mendelsohn & Dinar, 1999, Easterling & App, 2005).

Keller, Siegrist & Gutscher (2006) showed that people's judgements about risk are influenced by the ease with which relevant events come to mind. To complete this idea, evidence from Bickerstaff & Walker (2001) and Howe et al. (2014) suggest that personal experiences may help anchor people's understanding of climate change by making the risk more concrete. Thus, experiences are likely to affect the psychological distance between individuals and environmental issues.

What are such salient experiences that could affect perceptions? Li, Johnson & Zaval (2011), Egan & Mullin (2012), Borick & Rabe (2014) and Brooks et al. (2014) showed that cool temperatures and cold weather events affect levels of concern about climate change. On the other hand, evidence from Lorenzoni & Pidgeon (2006), November et al. (2009), Coumou & Rahmstorf (2012), Capstick et al. (2016) suggest that extreme weather events such as floods are also likely to influence perceptions related to global warming. Konisky, Hughes & Kaylor (2015) also show that this relationship is valid only for disasters whose origin can be attributed to climate change, suggesting that all types of disasters do not have the same effect. This literature is generally framed to study the effect of natural disasters on four dimensions:

- Frequency of disasters (more frequent disasters lead to higher support for pro environmental policies)
- Temporal distance (more recent disasters have a higher effect)
- Severity (more violent disasters have a higher effect)
- Education (a more educated population reacts more to these events).

However, all of these studies consider answers to surveys as their outcome variable. One can argue that surveys are very often subject to many biases that limit their empirical validity (Olson, 2006). Moreover, even considering that these results are unbiased, it is impossible to know whether these answers will translate into concrete actions. That is the reason why studying voting outcomes is relevant: unlike changing an answer to a survey, changing one's vote has consequences and is a choice that is more committed.

Using natural disaster as an exogenous shock to study voting outcomes is frequent in the literature. For instance, Rudolph and Kuhn (2017) studied how floods in Germany affected political participation from 2002 to 2013. They find a negative and significant effect, which suggests that natural disasters could indeed affect voting decisions. On the other hand, Baccini and Leeman (2020) investigate whether floods in Switzerland affected answers to referendums related to environmental issues and they find a positive and significant effect of floods on pro-environment votes. Their framework is very similar to ours. Hazlett and Mildenberger (2020) also showed that wildfire exposure increases pro-environment votes for climate related ballot measures by 5 to 6 percentage points for those living within 5km of the event. These results suggest that the effect of extreme weather events can indeed translate in voting outcomes, in particular towards green measures.

The other types of events we will study in the following sections are PM_{10} pollution peaks. To my knowledge, there is no study that investigates the role of pollution peaks on voting outcomes. However, there is a large literature that investigates whether pollution can affect welfare (Welsch, 2006, Duflo, Greenstone & Hanna, 2008, Salthammer et al., 2016, Orru et al., 2016). Luechinger (2010) looks at the effect of local pollution on subjective well-being and finds a negative effect. He instruments local pollution by pollution of neighbors to overcome the endogeneity issue[6]. Zang, Beibei and Liu (2020) show that because of health consequences of $PM_{2.5}$ pollution,

[6] This endogeneity issue is detailled in 5

individuals have a higher willingness to pay to improve air quality in highly polluted areas. They also instrument pollution through ventilation coefficients: the higher the ventilation, the lower the level of pollution should be. What we will study into following sections is whether this increasing willingness to pay translates in voting decisions.

In order to approach the question of voting outcomes towards green parties, one needs also to understand what the standard determinants of this decision are. There is a large body of literature dealing with this question. The paper that is the closest to our approach is the one of Schumacher (2014). The author examines the effect of proximity to a nuclear power plant on green voting in Germany and finds a positive effect, suggesting that individuals who are scared of the risk of a nuclear disaster are more likely to vote for green parties that held anti-nuclear views in Germany. The author also studies the standard determinants of green votes and finds a positive correlation with education, income and density. These results are supported by the papers of Thalmann (2004), Coan & Holman (2008), Cutter & Wu (2011), Comin & Rode (2013) and Persico & Gougou (2020). It suggests that the typical green voter lives in well-educated and wealthy urban areas. Evidence from Salka (2001), Kahn (2007) and Coan & Holman (2008) also show that the share of workers in agriculture and industry is negatively correlated with the vote for green parties. A reason could be that individuals who work in polluting sectors are less likely to vote for green parties because they do not want to loose their job. The effect of age is quite ambiguous: younger individuals are generally more concerned by environmental issues, but they are also less likely to experience health consequences due to pollution (Schumacher, 2014).

3 Data and Descriptive Statistics

In this section, I present the data and provide descriptive statistics. In order to make data comparable across years, I adopted the boundaries of 2020 municipalities, meaning that I converted all of the before-2020 municipality codes to the ones of 2020.

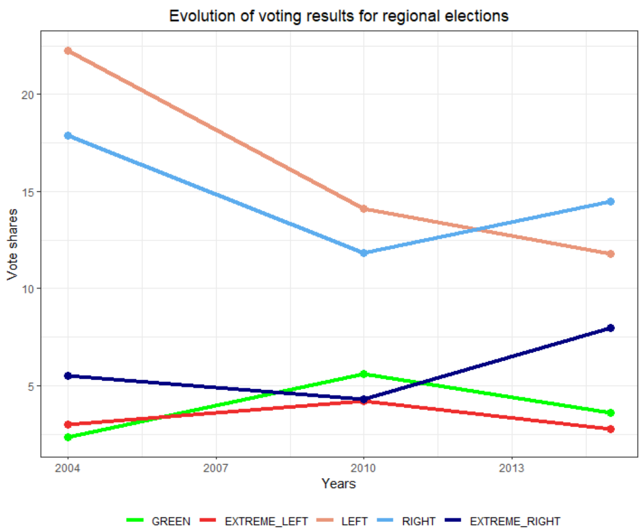
3.1 Elections

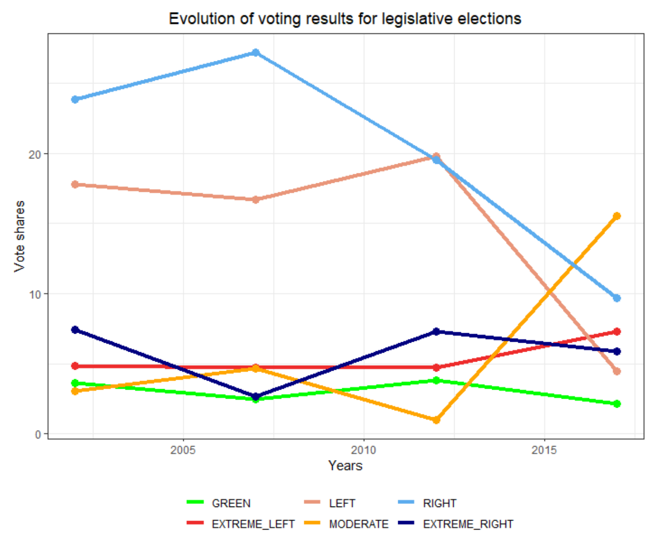
3.1.1 Election Results Through Time

The outcome variable used for the analysis is the share of votes received by green parties for 3 panels of elections: Regional elections of 2004, 2010 and 2015, Legislative elections of 2002, 2007, 2012 and 2017, and European elections of 2004, 2009, 2014 and 2019. Data on election results is available online on *Data.gouv.fr* at the municipality scale. I only considered the results of the first round for each elections. To lead the analysis, each candidate has been put in one of the following categories: green, extreme-left, left, moderate, right and extreme-right.

Abstention is considered an outcome in order to estimate the effect of pollution peaks and natural disasters on the entire population of each municipality, instead of taking into account only those who voted. In the econometric analysis of section 6, I also excluded year 2004 for Regional elections. Indeed, at that time there were some regions with no green candidate. Hence, it does not seem possible to study an effect on green votes if there is no green candidate. The distribution of the vote for green parties for this election round is available in section A.3.

Voting outcomes for each panel of elections are plotted on figure 1. What we can see from figure 1 is that voting





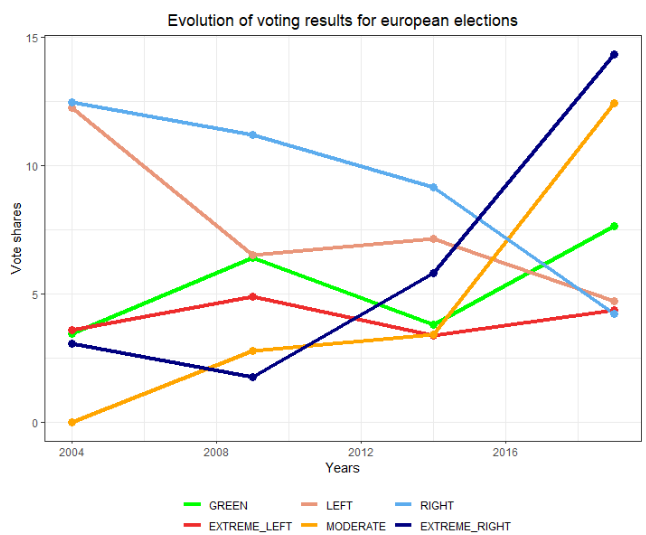


Figure 1: Evolution of voting outcomes for each type of political party for respectively Regional, Legislative and European elections

patterns are very different across elections. For European elections, results vary a lot across years. For Legislative elections, we see that left-wing and right-wing political parties represent the majority of the votes until 2017. In 2017, the share of moderate parties increases a lot, due to the emergence of *En Marche!* the party led by Emmanuel Macron. For Regional elections, trends are almost flat: left-wing and right-wing parties represent the largest share of the votes. This figure illustrates how determinants of voting decisions are different across elections. That is why I will differentiate the effect depending on elections in section 6.

3.1.2 Vote for Green Parties

Before describing the explanatory variables, I would like to develop on the interest of studying voting outcomes of green parties. The political party that gathers the most important number of votes among them is Europe Ecologie Les Verts (EELV). For Regional elections and for Legislative election of 2017, EELV made alliances with left-wing parties. In order to analyze only green voting and not confound it with the vote for left-wing parties, I did not register these common lists as being green[7].

The underlying question of this study is whether natural disasters and pollution peaks could affect perceptions on environmental issues. Even if green parties are generally classified as being left-wing, their main distinction is the weight they put on environmental issues while other left-wing parties such as *Le Parti Socialiste* consider more redistribution and societal issues (Buton, 2016). Actually, the criticism that was often made to green parties is that they are "too green" and do not have clear guidelines concerning other political aspects (Boy, 2011 and 2014). That is why studying this outcome seems relevant to make the link with perceptions on environmental issues. I am actually making here the same assumption as Schumacher (2014): voting for a green party reveals one's green preferences.

On figure 2 is displayed the distribution of green votes in terms of percentiles by election[8]. We see that almost all municipalities show a share of individuals voting green superior to zero in the case of European elections, which is not the case for Regional and Legislative elections. We can see from the last percentiles that for Legislative elections, the vote for green parties seems much more concentrated in a few municipalities as compared to other elections. We also see that the vote for green parties is higher in European elections than in the Regional and the Legislative ones. These differences once again justify that we should differentiate between elections in following sections.

3.2 Natural Disasters

The first type of explanatory variable required for this work is natural disasters. The dataset on natural disasters in France is called *GASPAR* (Gestion Assistée des Procédures Administratives relatives aux Risques) and is publicly available online. It gathers information coming from municipalities that experienced a natural disasters and ask for public insurance (Barraqué & Moatty, 2020). Data is available from 1982, which allows me to link this data with election results from the early twenty-first century.

The *GASPAR* dataframe allows to differentiate disasters according to their types. I gathered the 49 categories

[7] More details on the composition of the political groups considered as green in this study is available in A.1.
[8] Elections are decomposed by year in section A.2

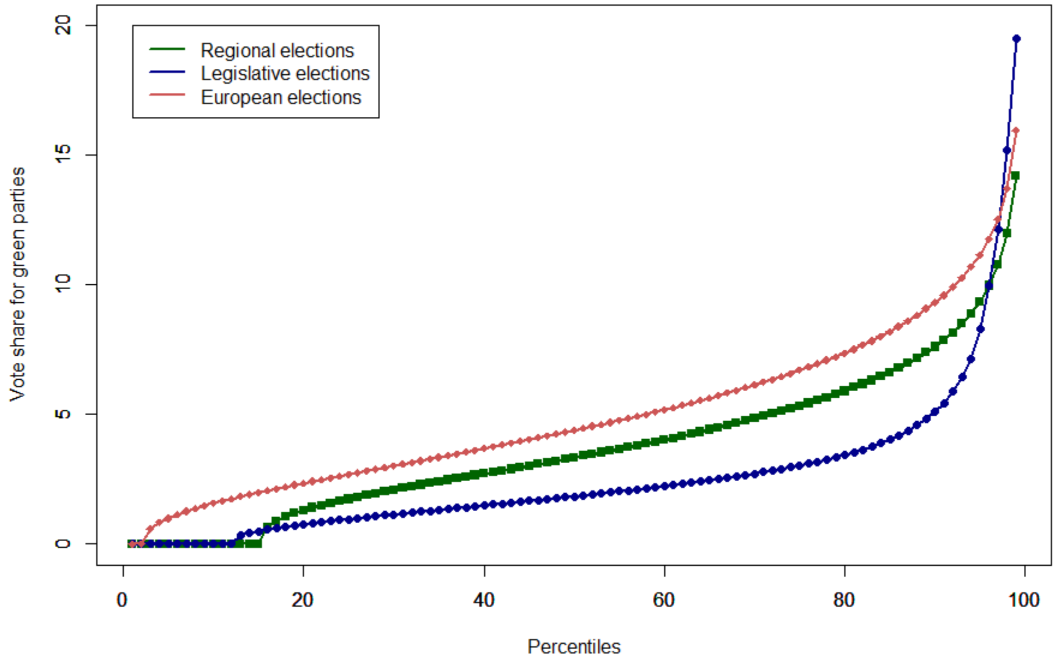


Figure 2: Distribution of green votes by percentile

in 4 groups[9]: floods, earthquakes, storms and drought-related disasters. The total number of disasters recorded by year is available on figure 3. What we can see from this figure is that the number of disasters does not seem to increase with time. However, we observe a big increase in drought-related disasters from 2016 to 2019. One can also see that earthquakes and storms are very rare events. In particular, we will omit storms in following sections because the total number of events is too low.

Drought-related disasters are actually earthquakes that arise because of high temperatures and can impact constructions. The magnitude of the damage is affected by ground composition[10] and by buildings architecture. It can go from a crack in the construction to buildings collapsing (Mauroux, 2015). These disasters are also correlated with very high temperatures that can affect agricultural earnings (Baas, Trujillo & Lombardi, 2015, Conforti, Ahmed & Markova, 2018). A drought is also likely to influence perceptions as it can be interpreted as a consequence of climate change. Thus, drought-related disasters are likely to be salient drivers of perceptions regarding environmental issues: they potentially cause a lot of damage and can easily be interpreted as a consequence of global warming. We will investigate their effect in section 6.3.

This dataset also characterizes each natural disasters by its length in days. This is convenient for my setup: it gives a measure of disasters' intensity. Even if the duration of a disaster is not a perfect measure for the damages endured, it still gives a coherent approximation. I will use this measure as a robustness checks for the results I will obtain in section 6. This approach is similar to the one of Konisky, Hughes & Kaylor (2015) who also use the length of a disaster as a proxy for its severity. The average disasters' length depending on their type is available on

[9]Details for the composition of these groups are available in section A.4
[10]in particular, damages can be higher when a construction is built on clay soil that need to be regularly re-hydrated

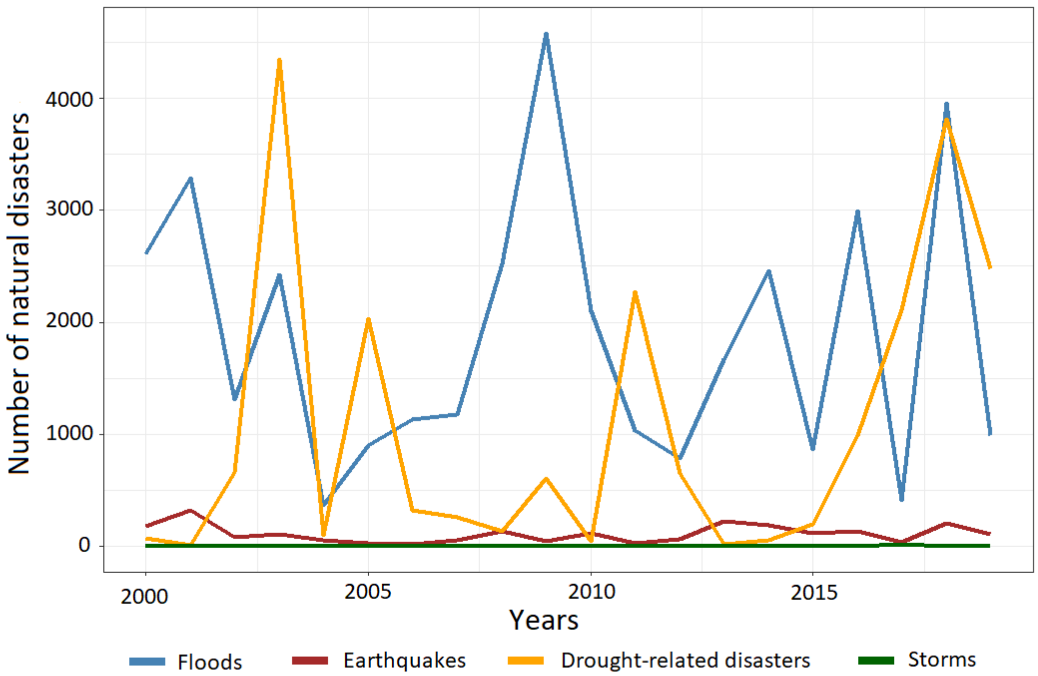


Figure 3: Total number of natural disasters recorded by year from 2000 to 2019

table 1[11]. One can observe that floods and earthquakes usually last several days, while drought-related disasters are much longer[12]. The consequences of a drought are also very different and do not affect the same individuals. That is why the effects of each type of disaster are likely to be different and why I will distinguish between these different types of disasters in section 6.3.

Some summary statistics are presented on table 1. These figures show us that the average annual frequency of occurrence of drought-related disasters almost doubled during the 2015-2019 period as compared to the 2000-2019 period. It confirms what we saw from figure 3: the number of drought-related disasters is relatively high since 2015. This table also gives us important insights on the frequency of natural disasters: over the 2000-2019 period, two third of municipalities have been affected by a natural disaster at least once, over the 2015-2019 period, it is the case for one third of the municipalities. These numbers show that natural disasters are not anecdotal events and that they are actually quite frequent in France[13].

