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Abstract

The emergence of green constituencies enables climate action. Conventional wisdom holds that first-hand experience with natural disasters helps build green coalitions by increasing the salience of the costs of environmental degradation. Focusing on fires in Brazil, we argue instead that the impact of disasters on support for green candidates is conditional on the economic damages and profit opportunities they generate. By destroying natural vegetation, fires increase opportunities for land grabbing and expanding agricultural and livestock production. We test our argument by applying causal inference techniques and leveraging satellite, administrative, electoral, and survey data. We show that large-scale fires increase support for green candidates only in municipalities with low shares of employment in soy production and cattle ranching, which are arguably less likely to benefit from fires. We conclude that the potential of natural disasters to create green coalitions is conditional on their distributive implications.

1 Introduction

A key enabler of climate action is the presence of green constituencies supporting ambitious environmental policy. This is increasingly important in emerging economies, which represent a growing share of greenhouse gas emissions (IPCC, 2018). Conventional wisdom holds that experiencing natural disasters first-hand can increase the salience of environmental issues, shift attitudes toward more progressive views on environmental policy and thus help build a coalition that supports green policies (Hazlett and Mildenberger, 2020; Baccini and Leemann, 2021; McAllister and bin Oslan, 2021; Hoffmann et al., 2022). In the present paper, we argue that the effect of environmental disasters on support for environmentalist political platforms is conditional on the balance between the damages and profit opportunities they generate.

Perhaps due to the literature's focus on developed countries, natural disasters are often deemed unambiguously costly for the affected populations. However, natural disasters have distributive implications, affecting certain groups more negatively than others and, in some cases, even creating profit opportunities (Felbermayr et al., 2022). Profit opportunities might emerge in particular when affected populations depend on primary or extractive activities. For example, large-scale fires, by clearing land previously covered by native vegetation and wildlife, make affected areas more readily available for agriculture, animal husbandry, and real estate speculation. By focusing predominantly on developed countries (e.g., Hazlett and Mildenberger, 2020; Baccini and Leemann, 2021; Hilbig and Riaz, Forthcoming), where such primary economic activities are relatively less important, the literature on the effect of natural disasters on support for green candidates and policies overlooks the role of profit opportunities that natural disasters may generate.

Here, we focus on the case of fires in Brazil. Large-scale fires are a major source of greenhouse gas emissions in tropical countries (Randerson et al., 2018). Moreover, the protection and expansion of tropical forests is a key – and low-cost – strategy to achieve global climate mitigation goals. Every year, however, fires destroy large extensions of tropical forests, wetlands, and savannas, reducing their capacity to absorb carbon dioxide and jeopardizing their fundamental role in regulating the global climate (IPCC, 2019). Because about 60 percent of the Amazon forest and 12 percent of the world's total forested areas are located in Brazil (Food and of the United Nations, 2020), voters in this country are uniquely positioned to influence policies that can preserve natural environments and contribute to global climate mitigation efforts.

Despite their adverse environmental and human impacts, large-scale fires might create profit opportunities for some groups. By destroying the natural environment, fires increase the availability of land for farming and grazing, which also facilitates land theft. Historically, the production of soy and cattle in Brazil – two important products of this