Geographical distribution of floods, earthquakes and drought-related disasters are available on figure 4 over the 2015-2020 period. What we can see from these maps is that natural disasters do not seem to be randomly distributed across France. Let take drought-related disasters for example: one can observe that the North of France is almost never affected by these disasters, unlike the South and the West. In the case of floods, we see that along the costs, particularly in the South, the probability of occurrence seems higher than in the middle of France. One

[11]The distribution of the length of disasters depending on their type is available in section A.5

[12]It is also due to the fact that drought-related disasters are generally recorded by trimester.

[13]These aspects are developped in the report of *Caisse Centrale de Réassurance* entitled *Les catastrophes naturelles en France - Bilan 1982-2018*

Table 1: Summary Statistics for Natural Disasters

	Type of disaster	From 2000 to 2019	From 2015 to 2019
Average annual number of disasters	Floods	1878	1842
	Earthquakes	113	121
	Drought-related disasters	1059	1917
	All disasters	3050	3880
Average length of disasters in days	Floods	4.4	4
	Earthquakes	21	20
	Drought-related disasters	136	160
Proportion of municipalities that experienced at least a single disaster	Floods	57%	21%
	Earthquakes	5%	2%
	Drought-related disasters	30%	21%
	All disasters	67%	36%

could explain this phenomenon by topography and geographical disparities. The probability of being flooded is indeed much lower at a high altitude as compared to another area that would be close to a river (Giuseppe, Felix & Adekola, 2019). If these geographical characteristics are also correlated with the vote for green parties, then there would be an omitted variable bias in our results. However, these characteristics are time invariant across the 2000-2019 period. It justifies the use of a within model in section 5, in order to control for this unobserved heterogeneity.

I also consider in this study the effect of protection plans that aim to prevent damages from natural disasters. The objective of these plans is to prevent the municipality from constructing new buildings on areas that are likely to experience natural disasters in the future. They also consist of building new infrastructures, such as dikes for example, to prevent from the potential damages that could cause a natural disaster (A. Mauroux, 2015). There are various types of plans but the ones of interest for this study are Plan de Protection des Risques naturels (PPRn). Data on these protection plans is available at the municipality scale. A standard motivation for implementing these plans from the point of views of local authorities is that they lower the insurance franchise that has to be paid when a new disaster occurs (Gathié, 1998). In section 6, I will investigate whether implementing these plans also affect perceptions of individuals regarding climate change. If it is the case, then it could be another motivation for a non-green incumbent to implement these plans.

3.3 Pollution Levels

For the purpose of this study, I use data on pollution in two different ways. First, I will discuss the effect of average annual exposure to $PM_{2.5}$ pollutant. The reason for this decision is to control for the degree at which the economy of a municipality relies on polluting activities. The second variable is the number of PM_{10} pollution peaks. It will be a variable of interest in regressions of section 6.

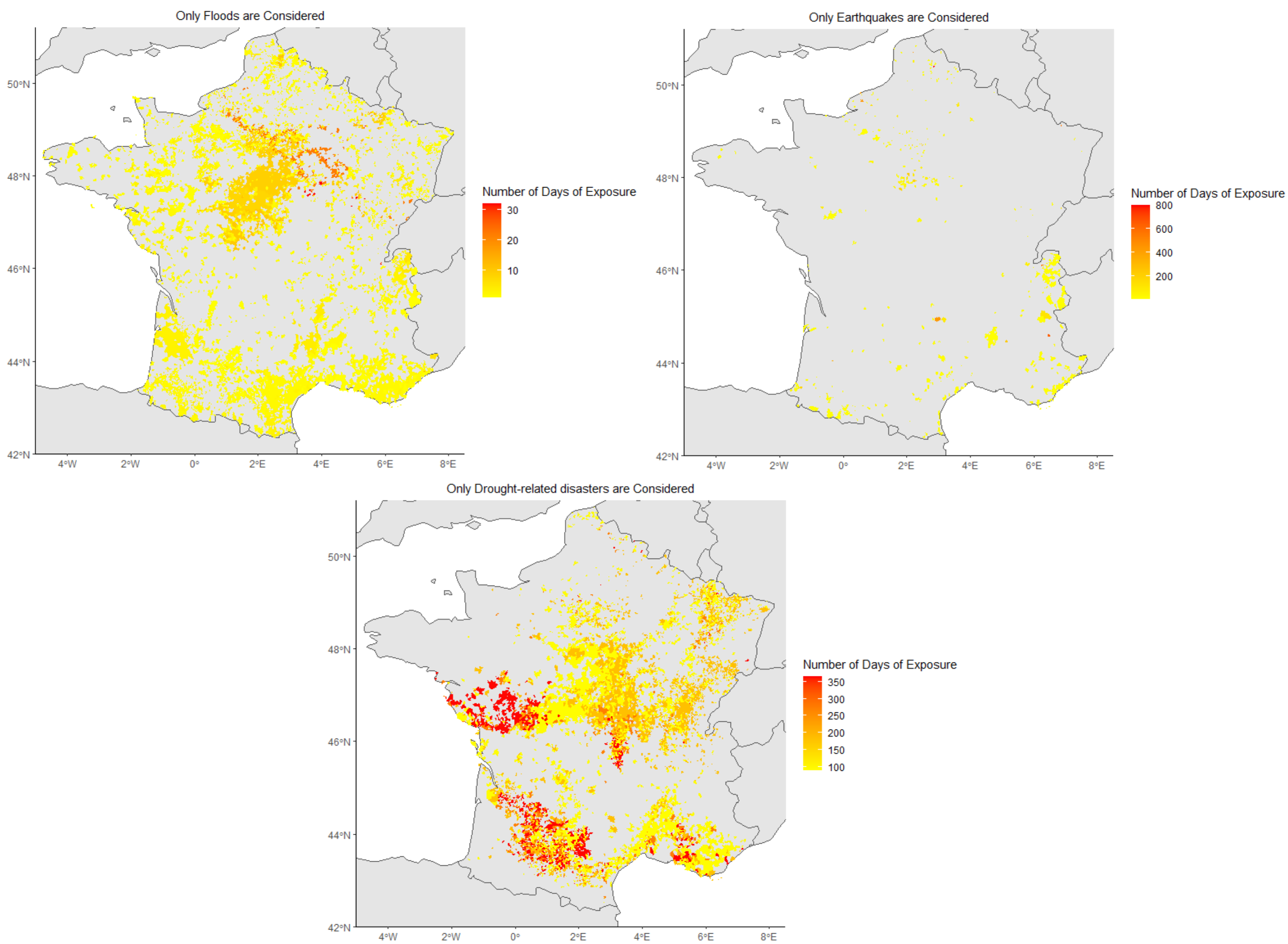


Figure 4: Geographical distribution of floods, earthquakes and drought-related disasters from 2015 to 2019

3.3.1 Average Exposure to $PM_{2.5}$

Exposure to fine particules ($PM_{2.5}$) depends on housing, services, industry and car traffic. Determining the degree at which these factors contribute to $PM_{2.5}$ exposure is quite complicated to determine, in particular because it varies a lot through regions depending on the development of each sector[14]. I will use this variable as a control later on, in order to take into account the level of dependence of a municipality to polluting activities.

For this study, I use the same dataset as P. Champalaune (2020): *Inequality in Exposure to Air Pollution in France: Measurement and Impact of a City-Level Public Policy*. Data is obtained from the Atmospheric Composition Analysis Group (ACAG) in Dalhousie University, Canada. The researchers exploited both remote-sensing sources and ground-level monitor data gathered by the European Environment Agency (EEA) in order to deduce the spatial distribution of fine particulate matter throughout the whole of Europe. The level of $PM_{2.5}$ at the municipality level is obtained by computing a weighted mean of the average $PM_{2.5}$ concentration of grids of .01 × .01 degrees, i.e., approximately 1 km2 at the equator. The boundaries are those of the 2020 municipalities. More details are available in the Data section of *P. Champalaune (2020)*.

3.3.2 PM_{10} Pollution Peaks

Measure of PM_{10} pollution peaks is done by Regional associations called ASQAA (Associations Agréées de Surveillance de la Qualité de l'Air). Their goal is to measure and predict air pollution. They remain independent from each other and some of them do not have the data for pollution peaks before 2007. For regions Occitanie and Bretagne, the ASQAAs were not able to provide me with the information on PM_{10} pollution peaks. I thus excluded these regions from the analysis. I gathered data for the measuring stations located in the ten remaining regions.

These stations are called background stations and their role is to measure the exposure of citizens to pollution, particularly in urban areas. They cover an area that goes from 100m to 2km away[15]. They are of particular interest for us since communication about pollution peaks is based on the measure of these stations[16]. Background stations are plotted on figure 5. One can observe that almost every gray area has a station in his center, showing that these measuring stations particularly concern urban areas. As explained before, Occitanie and Bretagne are excluded from the analysis because data is not available.

For each station, I obtained the average daily concentration in PM_{10} particules in $\mu g/m^3$. The recommendation threshold for a pollution peak is reached when this measure exceeds $50\mu g/m^3$. There is another threshold called the alert threshold that is reached when daily concentration in PM_{10} particules goes above $80\mu g/m^3$. These thresholds were fixed by the 2008/50 directive. It first had been decided at the EU level in 2008 and was then implemented in French law[17]. There is no compelling measure for prefectures when the recommendation threshold is reached. However, the prefecture can decide to put in place some restrictions on the industrial sector or in terms of car traffic such as for example making public transport free or lowering speed limitations. It is different for the alert threshold: when it is reached, the prefecture is compelled to take measures[18]. Thus, while average concen-

[14] see Citepa (2019). Gaz à effet de serre et polluants atmosphériques : Bilan des émissions en France de 1990 à 2017. 450 p.

[15] see *Classification and Criteria for Setting Up Air-Quality Monitoring Stations,ADEME*

[16] The two other types of stations are traffic stations and industrial stations, but their objective is to measure a local level of pollution close to a road or a factory in order to make previsions. If a pollution peak is measured by these stations, the information is generally not covered by media.

[17] Code de l'environnement, articles R221-1 and R221-3

[18] for more details, see *La gestion des pics de pollution de l'air, Report by the French Ministry of Ecological Transition, 2015.*

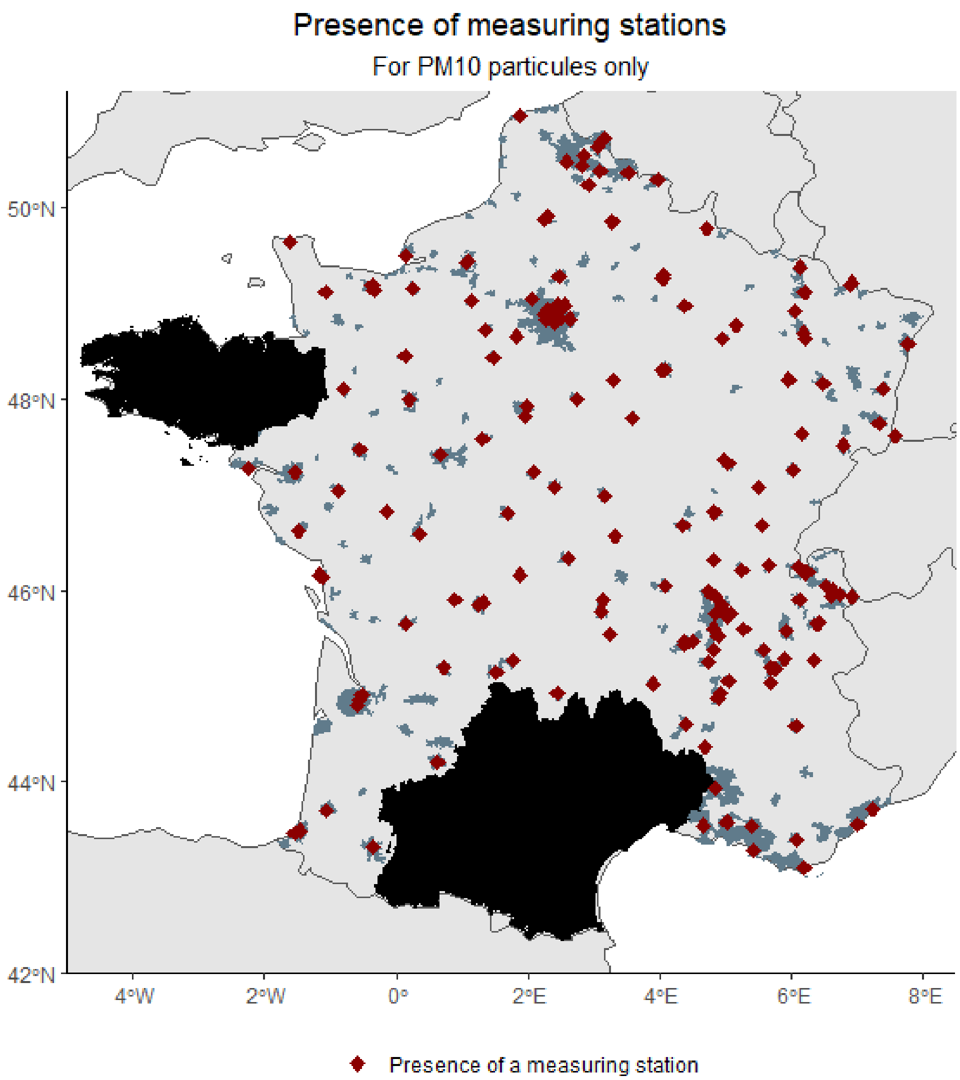


Figure 5: Location of PM_{10} measuring stations. Areas in gray are urban areas as defined by *INSEE*.

tration of pollutants is relatively complicated to observe for citizens, pollution peaks are more visible: concrete measures are taken such as limiting traffic and journals very often publish articles related to these events (see the website of the *French Ministry of Health* for more details[19]).

The nature of pollution peaks is different than the one of natural disasters: natural disasters can be perceived as a consequence from climate change while pollution peaks are due to human activity affecting the environment. However, both events can have consequences in terms of health and are visible. That is why they can be considered as salient events that can affect perceptions, and why they are a subject of interest for our framework.

Data on pollution peaks is available from 2007 in most regions[20]. That is why I will only consider post-2007 pollution peaks. The total number of PM_{10} pollution peaks recorded through time is plotted on figure 6. One can see that the number of pollution peaks decreased a lot since 2013. This phenomenon results from the implementation of *Plans de prévention de l'atmosphère* from 2012 to 2014 (see figure 6 in P. Champalaune, 2020). Since 2018, one can also see that the number of pollution peaks reaching the alert threshold has been almost equal to zero.

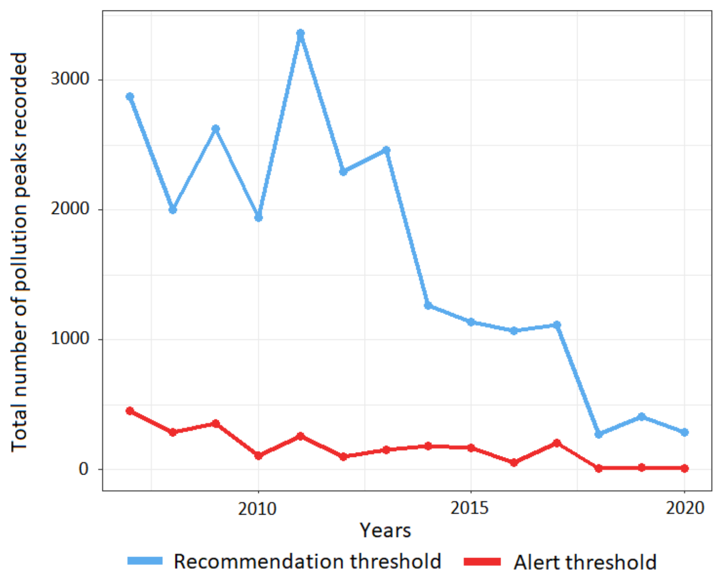


Figure 6: Total number of pollution peaks recorded through time. Occitanie and Bretagne are excluded from the analysis.

It is very likely that when a pollution peak is declared in a municipality, the municipalities around are also affected by the event. One could think about local journals that are distributed in several municipalities covering the event or about the fact that if traffic is limited in a given city after a pollution peak, people living in municipalities around who regularly go to this city are affected too. To take this spillover effect into account, I apply a decreasing linear weighting function to the municipalities around those who declared a pollution peak. This function works

[19]https://solidarites-sante.gouv.fr/sante-et-environnement/air-exterieur/qualite-de-l-air-exterieur-10984/article/recommandations-en-cas-d-episode-de-pollution

[20]Methods of measures have also evolved in 2007, such as there is a big jump in the number of pollution peaks recorded in 2007.

as follows. An arbitrary threshold is determined, let say $\bar{D}$. Then the weight given to each municipality j located at distance d_{ij} from municipality i is

$$w_{ij} = \begin{cases} \frac{\bar{D}-d_{ij}}{\bar{D}} & if \quad d_{ij} \leq \bar{D} \\ 0 & otherwise \end{cases}$$

Thus, weights are so that they decrease linearly with distance, up to a given threshold $\bar{D}$. For the purpose of this study, I will fix $\bar{D}$ =15km[21]. The before/after figures are plotted on 7 for the municipality of Lyon. This methodology is similar to Schumacher (2014)[22]. The detailed methodology is available in section A.7.

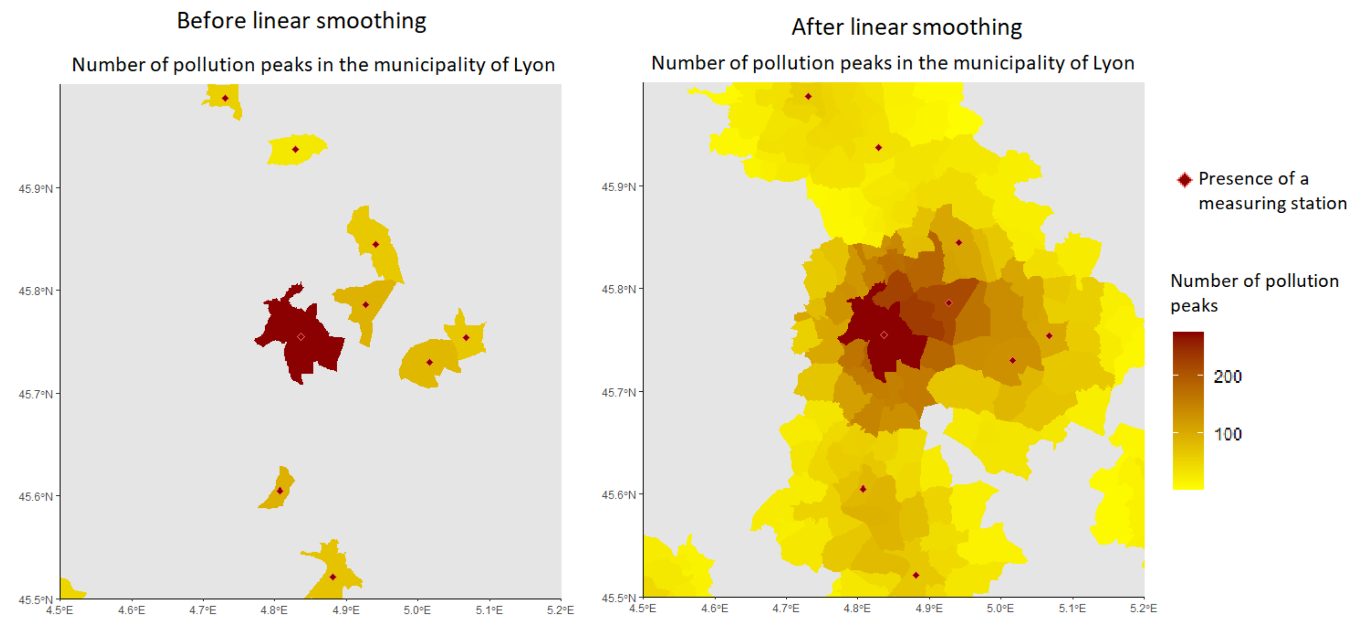


Figure 7: On the left hand side are the number of pollution peaks initially recorded in each municipality from 2013 to 2020. On the right hand side, one can see the effect of applying a linear smoothing function to municipalities around.

The map for France after applying the linear weighting function is displayed on figure 8. One can observe a particularly high number of pollution peaks in Paris and Lyon, respectively the first and the third cities in France in terms of population[23]. One can also see a high number of pollution peak at the East of Lyon. This area is called vallée de l'Arve. It is a region with a high altitude and cold temperatures, that is why there is a very frequent use of heating in these municipalities, which explains the high level of pollution (*La pollution atmosphérique en vallée de l'Arve*, CERES report, 2019). Once again, we see that geographical characteristics matter, which will justify the use of a within model is section 6.

One could be concerned about the fact that some areas are not covered by any station, meaning that some

[21] I will make very this threshold in the section 6 in order to assess the robustness of the results

[22] In *Schumacher (2014)*, the author used an inverse smoothing function for the spreading effect of nuclear power plants. The contexts are different but the reasoning is similar.

[23] 2 187 526 inhabitants for Paris, 516 092 in Lyon, Source: *INSEE*

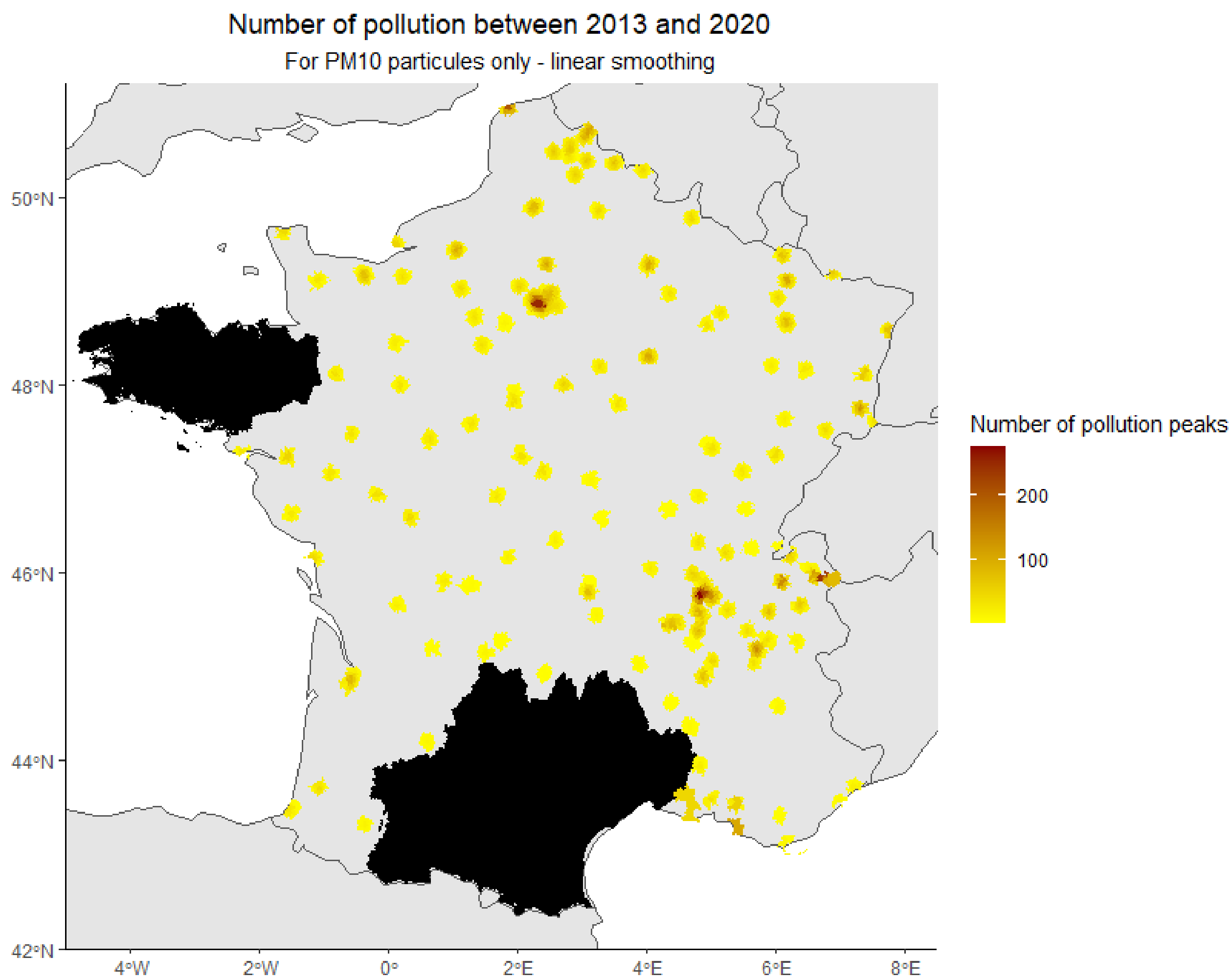


Figure 8: Number of PM_{10} pollution peaks after applying the linear weighting function.

pollution peaks are not detected. I would argue two things. First, background stations are actually localised so that they are likely to capture well the number of pollution peaks. Put differently, if there is no measuring station in an area, it also means that the probability of having a pollution peak in this area is relatively low. Secondly, what matters for this study is not pollution peaks in themselves but their effects on perceptions. Since information related by media and prefectures about pollution peaks only comes from measures of background stations, one should not be concerned about unmeasured pollution peaks and their effect on perceptions.

3.4 Census Data

In order to control for potential omitted variables in further regressions, I also included census data in the analysis, which will also be useful in order to study the standard determinants of the vote for green parties. These variables are the share of individuals with a baccalauréat (French high-school diploma), the share of individuals who are above 55, the log of the median income, the log of municipality's density, the share of individuals working in agricultural and industrial sectors, and the share of individuals who take the car to go to work. Data is publicly available online on the *INSEE* website.

To conclude on this data section, Table 8 shows the unweighted mean and standard deviation for each variable that will be put in empirical specifications[24]. Computations to get this table come from the dataset with all elections pooled together. I also provide on Table 3 the correlation table for each type of natural disaster and PM_{10} pollution peaks. One can observe that these events seem relatively independent from each other, except from earthquakes and floods which show a correlation coefficient of 0.14.

[24]The share of individuals working in agriculture and industry could seem very high. The explanation is that means are unweighted on table 8 and there are lots of municipalities with a low population and a high share of individuals working in these sectors. Thus, considering weighted means would lower this proportion.

Table 2: Unweighted Mean and Standard deviation for all variables.

Variable	**Unit**	**Mean**	**Standard Deviation**
Share of individuals voting green	Percentages	4,00	3,56
Floods since the last election	Number	0,25	0,55
Earthquakes since the last election	Number	0,01	0,14
Drought-related disasters since the last election	Number	0,12	0,40
Protection plans	Number	1,56	0,34
PM_{10} pollution peaks (recommendation threshold)	Number	0,18	7,30
PM_{10} pollution peaks (alert threshold)	Number	0,11	1,05
Share of individuals with a *baccalauréat*	Percentages	36,66	10,23
Share of individuals above 55 years old	Percentages	33,40	9,14
Annual Median Income	Number	18632,16	3681,08
Density by km^2	Number	158,79	715,39
$PM_{2.5}$ particules concentration	$\mu g/m^3$	10,27	2,22
Share of individuals working in agriculture and industry	Percentages	36,63	33,97
Share of individuals taking the car	Percentages	84,55	12,00

Table 3: Coefficients of correlation between each type of disaster and PM_{10} pollution peaks.

	PM_{10} Pollution Peaks	**Floods**	**Earthquakes**	**Drought-related disasters**
PM_{10} Pollution Peaks	1	0.03	0.02	0.02
Floods	0.03	1	0.14	0.08
Earthquakes	0.02	0.14	1	0.01
Drought-related disasters	0.02	0.08	0.01	1

4 Standard Determinants of the Vote for Green Parties

Before dealing with the effect of salient events on green votes, it seems essential to understand well what are the effect of each variable on green voting and link our findings to what is commonly found in the literature. For this purpose, I run the following specification

$$Green_{it} = \alpha + \beta_1 X_{it} + Year_t + \eta_{it}$$

The X_{it} variables are the determinants of green votes listed on figure 9. $Year_t$ are year fixed effects. $Green_{it}$ is the percentage of votes received by green parties at time t for municipality i, so that β_1 can be interpreted as the marginal effect of X_{it} on the vote for green parties in *percentage points*. I run this model on 4 datasets: a comprehensive dataset with all elections pooled together and three other datasets, one for each panel of election (Regional, Legislative and European). Results are displayed on figure 9. Outliers are excluded from the analysis (details on these outliers are available in section A.8)

First, one can observe that R^2 values are not similar across elections. The model explains much more the variation in the data for European and Regional elections than for Legislative elections: R^2 value is almost five times higher for European elections as compared to the Legislative ones. It illustrates, how voting determinants differ across elections, so that we are not able to explain much of the variation in green voting for Legislative elections.

One can observe positive signs for the coefficients associated to the share of individuals with a baccalauréat, the Log median income and the Log density. All coefficients are significant at the 1% threshold. These are very standard result in the literature (see Thalmann, 2004, Nelson et al., 2007, Coan & Holman, 2008, Comin & Rode, 2013, Cutter & Wuu, 2011, Schumacher, 2014, Piketty, 2018). The magnitude of the signs for the effect of education are also very similar to the paper of Schumacher (2014)[25]. These results suggest that the typical green voter leaves in well educated, wealthy urban areas.

Concerning the share of individuals who are above 55, we observe varying signs. The effect of age is indeed quite ambiguous in the literature. On the one hand, older individuals are more likely to be victim of health risks associated to pollution, which could encourage them to vote more for green parties. On the other hand, younger individuals are generally more concerned by environmental issues given their education and the fact that they are more likely to see the consequences of climate change (Schumacher, 2014).

As explained in section 3, I included the Log Average $PM_{2.5}$ concentration in order to take into account how much municipalities rely on polluting activities. The coefficients obtained are negative for all elections. It could be due to self selection: people who tend to care less about pollution will live more in polluted areas and will vote less for green parties. Another explanation could be that the more a municipality emits pollution, the less should be the share of the population voting green as the economy of this area relies on these emissions. The rationale for including the share of individuals working in agriculture and industry is very similar: the more individuals rely on polluting activities, the less they should vote for green parties. Kahn (1997), Salka (2011) and Coan & Holman (2011) found a negative effect of the share of industry on the vote for green parties. It is consistent with this last explanation.

[25] The specifications are not exactly the same, but running the same specification as the author yields similar magnitudes

	Dependent variable:			
	Vote share for green parties			
	All elections	Regional	Legislative	European
	(1)	(2)	(3)	(4)
% of indidivuals with a baccalaureat	0.068***	0.087***	0.043***	0.089***
	(0.0004)	(0.001)	(0.001)	(0.001)
% of individuals who are above 55	-0.002***	0.001	-0.007***	0.002***
	(0.0004)	(0.001)	(0.001)	(0.001)
Log Income Median	0.614***	0.466***	0.367***	0.861***
	(0.028)	(0.067)	(0.039)	(0.046)
Log Density	0.053***	0.031***	0.002	0.109***
	(0.003)	(0.007)	(0.004)	(0.005)
Average PM concentration	-2.018***	-2.165***	-1.327***	-2.614***
	(0.020)	(0.044)	(0.029)	(0.032)
% of workers in agriculture and industry	-0.002***	-0.003***	-0.001***	-0.003***
	(0.0001)	(0.0002)	(0.0001)	(0.0002)
Constant	-1.277***	2.334***	0.572	-2.057***
	(0.252)	(0.619)	(0.358)	(0.419)
Year fixed effects	Yes	Yes	Yes	Yes
Observations	324,734	65,276	132,315	127,143
R^2	0.430	0.303	0.087	0.408
Note:				*p**p***p<0.01

Figure 9: Regression table for standard determinants of green votes.

However, the effect of local pollution is generally quite ambiguous: it is also possible that a high level of emissions leads the population to ask for less pollution because of health consequences. More precisely, the associated health burden was recently estimated to 48,000 early deaths a year, which is equivalent to 2-year reduction in life expectancy at 30 on average (Medina et al., 2016). Schumacher (2014) found indeed a positive coefficient for the level of pollution on green voting. It shows that the effect of pollution is generally ambiguous but in the case of France, it seems that the effect is negative. An explanation for this phenomenon could be that even if pollution has concrete consequences in terms of health, the level of pollution of an area is not always known by residents. It should not be the case when we will consider pollution peaks that are more salient events.

Now that we understood more in depth the determinants of the vote for green parties, we will incorporate the effect of salient events such as natural disasters and pollution peaks.

5 Empirical Approach

In this section, I will present the empirical approaches and the endogeneity issues that could arise for the two types of events considered: natural disasters and pollution peaks.

5.1 Natural Disasters

The specification I run in order to estimate the effect of natural disasters on the votes for green parties is the following within model (Hausman & Taylor, 1981)

$$Green_{it} - \bar{Green_i} = \beta_1(Disaster_{it} - \bar{Disaster_i}) + \beta_2(X_{it} - \bar{X}_i) + Year_t + (\eta_{it} - \bar{\eta}_i) \quad (1)$$

With $\bar{X}_i = \frac{1}{T}\sum_t X_{it}$

$Disaster_{it}$ is the number of natural disaster experienced by a municipality between election t and election $t-1$. It is the variable of interest. The set of X_{it} variables are the controls presented in section 4. Controlling for these determinants is necessary in order to avoid an omitted variable bias as the probability of experiencing a natural disaster could be higher in rural areas where education and income could be lower.

The reason why I run a within specification is related to what we observed on figure 4: natural disaster do not seem to happen randomly and there are geographical characteristics that explain the occurrence of each type of disasters (Baccini and Leeman, 2020). Given that these characteristics are time invariant, implementing a within specification should account for their effect and achieve identification.

As I explained in section 3.2, data on the length of disasters in days is available. This measure could account as a proxy for the strength of a disaster. Thus, I also lead robustness checks consisting in replacing $Disaster_{it}$ by the number of *days of disaster* experienced by a municipality between election t and election $t-1$. It allows me to take into account the intensity of each disaster.

5.2 Pollution Peaks

Concerning PM_{10} pollution peaks, identification issues are quite different. The problem is that the effect of pollution peaks on the vote for green parties could be confounded by a self selection process: it is likely that pollution peaks occur more often in places where citizens care less about polluting emissions. This phenomenon could lead to endogeneity issues (Luechinger, 2010[26]). Another reason could be that people rely a lot on car traffic, or work in polluting industries, which would explain why they care less about pollution. Thus, there could be confounding factors implying that pollution peaks would not be exogenous. That is why controlling for the average $PM_{2.5}$ particules concentration, the share of individuals who take the car to go to work and the share of individuals who work in agriculture and industry is key in the identification strategy.

Another issue is that data on pollution peaks is more restricted. Data is only available from 2007 in most regions which restricts the number of years that can be studied. That is why I only considered elections from 2009 to 2019 and study the effect of pollution peaks that happened up to 2 years before the election. The other limitation is that data is not available for 2 regions (Bretagne and Occitanie) and for the region Pays de la Loire, data starts to be available in 2013. Thus, I excluded these 3 regions.

The econometric model is actually analogous to the one concerning natural disasters. It writes as follows

$$Green_{it} - \bar{Green_i} = \beta_1(Peaks_{it} - \bar{Peaks_i}) + \beta_2(X_{it} - \bar{X_i}) + Year_t + (\eta_{it} - \bar{\eta_i}) \quad (2)$$

With $\bar{X_i} = \frac{1}{T}\sum_t X_{it}$.

Where $Peaks_{it}$ is the number of PM_{10} pollution peaks that happened up to 2 years before election t. X_{it} includes the average $PM_{2.5}$ particules concentration, the share of individuals who take the car to go to work and the share of individuals who work in agriculture and industry. I run a within model to take into account geographical disparities that can affect the level of pollution. As we have seen with the *Vallée de l'Arve* in section 3.3.2, geographical characteristics such as altitude can indeed affect the probability of experiencing pollution peaks.

6 Results and Robustness Checks

I will now present the results for this study. I start by running a baseline regression that illustrates the two main findings:

- Floods and pollution peaks have a positive and significant effect only for Regional elections
- Drought-related disasters yield positive and significant coefficients across the three types of elections.

Then, I will focus on each finding separately and provide robustness checks.

6.1 Main Results

In order to investigate the effect of natural disasters and pollution peaks on green votes, I run equation (1) for each type of disaster and equation (2) for the alert threshold[27]. That is what is done on figure 10. The values of the coefficient of interest are plotted for 3 different datasets: one for each type of election.

[26] The author studies the effect of pollution on welfare. He highlights a similar self selection process

[27] see section 3.3.2 for more details about pollution peaks thresholds

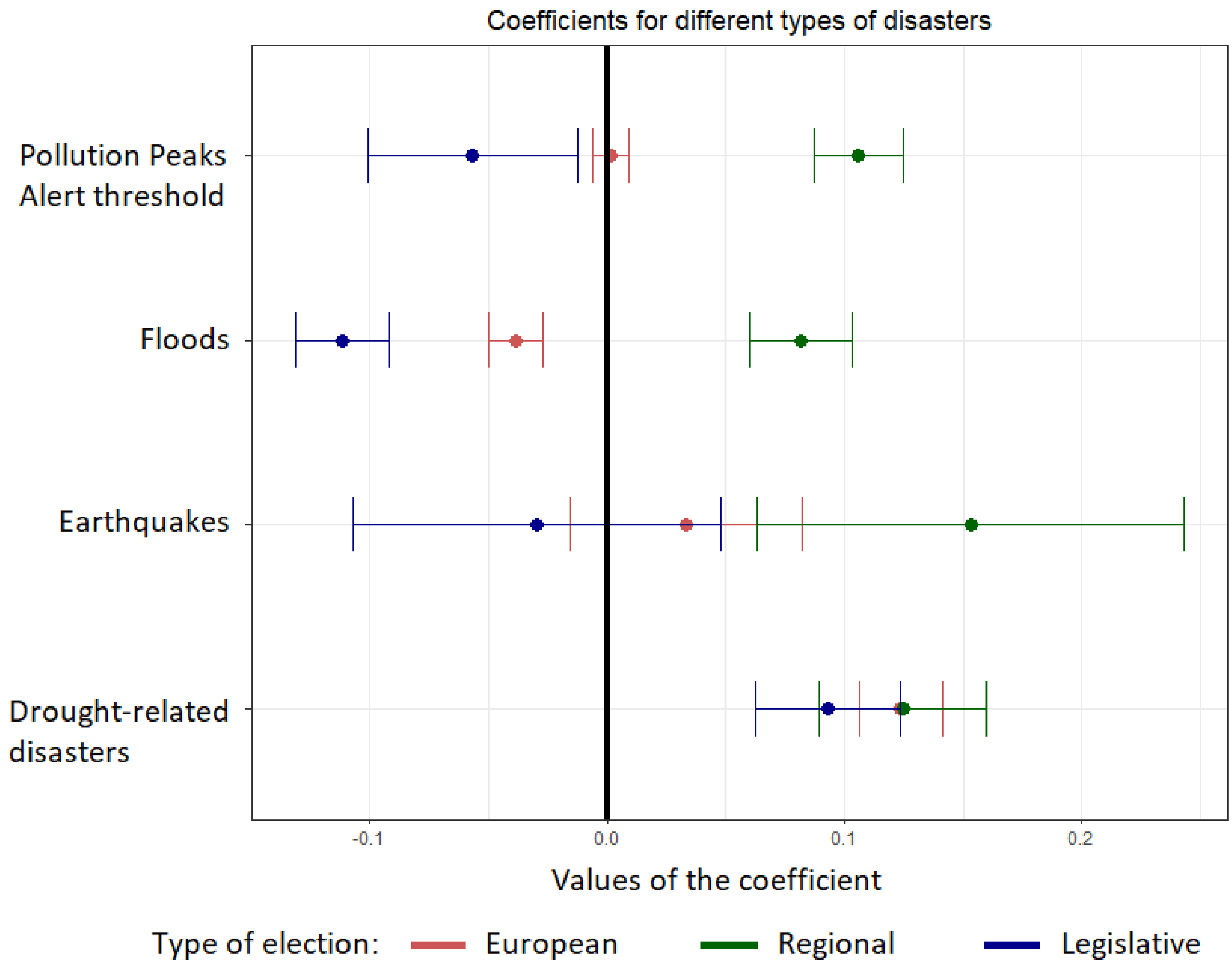


Figure 10: Values of β_1 in equations (1) and (2) for various types of disasters and pollution peaks.

There are two main insights coming from this figure:

- The coefficients associated to Regional elections are always positive and significant. An interpretation could be that natural disasters and pollution peaks do not change deep convictions towards climate changes issues. Individuals could indeed vote more in favor of green parties only for Regional elections because they hope that such events will not happen again in the future. It would make sense as Regional councils take decisions about landscape development, fight against pollution and transports at the local level[28]. On the other hand, politicians elected during Legislative and European elections take measures at a larger scale.

- The only type of event that seems to have a positive and significant effect on green voting for all elections are drought-related disasters. A possible explanation could be that since these events are due to high temperatures, they are more likely to be understood as a consequence from climate change. That is why they are more likely to influence deep perceptions regarding environmental issues (Konisky, Hughes & Kaylor, 2015).

We will investigate these aspects and comment on them in the two following subsections.

6.2 Focus on Regional Elections

In this section I will detail the results concerning floods, earthquakes and pollution peaks for Regional elections only. I will abstract from the case of drought-related disasters for now and I will comment on them in section 6.3.

6.2.1 Results

The regression that shows the results for Regional elections only is displayed on figure 11. What we observe here are positive and significant effects for all types of events considered. For pollution peaks, we see that the effect is positive and significant for both the recommendation and the alert threshold. One can also notice that the effect is smaller for the recommendation threshold, which is not surprising given that reaching this threshold does not compel the prefecture to take measures, unlike the alert threshold (see section 3.3.2 for more details). We also see that earthquakes are only significant at the 10% level.

Now, let investigate what happens when we make vary the time threshold for the number of disasters taken into account. On figure 11, this threshold was election $t-1$ for natural disasters, meaning that I took into account the effect of all disasters that happened between elections t and $t-1$. Concerning pollution peaks, the threshold was 2 years, meaning that I considered pollution peaks that happened up to 2 years before election t. On figure 12, I make vary these time thresholds in order to observe if the effect changes when taking into account only recent events. There seems to be a decreasing effect with time for both floods, earthquakes and PM_{10} pollution peaks. It makes sense since recent disasters are likely to affect more perceptions and it is consistent with what is generally found in the literature (Capstick et al. 2016).

6.2.2 Robustness Checks

I run three robustness checks.

First, to assess the robustness of the results concerning floods and earthquakes, I reproduce figure 12 but with the number of *days of exposure* to the disaster instead of the number of disasters as the variable of interest. Results

[28]see *https://www.gouvernement.fr/* for more details

	Dependent variable:				
	Vote share for green parties				
	(1)	(2)	(3)	(4)	(5)
Floods	0.082***				
	(0.023)				
Earthquakes		0.153*			
		(0.087)			
Drought-related disasters			0.125***		
			(0.032)		
Pollution peaks - recommended threshold				0.032***	
				(0.002)	
Pollution peaks - alert threshold					0.106***
					(0.014)
% of indidivuals with a baccalaureat	0.018***	0.018***	0.018***	0.018***	0.018***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
% of individuals who are above 55	-0.030***	-0.030***	-0.030***	-0.038***	-0.037***
	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)
Log Income Median	1.588***	1.597***	1.579***	1.980***	2.121***
	(0.282)	(0.281)	(0.281)	(0.290)	(0.290)
Log Density	-1.661***	-1.663***	-1.670***	-2.268***	-2.301***
	(0.283)	(0.283)	(0.283)	(0.275)	(0.275)
Average PM2.5 concentration	-5.814***	-5.702***	-5.700***	1.245***	1.014***
	(0.305)	(0.304)	(0.304)	(0.318)	(0.318)
% of workers in industry	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
% of individuals taking the car	-0.0002	-0.0001	-0.0001	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	68,886	68,886	68,886	54,054	54,054
R^2	0.287	0.287	0.287	0.405	0.403
Note:					*p**p***p<0.01

Figure 11: Regression table for the effect of natural disasters and pollution peaks for Regional elections only.

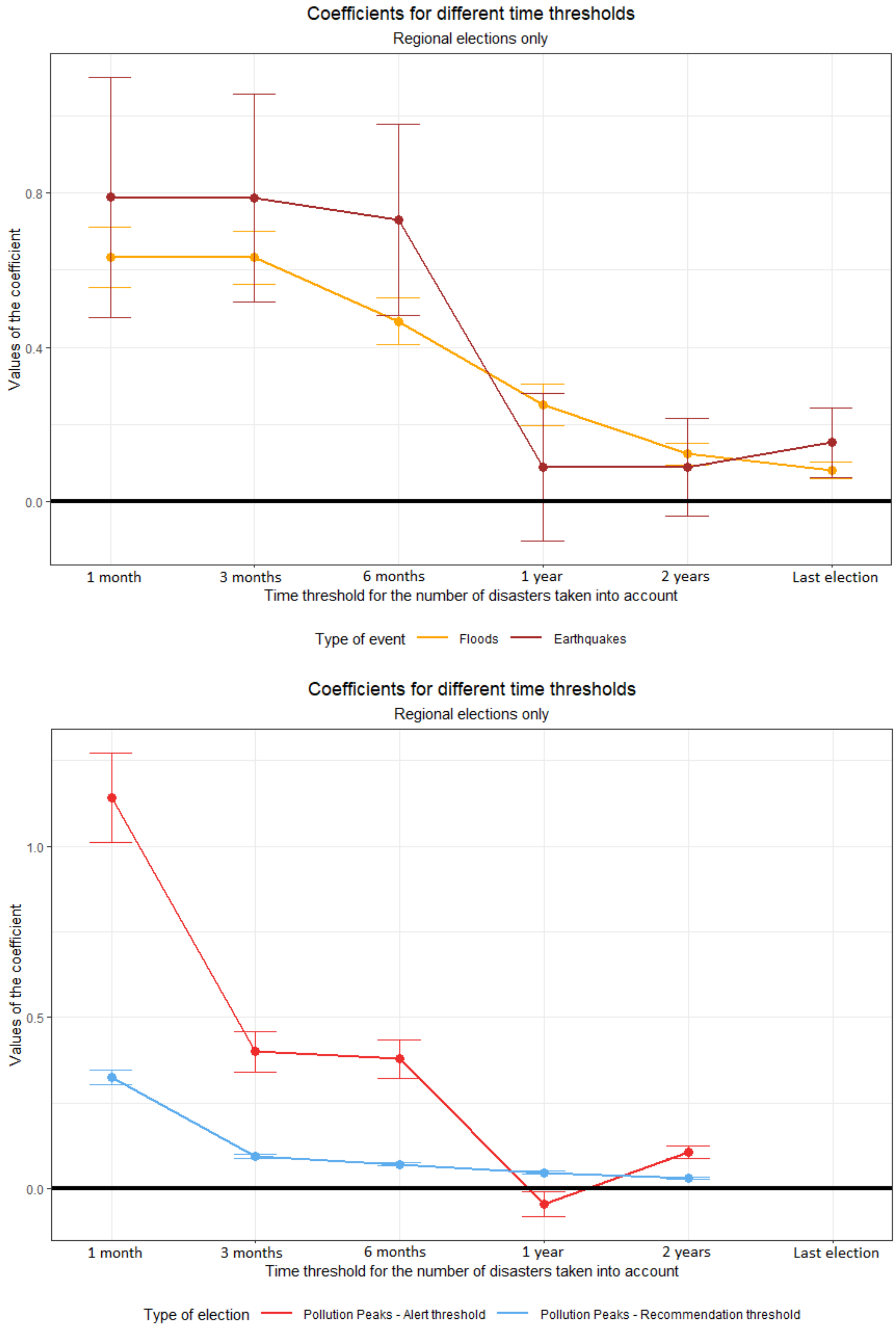


Figure 12: Values of β_1 for varying time thresholds.

are displayed on figure 13. One can observe that introducing the number of days of exposure does not change the trend for floods while the effect of earthquakes becomes non significant. The conclusion from this robustness check is that one should be more confident in the results concerning floods than in those related to earthquakes. For this reason, I will not consider the effect of earthquakes in following sections.

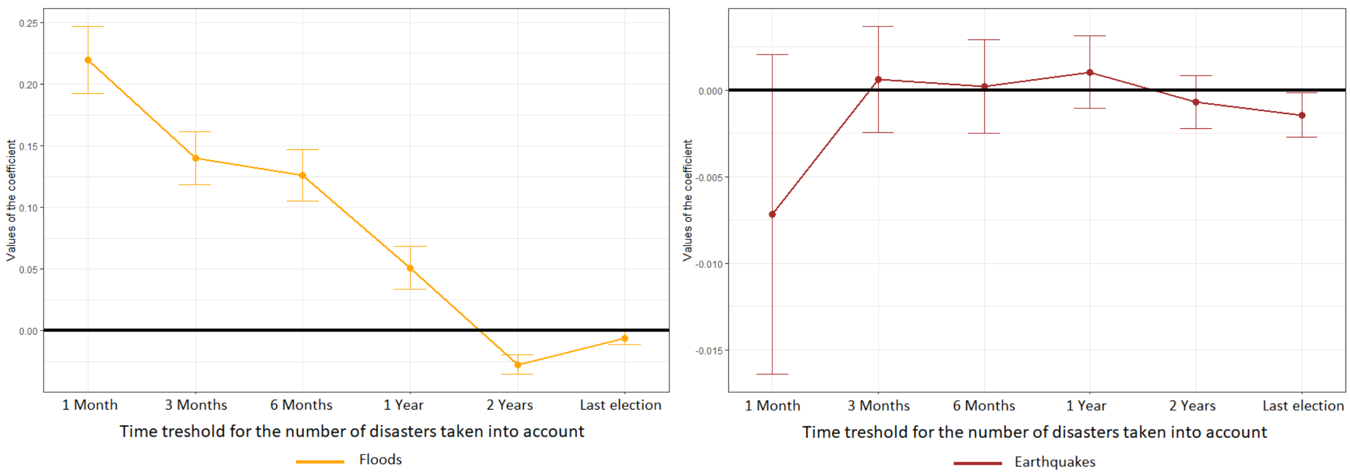


Figure 13: Value of β_1 for varying time thresholds. The explanatory variable is the number of days of disaster.

Secondly, concerning pollution peaks, one could be concerned about the arbitrary choice related to the smoothing function applied to municipalities, i.e. the value of $\bar{D}$ (see section 3.3.2 for more details about this weighting function). The value of $\bar{D}$ chosen for the linear smoothing function was 15km in the previous regression. On figure 14, I make vary this distance threshold and look at the value of β_1 for both the recommendation and the alert thresholds. In the two cases, we observe that the effect remains positive and significant.

Finally, one could also be concerned about the fact that green parties are often considered as being left-wing and thus that there could be redistribution aspects that drive the effect. To check whether it is the case, I change the outcome variable and consider the share of votes received by left-wing parties, which generally put more weight on redistribution issues. Results are displayed on figure 15. One can see that all of the coefficients associated to floods and pollution peaks are negative, showing that the effect is different for parties that put more weight on redistribution. It suggests that the effect we observed is indeed driven by environmental concerns.

6.2.3 Comments

The fact that the results obtained are only valid for Regional elections and not for Legislative and European ones, as it is shown on figure 10, could mean that the events considered do not affect perceptions, but rather influence the vote through a *backlash* channel. The role of Regional incumbents is indeed to propose solutions at a local level in terms of transport and landscape design for instance while National and European Parliaments deal with larger scale issues. It is likely that citizens do not vote more for a green party because they deeply believe that climate change is a major issue, but because they are directly affected by pollution and floods and they prefer to vote for

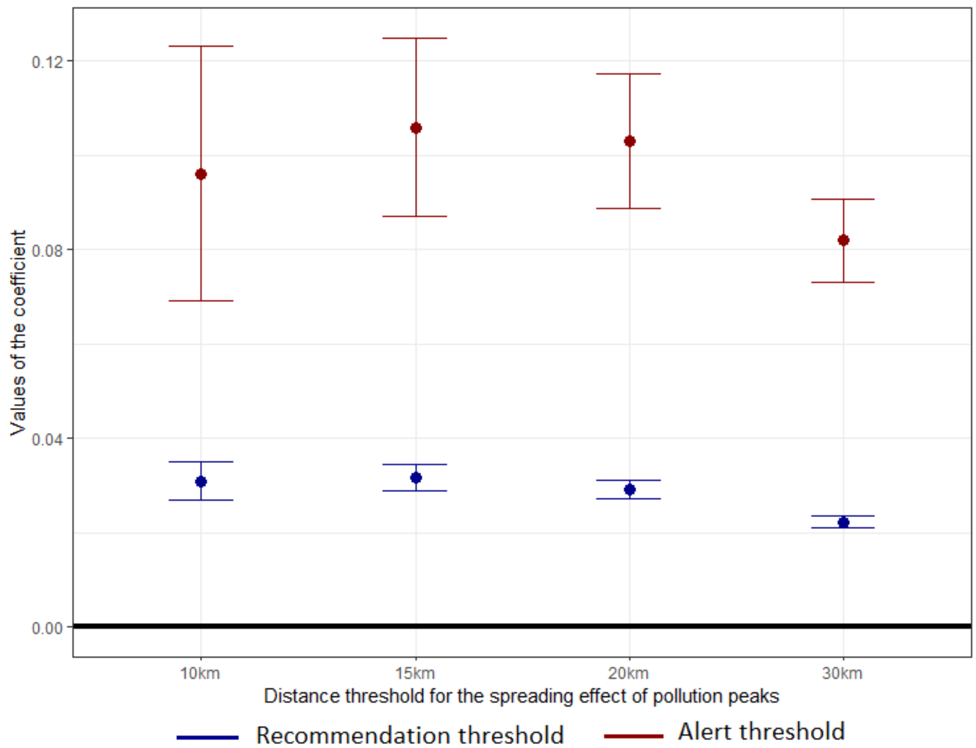


Figure 14: Values of β_1 for varying distance thresholds. The explanatory variable is the number of PM_{10} pollution peaks up to 2 years before the election.

	Dependent variable:		
	Vote share for left-wing parties		
	(1)	(2)	(3)
Number of floods	-0.176***		
	(0.038)		
Pollution peaks (Recommendation)		-0.104***	
		(0.005)	
Pollution peaks (alert)			-0.253***
			(0.035)
% of indidivuals with a baccalaureat	0.011*	0.006	0.005
	(0.007)	(0.007)	(0.007)
% of individuals who are above 55	0.057***	0.071***	0.069***
	(0.008)	(0.008)	(0.008)
Log Income Median	-4.326***	-4.074***	-4.561***
	(0.407)	(0.435)	(0.438)
Log Density	3.133***	3.654***	3.774***
	(0.345)	(0.380)	(0.382)
Average PM concentration	-9.210***	-18.852***	-18.128***
	(0.464)	(0.502)	(0.505)
% of workers in agriculture and industry	0.0004	-0.0003	-0.0002
	(0.001)	(0.001)	(0.001)
Year fixed effects	Yes	Yes	Yes
Observations	68,886	54,054	54,054
R^2	0.372	0.415	0.407
Note:			*p**p***p<0.01

Figure 15: Regression table for Regional elections only. The outcome variable is share of votes received by left-wing parties.

someone that would take these issues into consideration. The difference is that the backlash channel is based on more individualistic reasoning that do not take into account climate change as global issue, unlike the perception channel.

The decreasing effect through time I highlighted on figure 12 shows that the salient effect of floods and pollution peaks can act like a shock which has limited long term effects. It is an insightful result: it shows that salient events such as floods and pollution peaks are not sufficient to change perceptions in the long term. This phenomenon is consistent with the fact that floods and pollution peaks do not to change deep perceptions on environmental issues, and that the positive effect we observe on Regional elections is driven by a more individualistic reasoning.

In order to get more intuition about the magnitude of these results, Table 4 provides an interpretation of the results. It first compares the effect of each event to the effect of education and income. One can see that magnitudes are pretty high: a flood and a pollution peak at the alert threshold are equivalent to an increase in 5 percentage points in the share of individuals with a *baccalauréat*. Thus, when these events happen, they seem to have a high impact on perceptions.

I also computed the aggregate effect of each event, meaning that I computed how much green voting would decrease if the number of events was equal to zero according to the model. It gave me the level at which each event should account for the share of votes going to green parties. One can see that aggregate effect at the recommendation threshold for pollution peaks is higher than the one at the alert threshold. The reason is that the recommendation threshold is reached much more often than the alert one.

Table 4: Interpretation table for events related to Regional elections. Results are based on figure 11.

		Floods	Pollution peaks (Recommendation)	Pollution peaks (Alert)
Marginal effect of the event	In percentage points	0.08	0.03	0.11
	In percentages	1.79%	0.70%	2.33%
Equivalent increase in the share of individuals with a *baccalauréat*	In percentage points	4.53	1.79	5.93
Equivalent increase in median income	In percentages	5.14%	1.60%	5.00%
Aggregate effect of the event	In percentages	1.14%	2.41%	0.87%
Equivalent increase in the share of individuals with a *baccalauréat*	In percentage points	0.63	1.37	0.49
Equivalent increase in median income	In percentages	0.72%	1.22%	0.41%

Let focus on PM_{10} pollution peaks. We have shown that the occurrence of these events should favor green parties and account for around 2.41% of their votes at Regional elections. It is an important result which shows that pollution can affect perceptions towards climate change and that these perceptions can translate in concrete decisions such as vote. What we learn from this phenomenon is that fighting against pollution at the local level is a factor that drives voting decisions. That is why this result is particularly interesting for an incumbent who would look for a future election. We will go further on this discussion in section 8.

6.3 Focus on Drought-related disasters

In this section, I will present the results and some robustness checks related to drought-related disasters only. It seems that for this type of disasters, the effect on green voting is positive for all elections.

6.3.1 Results

Figure 16 displays the results for drought-related disasters only. On the first column, I replicated equation (1) for all elections pooled together. The three remaining columns are the results for each panel of election. We can see that coefficients are positive and significant across elections, showing a positive effect of drought-related disasters on green voting.

Figure 17 shows how the effect evolves for various time thresholds for the number of disasters taken into account. The time thresholds for 1 month and 3 months for Regional elections are not available because there was not any drought-related disaster that happened within these time periods. What we can see from this figure is that there does not seem to be any clear effect that would be decreasing through time. For Legislative and European elections, the trend is almost flat indeed. For Regional elections, one could observe a decreasing curve, but given that standard errors are very large, this trend is not really clear.

Another concern that we could have when facing these results is whether there is something that can be done to overcome the effect of drought-related disasters on green voting. A possibility could be to build protection plans in order to prevent an incumbent from a vote turnout towards green parties. I explore this possibility in figure 18 by adding an interaction variable for the number of protection plan that was implemented in each municipality[29]. One can not see any significant effect for the interaction variable when taking each panel of election independently. However, when pooling all elections together, there seems to be a negative and significant effect on green voting. A possible explanation could be the following: if people suffer less from a natural disaster, their perception regarding this disaster will be affected too. As a matter of fact, building infrastructure to prevent citizens from the consequences of drought-related disaster could be a good decision from the point of view of an incumbent who wants to prevent himself from a vote turnout towards green parties.

6.3.2 Robustness Checks

In order to assess the robustness of these results, I ran the same robustness checks as in section 6.2.2, meaning that I replaced the variable of interest by the number of days of disaster and replaced the outcome variable by the share of the votes going to left-wing parties. Results are displayed on figures 19 and 20. One can see that introducing

[29] see section 3.2 for more details on protection plans.

	Dependent variable:			
	Vote share for green parties			
	All elections	Regional	Legislative	European
	(1)	(2)	(3)	(4)
Number of disasters	0.060***	0.125***	0.093***	0.124***
	(0.012)	(0.032)	(0.022)	(0.015)
% of indidivuals with a baccalaureat	0.020***	0.018***	0.010***	0.029***
	(0.002)	(0.005)	(0.003)	(0.003)
% of individuals who are above 55	-0.009***	-0.030***	-0.008**	-0.006*
	(0.002)	(0.007)	(0.004)	(0.003)
Log Income Median	0.920***	1.579***	1.047***	0.823***
	(0.110)	(0.281)	(0.185)	(0.132)
Log Density	0.001	-1.670***	-0.617***	1.043***
	(0.093)	(0.283)	(0.125)	(0.143)
Average PM concentration	-3.032***	-5.700***	-1.339***	-2.791***
	(0.094)	(0.304)	(0.166)	(0.107)
% of workers in industry	-0.0004	-0.001	-0.001	-0.0001
	(0.0003)	(0.001)	(0.001)	(0.0004)
% of individuals taking the car	-0.002**	-0.0001	0.0002	-0.004***
	(0.001)	(0.002)	(0.001)	(0.001)
Year fixed effects	Yes	Yes	Yes	Yes
Observations	344,430	68,886	137,772	137,772
R^2	0.288	0.287	0.046	0.442
Note:				*p**p***p<0.01

Figure 16: Regression table for drought-related disasters only.

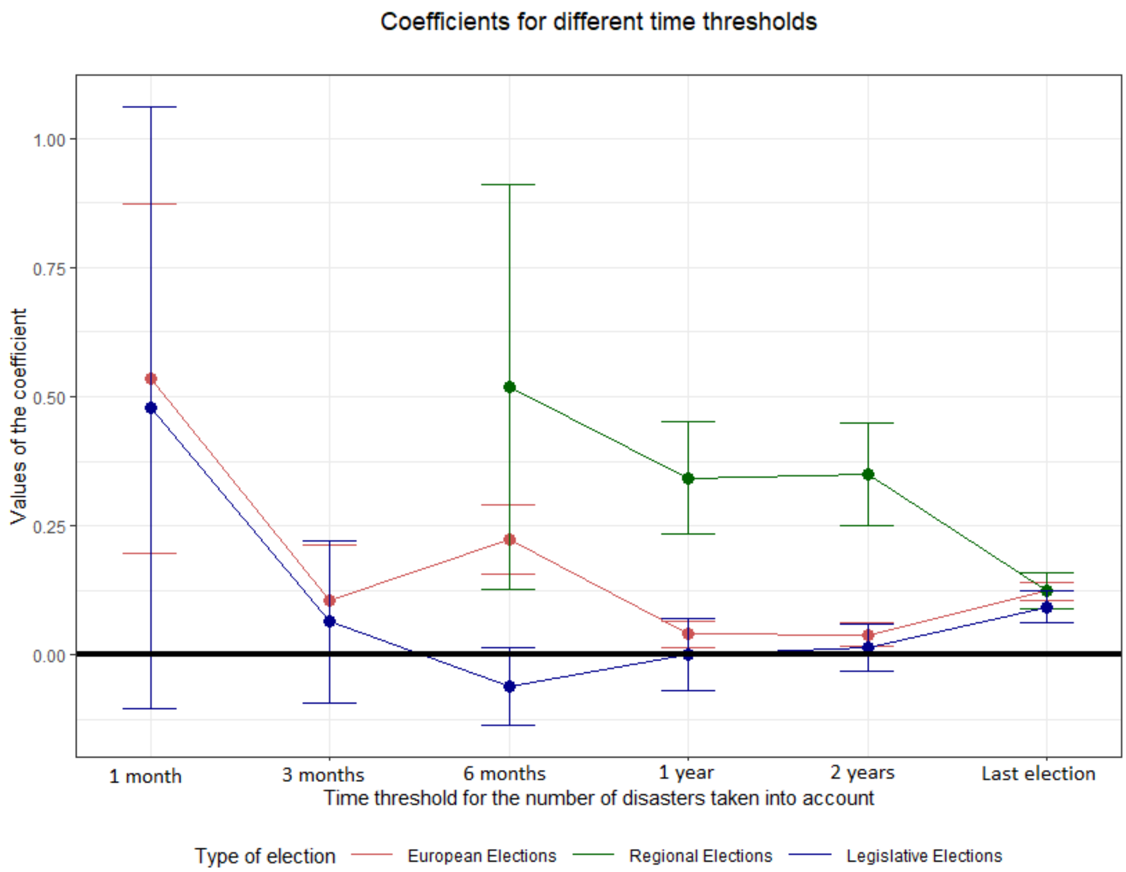


Figure 17: Values of β_1 for varying time thresholds. The explanatory variable is the number of drought related disasters.

	Dependent variable:			
	Vote share for green parties			
	All elections	Regional	Legislative	European
	(1)	(2)	(3)	(4)
Number of disasters	0.082***	0.138***	0.084***	0.139***
	(0.014)	(0.036)	(0.027)	(0.017)
Presence of a protection plan	0.298***	-0.354***	-0.308***	0.581***
	(0.049)	(0.130)	(0.071)	(0.054)
Disasters x protection plan	-0.080***	-0.050	0.061	-0.013
	(0.026)	(0.069)	(0.045)	(0.032)
% of indidivuals with a baccalaureat	0.020***	0.018***	0.010***	0.029***
	(0.002)	(0.005)	(0.003)	(0.003)
% of individuals who are above 55	-0.009***	-0.029***	-0.008**	-0.007**
	(0.002)	(0.007)	(0.004)	(0.003)
Log Income Median	0.925***	1.575***	1.048***	0.852***
	(0.110)	(0.281)	(0.185)	(0.132)
Log Density	-0.003	-1.664***	-0.613***	1.029***
	(0.093)	(0.283)	(0.125)	(0.143)
Average PM concentration	-2.981***	-5.753***	-1.389***	-2.667***
	(0.094)	(0.306)	(0.167)	(0.108)
% of workers in industry	-0.0004	-0.001	-0.001	-0.0001
	(0.0003)	(0.001)	(0.001)	(0.0004)
% of individuals taking the car	-0.002**	-0.0002	0.0002	-0.004***
	(0.001)	(0.002)	(0.001)	(0.001)
Year fixed effects	Yes	Yes	Yes	Yes
Observations	344,430	68,886	137,772	137,772
R^2	0.288	0.287	0.046	0.443
Note:				*p**p***p<0.01

Figure 18: Regression table for the effect of protection plans. The variable of interest is the interaction between the number of drought-related disasters and the number of protection plans that has been implemented.

the number of days of exposure does not change the sign of the coefficients, and that the effect of drought-related disasters on left-wing parties is either negative or non significant. These results assess the robustness of our previous findings, as explained in section 6.2.2.

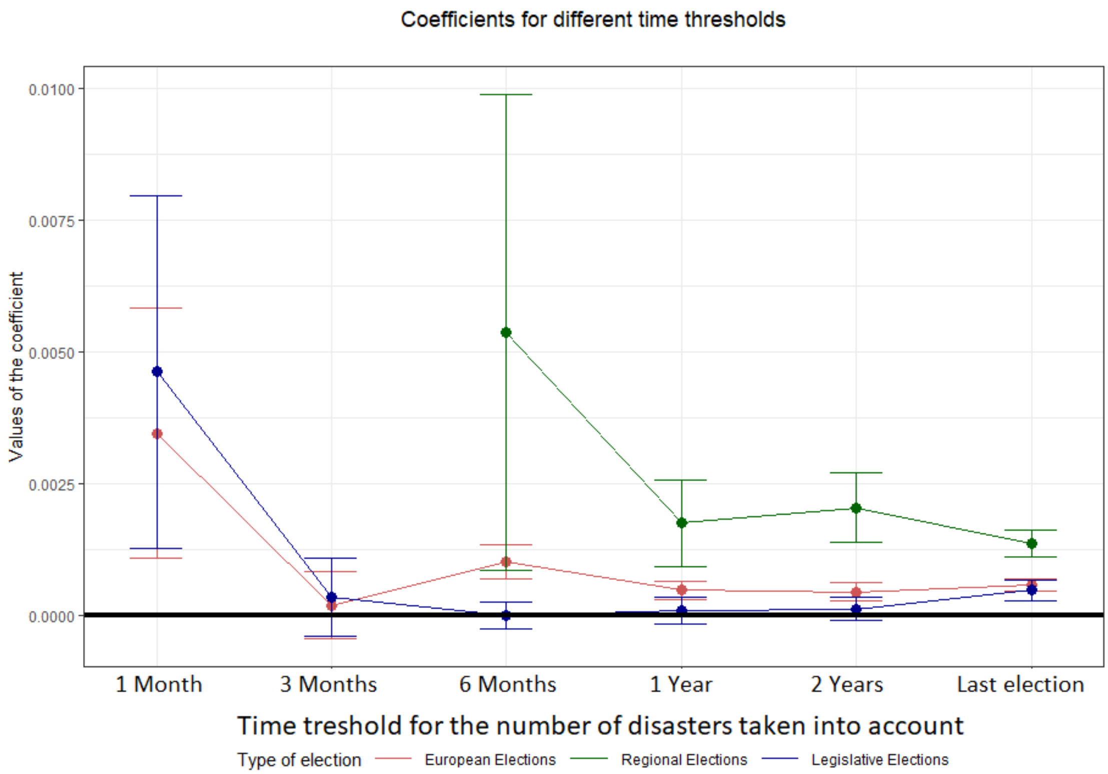


Figure 19: Values of β_1 for varying time thresholds and for Drought-related disasters only. The explanatory variable is the number of days of disaster.

6.3.3 Comments

Table 5 gives interpretations for the results concerning drought-related disasters. One can see that marginal effects are pretty high (from a 2.5% to a 3.5% increase in the votes for green parties). However, aggregate effects are much smaller (less than 1%). It is mainly due to the fact that the municipalities affected by drought-related disasters generally have a low population, meaning that even if the effect in these municipalities is high, they do not weigh much in the end. Moreover, it is quite striking to see how aggregate effects are similar across elections.

The fact that we observe a positive and significant effect that is robust to all elections suggests that the effect of drought-related disasters is of a different nature as compared to floods and pollution peaks. An interpretation could be that these disasters, which are very often correlated with high temperatures, can have consequences in terms of perceptions of global warming in the long run. The fact that we do not observe any decrease with time seems consistent with this idea: drought-related disasters do not have a temporary impact on environmental views

	Dependent variable:			
	Vote share for left-wing parties			
	All elections	Regional	Legislative	European
	(1)	(2)	(3)	(4)
Number of disasters	-0.052*	-0.206***	-0.180***	-0.017
	(0.028)	(0.062)	(0.056)	(0.023)
% of indidivuals with a baccalaureat	0.002	0.012*	0.001	0.004*
	(0.003)	(0.007)	(0.005)	(0.002)
% of individuals who are above 55	0.016***	0.057***	0.004	0.021***
	(0.003)	(0.008)	(0.006)	(0.003)
Log Income Median	0.539***	-4.311***	2.610***	-0.103
	(0.172)	(0.407)	(0.323)	(0.155)
Log Density	0.007	3.151***	-0.742***	-0.041
	(0.120)	(0.345)	(0.198)	(0.119)
Average PM concentration	-0.278	-9.441***	2.864***	-0.892***
	(0.170)	(0.463)	(0.347)	(0.131)
% of workers in agriculture and industry	-0.00002	0.0004	0.001	-0.0004
	(0.0004)	(0.001)	(0.001)	(0.0003)
Year fixed effects	Yes	Yes	Yes	Yes
Observations	344,430	68,886	137,772	137,772
R^2	0.618	0.372	0.611	0.625
Note:				*p**p***p<0.01

Figure 20: Regression table for Drought-related disasters only. The outcome variable is the share of the votes going to left-wing parties.

Table 5: Interpretation table for events related to Drought-related disasters. Results are based on figure 16.

		Regional election	Legislative election	European election
Marginal effect of a disaster	In percentage points	0.12	0.09	0.12
	In percentages	2.74%	3.49%	2.45%
Equivalent increase in the share of individuals with a *baccalauréat*	In percentage points	7.00	9.77	4.30
Equivalent increase in median income	In percentages	7.89%	8.88%	15.32%
Aggregate effect of the disaster	In percentages	0.76%	0.82%	0.83%
Equivalent increase in the share of individuals with a *baccalauréat*	In percentage points	0.42	0.86	0.29
Equivalent increase in median income	In percentages	0.48%	0.78%	1.02%

but are able to influence perceptions more deeply in the long term. This result is consequent with a large literature showing that temperatures affect climate change considerations (see section 2 for more details).

7 Extensions

To build on the results we obtained in the previous section, I propose two extensions in order to understand more in depth how these effects behave. First, I will explore heterogeneity in the effect depending on education, time and $PM_{2.5}$ concentration. Secondly, I will investigate the cumulative effect of natural disasters and PM_{10} pollution peaks.

7.1 Effect Heterogeneity

In this subsection I will explore heterogeneity in the effect for 3 variables. For each of these variables I run a different model and add an interaction term between the variable of interest (natural disasters and pollution peaks) and the variable for which I am looking for potential heterogeneity.

The first interacted variable is the share of individuals with a *baccalauréat*. The rationale for including this variable is that one could expect that if individuals are well documented about environmental issues, then they should be more likely to make the link between natural disasters, pollution peaks and climate change. The fact that more educated individuals react more to salient events is a standard result in the literature (see Baccini and Leeman, 2020). The second variable is the effect of natural disasters and pollution peaks during the last election. The underlying mechanism could be that as environmental concerns spread among the French population[30], the effect of natural disasters becomes stronger as people are more likely to make the link between disasters and climate change. That is why I included a dummy variable equal to 1 for the last year of each election (2015 for Regional, 2017 for Legislative and 2019 for European) and interacted it with the variable of interest. Finally, I study the heterogeneity depending on $PM_{2.5}$ concentration. We could expect a negative sign since people who rely more on polluting activities should be less willing to change their vote when a natural disaster or a pollution peak occurs.

Results for these 3 types of variables are presented on figure 21. Because I focused first on Regional elections and then on drought-related disasters in section 6, I presented the results about heterogeneity in a similar way. On the left hand side are results for Regional elections only and on the right hand side are results for drought-related disasters only.

One can see that lots of coefficients are non significant, suggesting that there is not much heterogeneity in the effect. However, for those who are significant, signs are consistent with what we expected concerning education and $PM_{2.5}$ concentration: a positive sign for the share of individuals with a baccalauréat and a negative sign for $PM_{2.5}$ concentration. For the variable *Last year*, we observe for the left part of figure 21 a positive coefficient for floods and negative coefficients for pollution peaks. It suggests that the effect of pollution peaks on perceptions decreased with time while the one of floods became more important.

7.2 Cumulative Effect

In this subsection, I will investigate whether the effect of a new disaster evolves with the number of past disasters. Put differently, are the results we obtained in the section 6 driven by the effect of the first disaster that acts like a shock affecting perceptions, or is it the accumulation of natural disasters and pollution peaks that matters?

The methodology I use to answer this question is the following: I define a given threshold L for each type of event. Then I define a dummy variable $C_{it}(L)$ as follows

$$C_{it}(L) = \begin{cases} 1 & if \quad Disaster_{it} > L \\ 0 & otherwise \end{cases}$$

Put differently, $C_{it}(L)$ is a dummy variable equal to 1 in municipality i at election t if the number of natural disasters since election $t-1$ is superior to L. I include this variable in the regression and the coefficient of interest becomes the one associated to this variable. The coefficient associated to $C_{it}(L)$ will be the marginal effect on the green vote of experiencing more than L disasters. Then I make L vary so that I can observe how the effect evolves depending on the number of disasters taken into account. Of course, I will consider different values for L depending on the type of disaster that is considered since their frequency of occurrence are not always similar (see section A.6 for more details about the distribution of each type of event). This methodology enables us to see what drives the effect: is it the first disaster experienced by a municipality that acts like a shock or the accumulation of events?[31]

[30] *Baromètre les français et l'environnement - vague 6*, 2019, ADEME

[31] I follow the same process for pollution peaks.

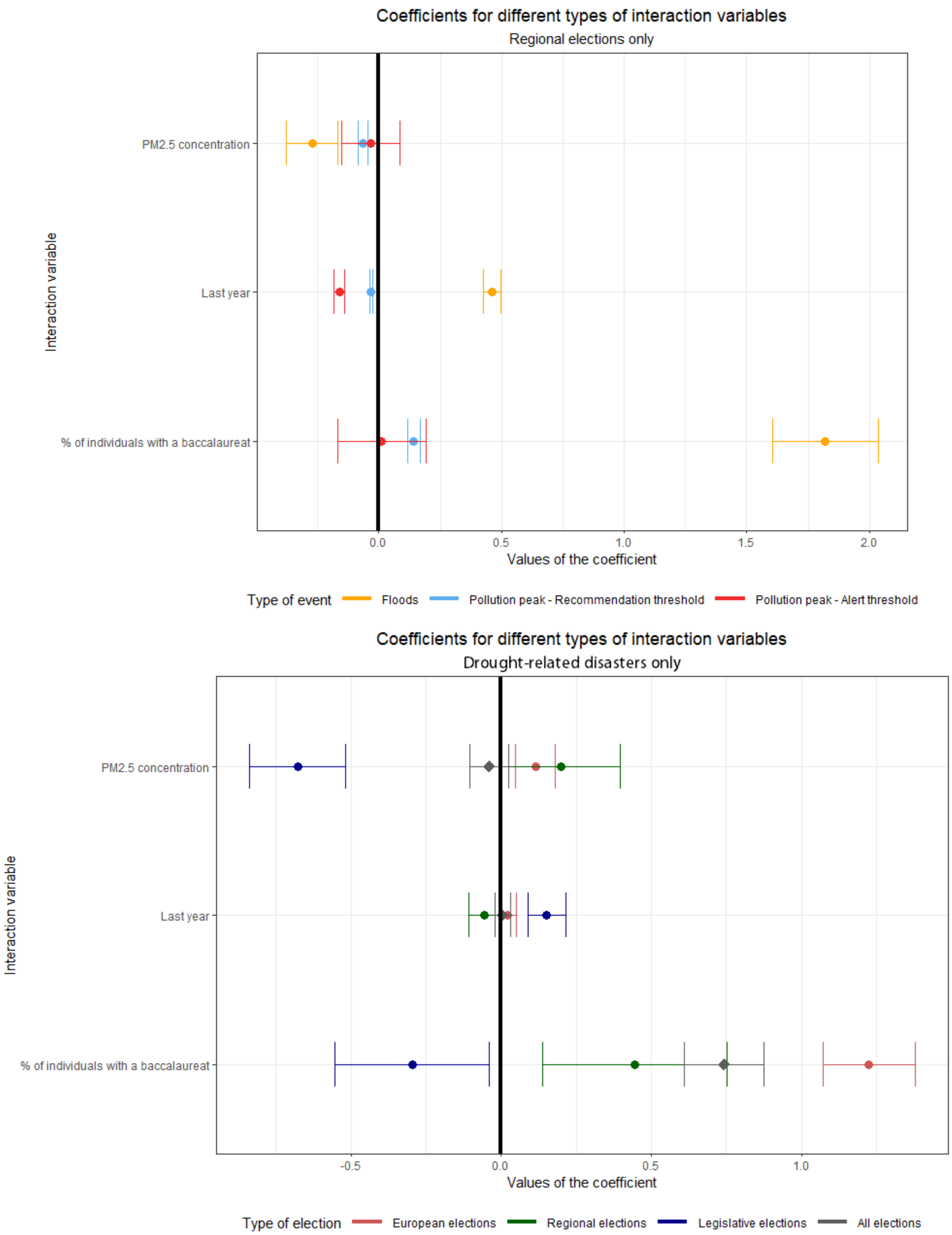


Figure 21: Values of the coefficient associated to the interaction term for each interacted variable on the y axis. The first picture concerns Regional elections only while the second picture is about drought-related disasters only.

Results are displayed on figure 22 for floods and pollution peaks during Regional elections and on figure 23 for drought-related disasters only. Concerning floods and pollution peaks (recommendation threshold), there seems to be an increasing effect with the threshold for the number of events taken into account. Put differently, experiencing multiple disasters seems to affect more perceptions than being victim of a single disaster. Thus, there seems to be an accumulation effect for these events. Regarding pollution peaks at the alert threshold, the first event seems to affect perceptions the same as multiple events: the trend is almost flat.

Concerning pollution peaks at the recommendation threshold, this result seems consistent with what we have seen before. It is likely that a single pollution peak is maybe not visible for most individuals: measures are rarely taken at the recommendation thresholds and journals may not cover an isolated event. However, the accumulation of events seems to be more salient since media are more likely to deal with this topic and prefectures to take measures. For the alert threshold, since prefectures are compelled to take measures immediately, perceptions are affected from the first event.

For drought-related disasters, the trend is quite flat for all elections. One can even observe a slight decrease for Regional and Legislative elections. There also seems to be a slightly increasing trend for European elections but as standard errors are large, this trend is not that clear. It suggests that for these events, the first disaster acts like a salient shock that affects perceptions, meaning that there does not seem to be any cumulative effect due to experiencing multiple disasters.

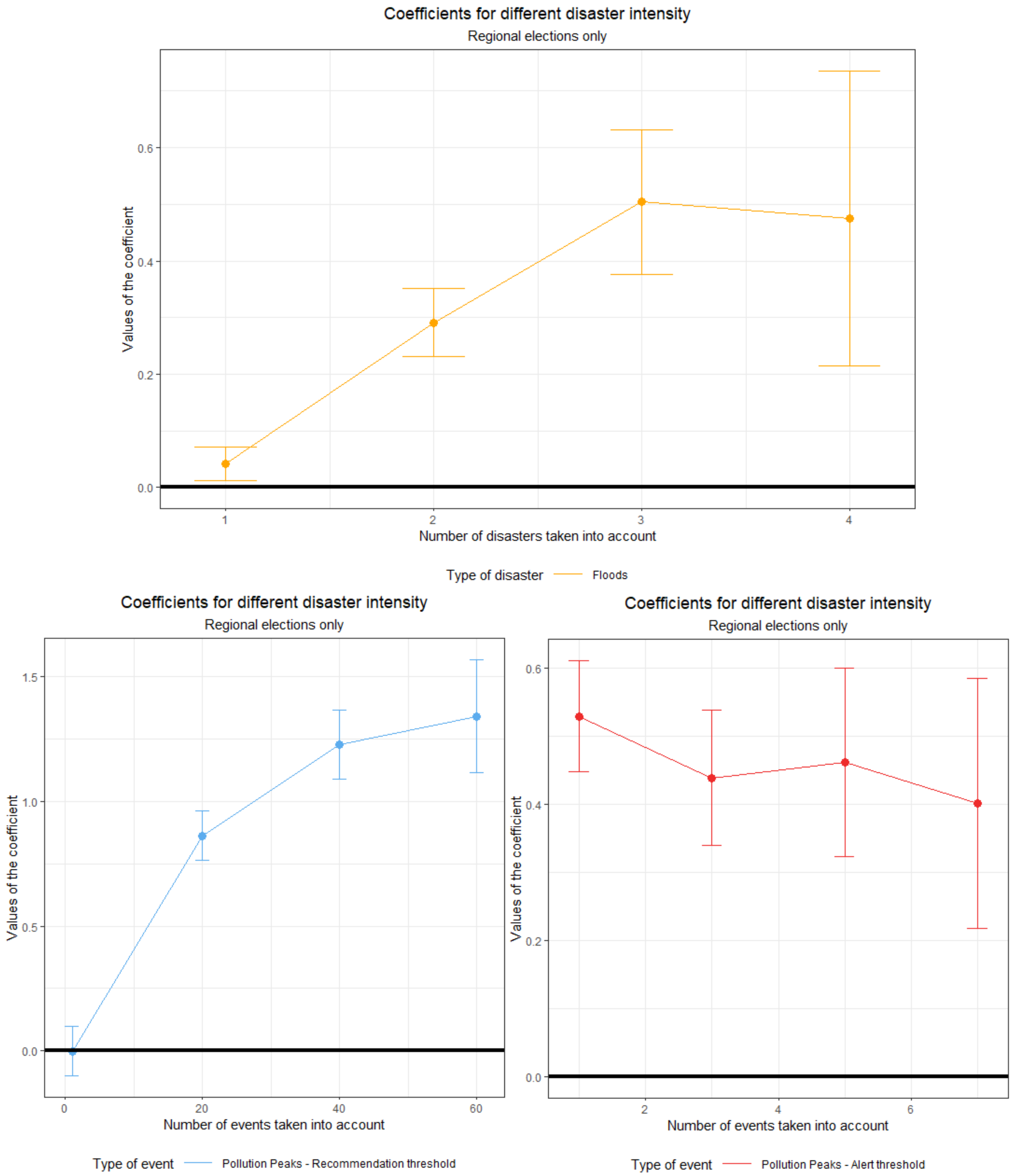


Figure 22: Values of the coefficient associated to $C_{it}(L)$ for varying values of L on the x axis. These coefficients only concern Regional elections for different types of events.

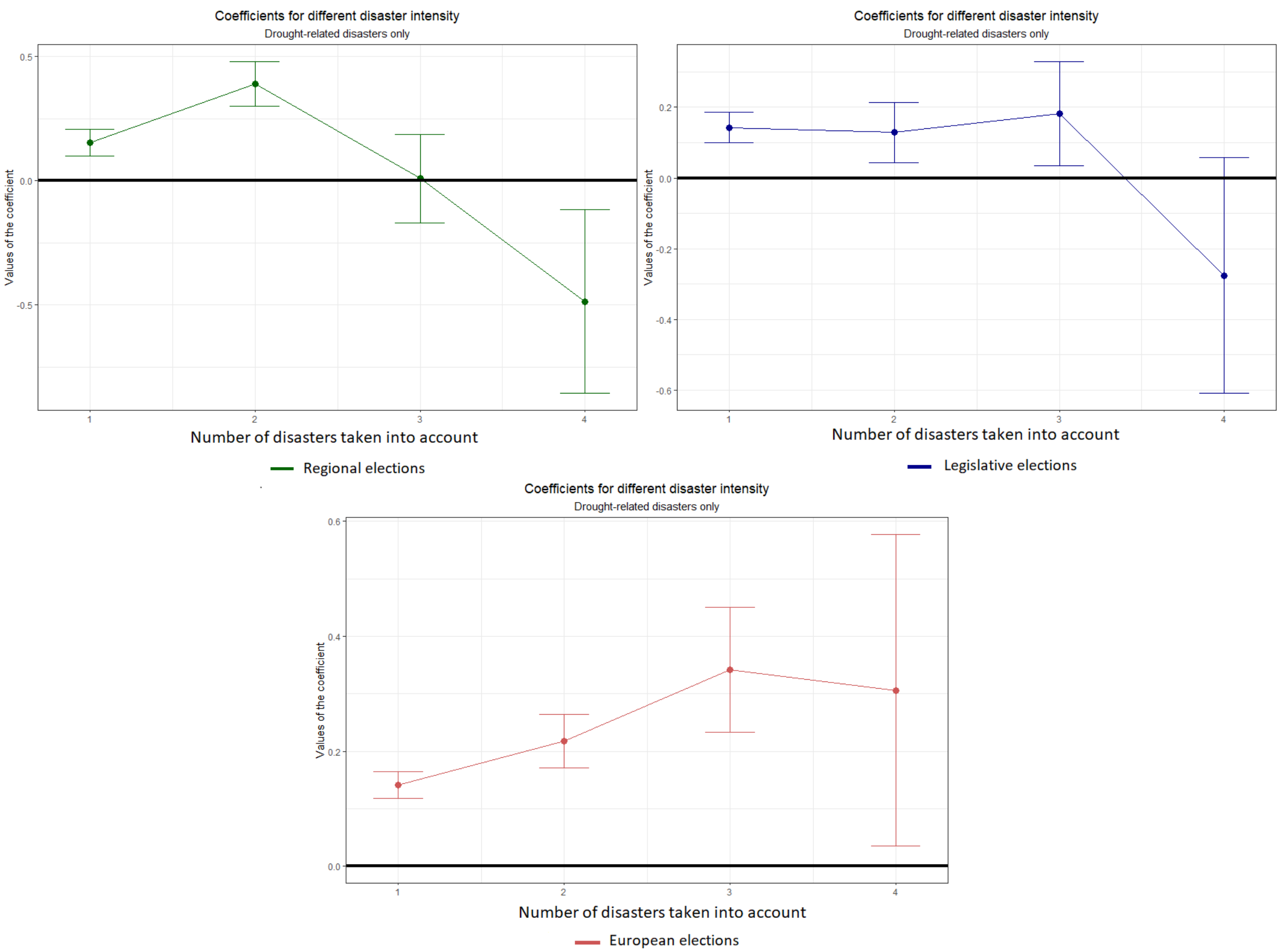


Figure 23: Values of the coefficient associated to $C_{it}(L)$ for varying values of L on the x axis. These coefficients only concern drought-related disasters for different types of election.

8 Conclusions

I have studied the determinants of the vote for green parties, and investigated whether natural disasters and pollution peaks could also affect this outcome.

Concerning these standard determinants, I found a positive and significant effect for education, income and density on green voting. I found a negative effect for the average level of PM2.5 concentration, showing that when an area relies more on polluting activities, the share of the votes received by green parties is likely to decrease. These results remain consistent across each type of election considered and coherent with the literature.

The core of this analysis documented the relationship between salient events and green votes. Let focus on the effect of floods. I found a positive coefficient for Regional elections only, which suggests that people vote more for a green party after a flood because they chose politicians who are more likely to be concerned by environmental issues at a local level. As a matter of fact, it does not seem that floods can affect perceptions regarding climate change as a global issue. I also find a cumulative effect of floods that is decreasing through time, suggesting that floods do not have long term effects.

Concerning PM_{10} pollution peaks, I find a similar result to the ones obtained for floods: a positive and significant effect for Regional elections only. I find a decreasing effect with time for both the alert and the recommendation thresholds, showing once again that these events do not seem to have long term effects. I also find a cumulative effect for the recommendation threshold but not for the alert one, which is consistent with what we could expect. It is interesting to compare these results to the ones of average $PM_{2.5}$ concentration: it seems that latent pollution, even if it has concrete health consequences, has a negative effect on green voting, while pollution peaks show a positive effect on Regional elections. It illustrates how salient events are able to affect perceptions, even if latent pollution has more consequences on health[32].

For drought-related disasters, I highlighted an effect that is robust to the three different types of elections. The effect does not seem to be decreasing with time and there does not seem to be any cumulative effect either. Thus, drought-related disasters, which are correlated with high temperatures, seem to act like a salient shock affecting perceptions in the long term. I also showed that building protection plans to prevent from the damages of a drought can also affect perceptions.

This work is of interest in terms of policy recommendations. As natural disasters will become more frequent in the following years, this study shows that there will probably be more support for pro environmental policies in the future. It should encourage politicians to care more about these issues in order to benefit from this trend. From the point of view of a non-green incumbent, it is also interesting to notice that building prevention plans can lower the effect of drought-related disasters and that pollution can affect citizens' votes. It means that dealing with these issue could be a good strategy in order to prevent a non-green incumbent from a vote turnout.

Now, a reasonable question would be, is it good news for the environment? An optimistic standpoint is that this study shows that views on global warming can change, that people react when they observe events that they think could be due to climate change. In the particular case of drought-related disasters, perceptions in the long run seem to be affected, which is encouraging. On the other hand, if the most efficient way of changing views on climate is to experience natural disasters and pollution peaks, then the situation could seem quite desperate. But

[32]See the website of *Santé Publique France*, http://www.santepubliquefrance.fr/determinants-de-sante/pollution-et-sante/air/articles/cas-particulier-des-pics-de-pollution.

one should keep in mind that I just highlighted a single channel through which perceptions can be altered. There exist many others such as lobbying from non profit organizations that can also have large scale impacts (Damania, 2001, Polk & Schmutzler, 2005, Delmas, Lim & Nairn-Birch, 2016).

The main limitation of this study is probably the assumption that voting for a green party reveals one's green preferences. There are indeed many factors that can explain voting outcomes which are sometimes completely uncorrelated from political programs (Wolfers, 2002, Martinelli, 2006). However, even if voting outcomes of green parties do not perfectly translate environmental concerns, I argue that it could be a relevant proxy. Moreover, as I developed in section 3.1.2, the interest of studying this outcome (as opposed to survey data) is that it provides insights on whether natural disasters and pollution peaks have concrete impacts.

Finally, I believe that it would be interesting to study whether green incumbents perform better than other political parties based on environmental criteria. Now that green mayors have been elected in several cities in France in 2020, it could give an adequate framework for future research on this topic.

References

[1] ADEME (2019), "Baromètre les français et l'environnement - vague 6".

[2] ADEME (2002), "Classification and Criteria for Setting Up Air-Quality Monitoring Stations".

[3] Baas, S., Trujillo, M., Lombardi, N. (2015), "Impact of disasters on agriculture and food security", FAO.

[4] Baccini, L., Leemann, L. (2020), "Do natural disasters help the environment? How voters respond and what that means", Political Science Research and Methods, 1-17.

[5] Barraqué, B., Moatty, A. (2020), "The French Cat' Nat' system: post-flood recovery and resilience issues", Environmental Hazards 19, 285-300.

[6] Bickerstaff K., Walker G. (2001), "Public understandings of air pollution: the 'localisation' of environmental risk", Glob Environ Chang 11, 133–145.

[7] Borick, C.P., Rabe, B. (2014), "Weather or Not? Examining the Impact of Meteorological Conditions on Public Opinion regarding Global Warming", Weather, Climate, and Society 6, 413-424.

[8] Boy, D. (2011), "Inscrire l'écologie politique dans la durée", Frontières, 55-67.

[9] Boy, D. (2014), "Les Verts, l'Europe et le pouvoir", CEVIPOF.

[10] Brooks, J., Oxley, D., Vedlitz, A., Zahran, S., Lindsey, C. (2014), "Abnormal Daily Temperature and Concern about Climate Change Across the United States", Review of Policy Research 31, 199-217.

[11] Buton, P. (2016), "La gauche et la question écologique", Revue Française d'Histoire des Idées Politiques 2, 63-92.

[12] Caisse Centrale de Réassurance (2018), "Les catastrophes naturelles en France - Bilan 1982-2018".

[13] CERES (2019), "La pollution atmosphérique en vallée de l'Arve".

[14] Champalaune, P. (2020), "Inequality in Exposure to Air Pollution in France: Measurement and Impact of a City-Level Public Policy", PSE Master Thesis.

[15] Citepa (2018), "Gaz à effet de serre et polluants atmosphériques: Bilan des émissions en France de 1990 à 2017".

[16] Coan, T. G., Holman, M. R. (2008), "Voting green", Social Science Quarterly 89, 1121-1135.

[17] Comin, D., Rode, J. (2013), "From green users to green voters", National Bureau of Economic Research.

[18] Conforti, P., Ahmed, S., Markova, G. (2018), "Impact of disasters and crises on agriculture and food security", 2017.

[19] Coumou, D., Rahmstorf, S. (2012), "A decade of weather extremes", Nat Clim Chang 2, 491–496.

[20] Damania, R. (2001), "When the weak win: the role of investment in environmental lobbying", Journal of Environmental Economics and Management 42, 1-22.

[21] Delmas, M., Lim, J., Nairn-Birch, N. (2016), "Corporate environmental performance and lobbying", Academy of Management Discoveries 2, 175-197.

[22] Demski, C., Capstick, S., Pidgeon, N., Sposato, R. G., Spence, A. (2016), "Experience of extreme weather affects climate change mitigation and adaptation responses", Climatic Change 140, 149-164.

[23] Duflo, E., Greenstone, M., Hanna, R. (2008), "Indoor air pollution, health and economic well-being", SAPI EN. S. Surveys and Perspectives Integrating Environment and Society.

[24] Easterling, W., Apps, M. (2005), "Assessing the Consequences of Climate Change for Food and forest Resources: A View from the IPCC", Climatic Change 70, 165–189.

[25] Egan, PJ., Mullin, M., (2012) "Turning personal experience into political attitudes: the effect of local weather on Americans perception about global warming", The Journal of Politics 74, 796-809.

[26] French Ministry of Ecological Transition (2015), "La gestion des pics de pollution de l'air".

[27] Gathié, H. (1998), "L'assurance des catastrophes naturelles", La houille blanche, 81-84.

[28] Giuseppe, C., Iyalomhe, F., Adekola., P.O. (2019), "Determinants of Flooding and Strategies for Mitigation: Two-Year Case Study of Benin City", Geosciences 9.

[29] Grünewald, F. (2020), "Rapport de l'évaluation de la réponse à la tempête Alex dans les Alpes-Maritimes", URD Report.

[30] Hausman, JA., Taylor, WE. (1981), "Panel data and unobservable individual effects," Econometrica 49, 1377-1398.

[31] Hazlett, C., Mildenberger, M. (2020), "Wildfire exposure increases pro-environment voting within democratic but not republican areas", American Political Science Review 114, 1359-1365.

[32] Howe, P., Markowitz, E., Ming Lee, T., Ko, C., Leiserowitz, A. (2014), "Global perceptions of local temperature change", Nat Clim Chang 3, 352–356.

[33] Huntingford, C., Marsh, T., Scaife, A. et al. (2014), "Potential influences on the United Kingdom's floods of winter 2013/14", Nature Clim Change 4, 769–777.

[34] Jones, C., Hine, D. W., Marks, A. D. G. (2017), "The future is now: Reducing psychological distance to increase public engagement with climate change", Risk Analysis 37, 331-341.

[35] Kahn, M. E. (2007), "Do greens drive Hummers or hybrids? Environmental ideology as a determinant of consumer choice", Journal of Environmental Economics and Management 54, 129-145.

[36] Keller C., Siegrist M., Gutscher H. (2006), "The role of the affect and availability heuristics in risk communication", Risk Anal 26, 631–639.

[37] Konisky, D., Hughes, L., Kaylor, C. (2015), "Extreme Weather Events and Climate Change Concern", Climatic Change.

[38] Li, Y., Johnson, E., Zaval, L. (2011), "Local warming: daily variation in temperature affects beliefs and concern about climate change" ,Psychol Sci 22, 454–459.

[39] Lorenzoni, I., Pidgeon, NF. (2006), "Public views on climate change: European and USA perspectives", Clim Chang 77, 73–95.

[40] Luechinger, S. (2010), "Life satisfaction and transboundary air pollution", Economics Letters 107, 4-6.

[41] Martinelli, C. (2006), "Would rational voters acquire costly information?", Journal of Economic Theory 129, 225-251.

[42] Mauroux, A. (2015), "Exposition aux risques naturels et marchés immobiliers", Revue d'économie financière, 91-103.

[43] Medina, S., M. Pascal, C. Tillier (2016), "Impacts de l'exposition chronique aux particules fines sur la mortalité en France continentale et analyse des gains en santé de plusieurs scénarios de réduction de la pollution atmosphérique", Santé publique France.

[44] Mendelsohn, R., Dinar, A. (1999), "Climate change, agriculture, and developing countries: does adaptation matter?", The World Bank Research Observer 14, 277-293.

[45] Nelson, E., Uwasu, M., Polasky, S. (2007), "Voting on open space: What explains the appearance and support of municipal-level open space conservation referenda in the United States?", Ecological Economics 62, 580-593.

[46] November, V., Penelas, M., Viot, P. (2009), "When flood risk transforms a territory: the Lully effect", Geography 94, 189–197.

[47] Olson, K. (2006), "Survey participation, nonresponse bias, measurement error bias, and total bias", International Journal of Public Opinion Quarterly 70, 737-758.

[48] Orru, K., Orru, H., Maasikmets, M., Hendrikson, R., Ainsaar, M. (2016), "Well-being and environmental quality: Does pollution affect life satisfaction?". Quality of Life Research 25, 699-705.

[49] Persico, S., Gougou, F. (2020), "La poussée (inachevée) de EELV: leçons tirées du 1er tour des municipales", Les notes de la FEP.

[50] Piketty, T. (2018), "Brahmin Left vs Merchant Right: Rising Inequality and the Changing Structure of Political Conflict", WID world Working Paper 7.

[51] Polk, A., Schmutzler, A. (2005), "Lobbying against environmental regulation vs. lobbying for loopholes", European Journal of Political Economy 21, 915-931.

[52] Rudolph, L., Kuhn, P. M. (2018), "Natural disasters and political participation: evidence from the 2002 and 2013 floods in Germany", German Politics 27, 1-24.

[53] Salka, W. M. (2001), "Urban-rural conflict over environmental policy in the western United States", The American Review of Public Administration 31, 33-48.

[54] Salthammer, T., Uhde, E., Schripp, T., Schieweck, A., Morawska, L., Mazaheri, M., Kumar, P. (2016), "Children's well-being at schools: Impact of climatic conditions and air pollution", Environment international 94, 196-210.

[55] Schumacher, I. (2014), "An empirical Study of the determinants of Green Party Voting", Ecological Economics 105, 306-318.

[56] Thalmann, P. (2004), "The public acceptance of green taxes: 2 million voters express their opinion", Public Choice 119, 179-217.

[57] Trope, Y., Liberman, N. (2010), "Construal-level theory of psychological distance", Psychological Review 117, 440-463.

[58] van der Linden, S., Maibach, E., Leiserowitz, A. (2015), "Improving public engagement with climate change: Five "best practice" insights from psychological science", Perspectives on Psychological Science 10, 758-763.

[59] Welsch, H. (2006), "Environment and happiness: Valuation of air pollution using life satisfaction data". Ecological economics 58, 801-813.

[60] Wolfers, J. (2002), "Are voters rational?: Evidence from gubernatorial elections", Stanford: Graduate School of Business, Stanford University.

[61] Wu, X., Cutter, B. (2011), "Who votes for public environmental goods in California?: Evidence from a spatial analysis of voting for environmental ballot measures", Ecological Economics 70, 554-563.

[62] Zhang, B., Wu, B., Liu, J. (2020), "PM2. 5 pollution-related health effects and willingness to pay for improved air quality: Evidence from China's prefecture-level cities", Journal of Cleaner Production 273.

A Appendix

A.1 Details for political groups

A.1.1 Green Parties

Table 6: Political parties considered as green for all elections.

Type of election	Year	Name of the list
Regional	2015	Liste d'Europe-Ecologie-Les Verts Liste Ecologiste Liste EELV et gauche
	2010	Liste des Verts
	2004	Liste des Verts Listes écologistes
Legislative	2017	Écologiste
	2012	Europe-Ecologie-Les Verts Ecologiste
	2007	Europe-Ecologie-Les Verts Ecologiste
	2002	Europe-Ecologie-Les Verts Ecologiste
European	2019	Europe Ecologie Décroissance 2019 Urgence Ecologie
	2014	Liste Europe-Ecologie-Les Verts
	2009	Liste des Verts
	2004	Liste des Verts Liste écologiste

A.1.2 Left-wing Parties

Table 7: Political parties considered as left-wing for all elections.

Type of election	Year	Name of the list
Regional	2015	Liste du Parti Socialiste Liste Union de la Gauche Liste du Parti radical de gauche Liste Divers gauche
	2010	Liste du Parti Socialiste Liste Union de la Gauche Listes Gauche-MoDem Liste Divers gauche
	2004	Listes de gauche Listes divers gauche
Legislative	2017	Parti socialiste Parti radical de gauche Divers gauche
	2012	Parti socialiste Parti radical de gauche Divers gauche
	2007	Parti socialiste Parti radical de gauche Divers gauche
	2002	Parti socialiste Parti radical de gauche Divers gauche
European	2019	Envie d'Europe Liste citoyenne
	2014	Liste Union de la Gauche Liste Divers gauche
	2009	Liste du Parti socialiste Liste divers gauche
	2004	Liste du Parti socialiste Liste divers gauche

A.2 Distribution of Green Votes by Percentiles

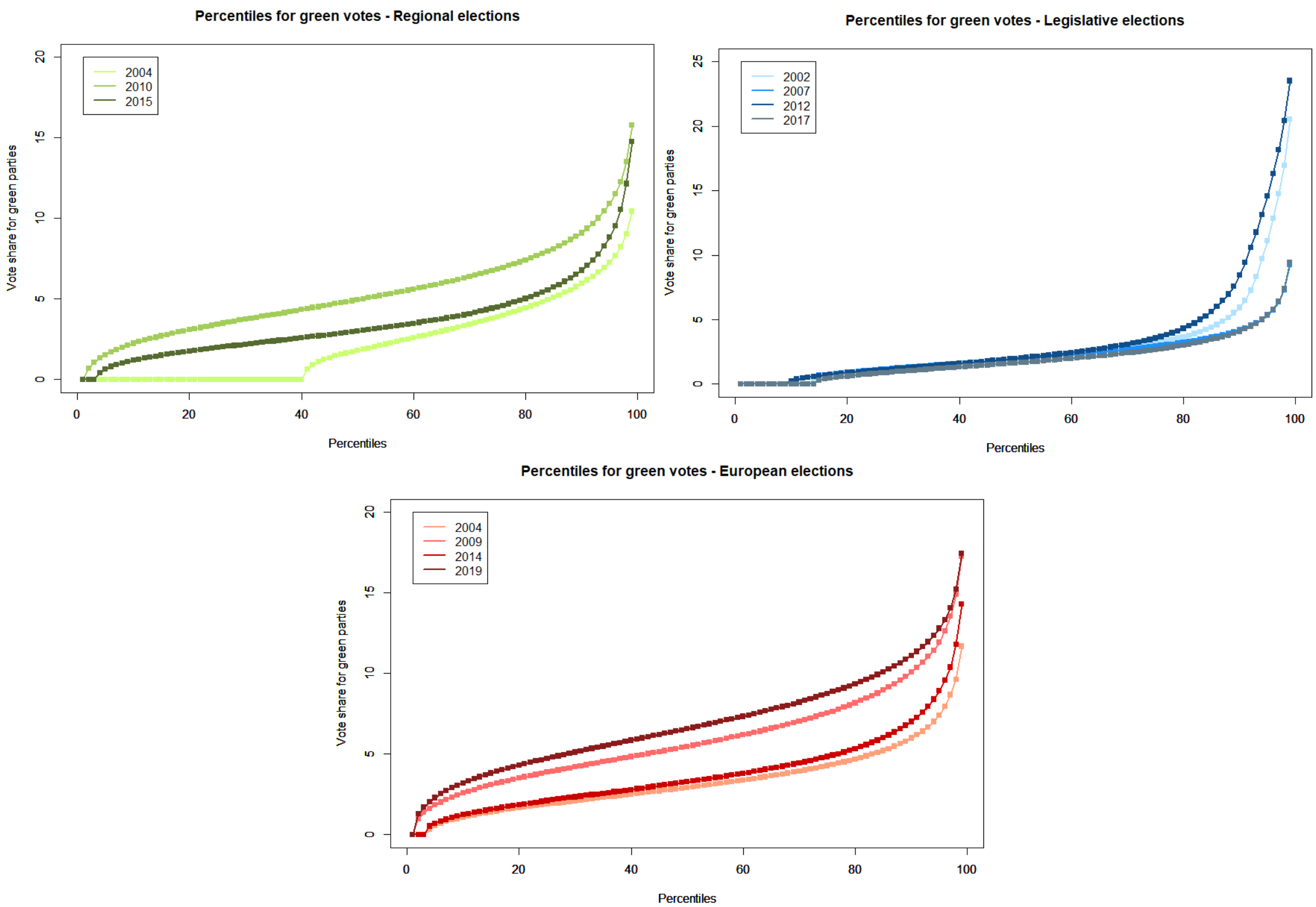


Figure 24: Distribution of the votes going to green parties by percentile by year for respectively Regional, Legislative and European elections.

A.3 Green Voting for Regional Election of 2004

I plotted the distribution of the votes for green parties for the Regional election of 2004 by region on figure **??**. One can see that the share of individuals voting green is null in some regions.

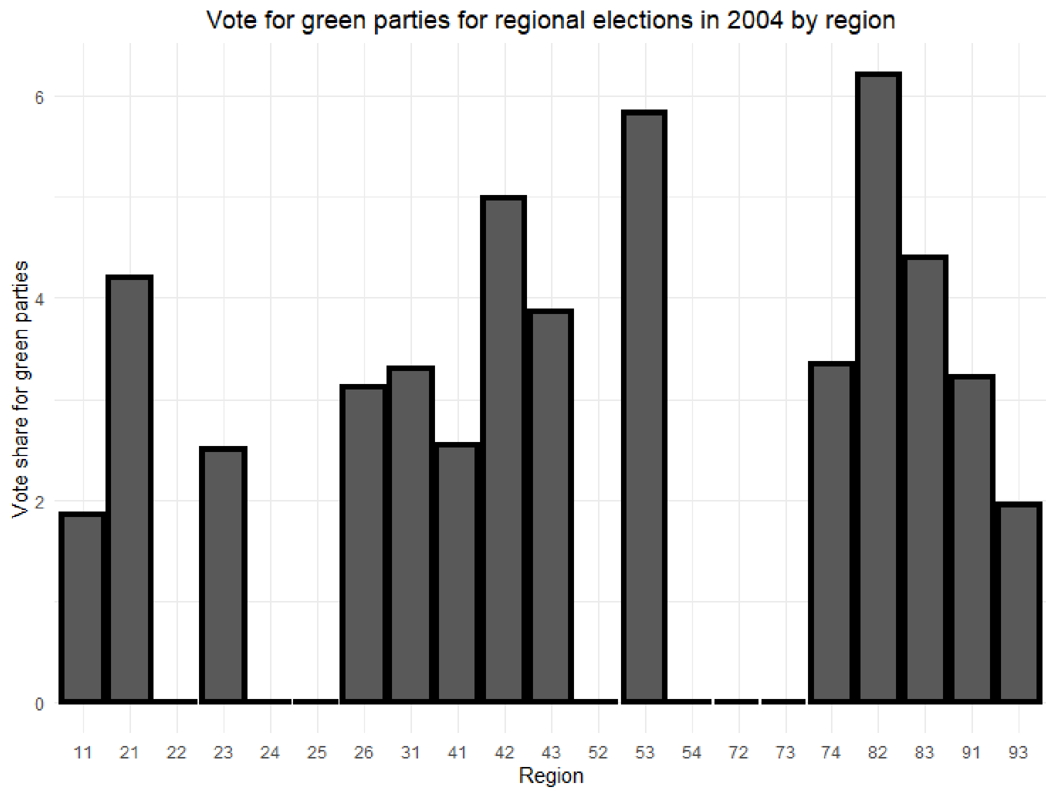


Figure 25: Distribution of green votes by region for Regional elections of 2004.

A.4 Details for Natural Disasters Typology

Table 8: Corresponding typology between the GASPAR database and the classification used in this study.

Type of disasters	Original typology in the *GASPAR* database
Floods	Inondations et coulées de boue Raz-de-marée Inondations, coulées de boue et mouvements de terrain Inondations par remontées de nappe phréatique Inondations et chocs mécaniques liés à l'action des vagues Inondations, coulées de boue et effets exceptionnels dus aux précipitations Inondations par remontée de la nappe phréatique et mouvements de terrain Inondations, coulées de boue et glissements de terrain Inondations et coulées de boue, vents cycloniques Inondations par remontées de nappe naturelle
Earthquakes	Séisme Avalanche Glissement de terrain Effondrements / éboulements Poids de la neige - chutes de neige Lave torrentielle Tassement de terrain Glissements de terrain et éboulements rocheux Eboulement ou effondrement de carrière Eboulements rocheux Eboulement de falaise Affondrement / éboulement de coteaux Affaissement de terrain Chocs mécaniques liés à l'action des vagues Eboulement de terrain Chutes de rochers / de blocs rocheux Coulées de boue et lave torrentielle
Storms	Tempête Tornade et grêle Phénomènes tropicaux Crues torrentielles et glissements de terrain Vents cycloniques chocs mécaniques liés à l'action des vagues, vents cycloniques
Drought-related disasters	Mouvements de terrain consécutifs à la sécheresse Mouvements de terrain différentiels consécutifs à la réhydratation des sols

A.5 Distribution of the Length of Disasters Depending on Their Type

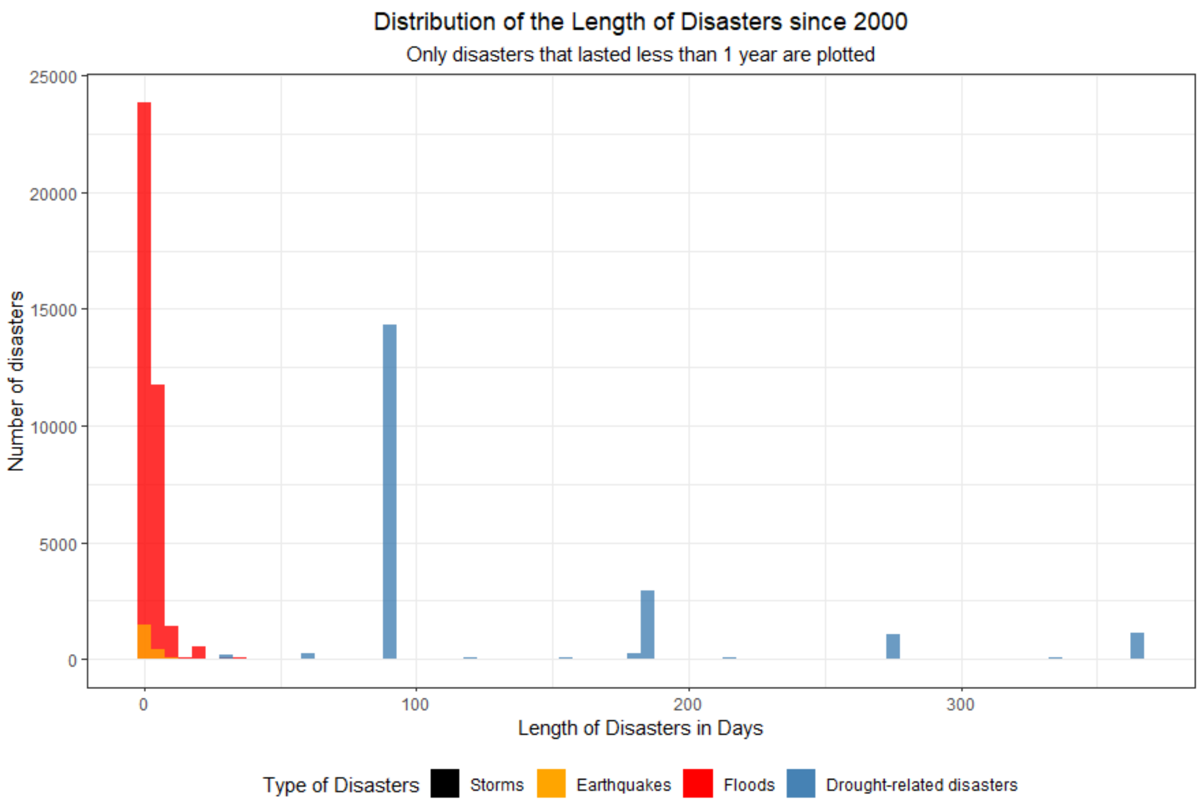


Figure 26: Distribution of the Length of Disasters recorded from 2000 to 2019

A.6 Distributions of Floods, Drought-related Disasters and Pollution Peaks

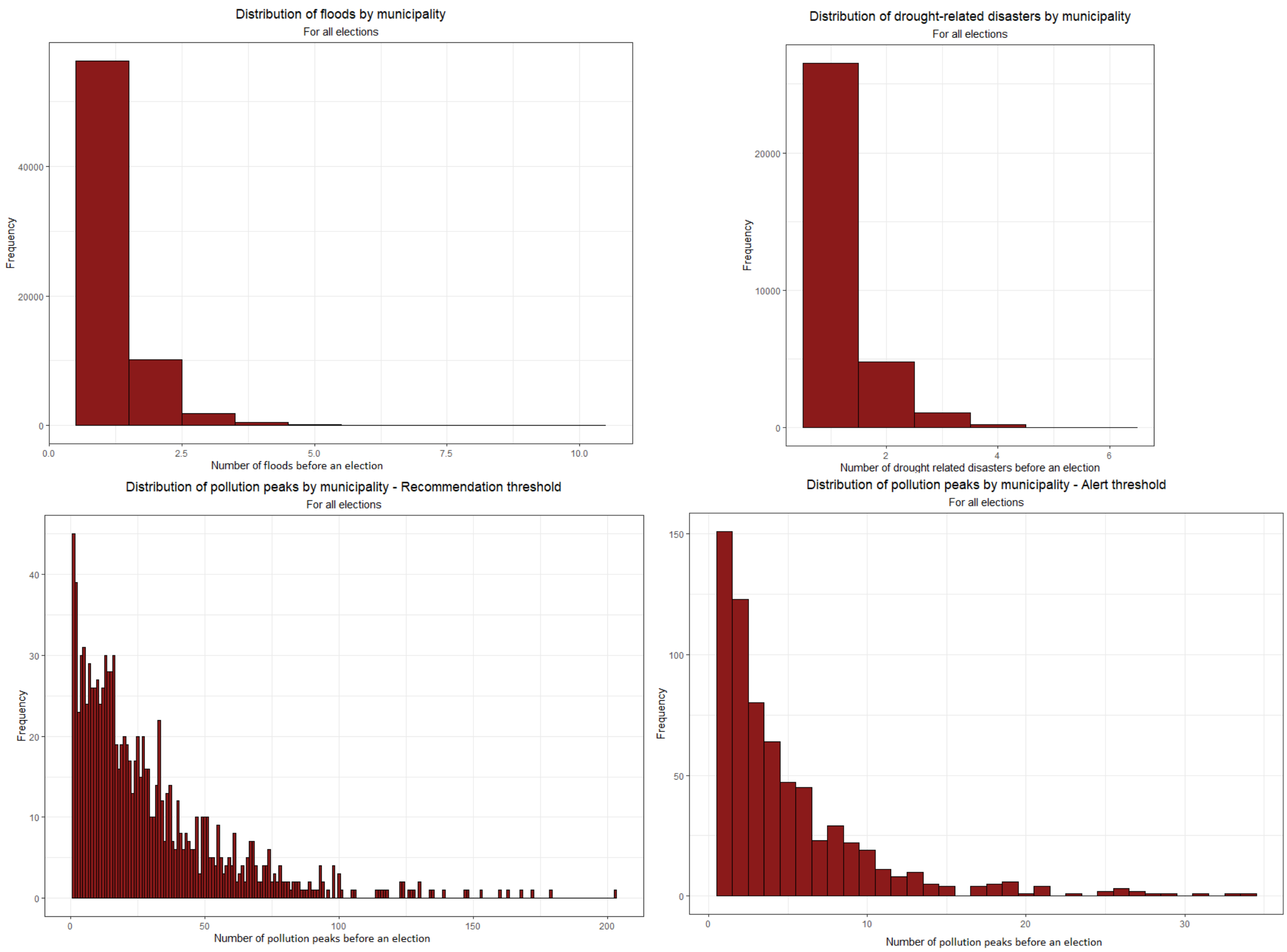


Figure 27: Distribution of the frequency of occurrence of respectively floods, drought-related disasters and pollution peaks between two elections.

A.7 Methodology for Linear Smoothing of the Effect of Pollution Peaks

In order to define the decreasing effect of pollution peaks, it is necessary to define adjacency matrices. These matrices are weight matrices that define "how close" are two municipalities. They have the following form with n the total number of observations.

$$W = \begin{pmatrix} w_{11} & w_{12} & ... & w_{1n} \\ w_{21} & w_{22} & ... & w_{2n} \\ ... & ... & ... & ... \\ w_{n1} & w_{n2} & ... & w_{nn} \end{pmatrix}$$

$w_{ij} \in \{0, 1\}$ defines the weight given between municipalities i and j. w_{ij} is equal to 1 if municipality i is close to municipality j. $w_{ii} = 1$ by definition, as distance between two identical municipalities is zero. Now one big challenge is to determine what is the criteria for municipalities to be close. The choice of the parametric form of the weight matrix will strongly influence the results.

For this study, I have defined *Radial Distance Weights*, which means that two municipalities have a weight of 1 if the distance between there centroïds is inferior to a threshold $\bar{D}$. This is the case represented on on figure 28 for a threshold of 15 kilometers. One can see that there is a red line between all municipalities that have a distance inferior to 15km.

Then, I applied smoothing functions to weights. The underlying concept is that the higher the distance between municipalities, the lower should be the weight given to the link between them. In this study I will the linear smoothing function $w_{ij} = 1 - \frac{d_{ij}}{\bar{D}}$. I applied this function to all weights computed in matrix W.

The model I want to run, as described in section 5.2 is the following

$$Green_{it} - \bar{Green}_i = \beta_1(Peaks_{it} - \bar{Peaks}_i) + \beta_2(X_{it} - \bar{X}_i) + Year_t + (\eta_{it} - \bar{\eta}_i) \quad (2)$$

With $\bar{X}_i = \frac{1}{T} \sum_t X_{it}$

However, it is impossible to run directly this computation in *R* given the very large number of municipalities. The weight matrix that is obtained is a 34450*34450 matrix that needs to be computed for each year. Thus, I had to compute the $Peaks_{it}$ vector thanks to an algorithm I defined by myself. It works as follows.

For a given year t, I first compute the weight matrix which is a 34450*34450 matrix. I extract the 1378 first rows. It yields a matrix with 34450 columns and 1378 rows. Then, I multiply this sub sample of my weight matrix with my unweighted vector for pollution peaks which has 34450 rows. It allows me to obtain a vector with 1378 rows corresponding to the first 1378 rows of $Peaks_{it}$. I loop this operation 25 times and bind the matrices obtained at each step, which finally gives me $Peaks_{it}$. I repeat this operation for each year. This procedure finally gives me the weighted vector $Peaks_{it}$ that I will use in further regressions.

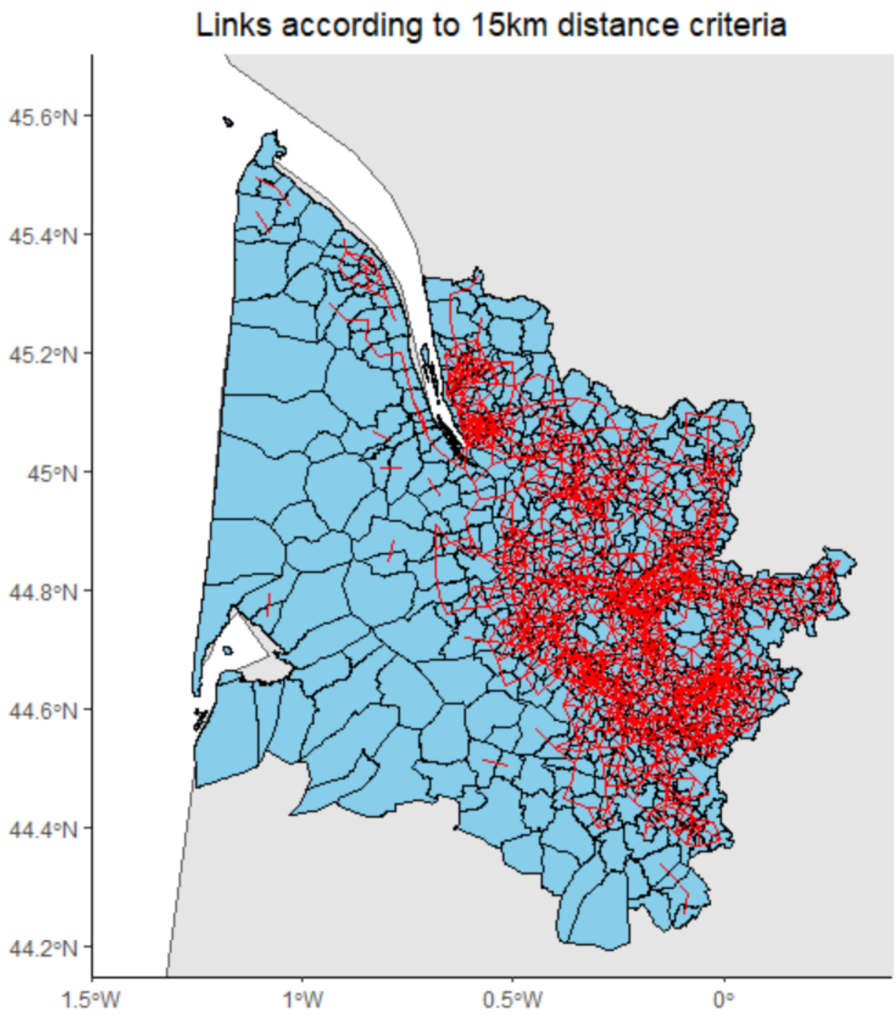


Figure 28: Radial distance weights for the 15km threshold.

A.8 Dealing With Outliers

The problem with considering small density municipalities is that, because population is generally low, there is a high variance in voting results. It is shown on figure 29. One can see that there is a high proportion of green votes in low density areas. The consequence from this phenomenon is that the effect of log density is convex, while the literature suggests more a linear increasing trend. This convex form is likely to be driven by influential observations in low density areas in which there is a very high variation in green votes due to the small populations within these municipalities. That is why I decided to exclude areas with more than 10% of green votes in figure 9.

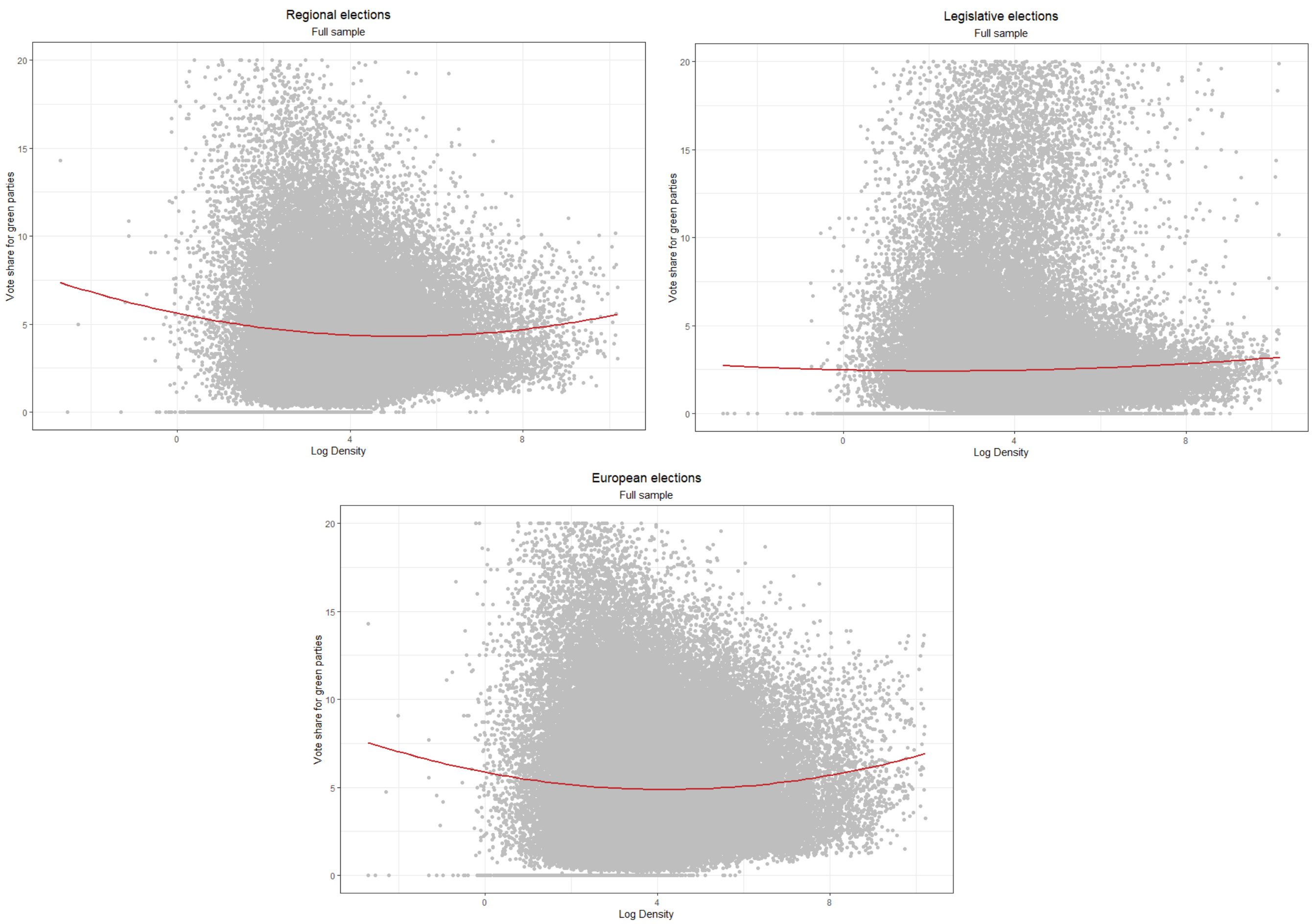


Figure 29: Scatter plot linking log density with the vote share of green parties. The red curve is of a polynomial form of degree 2.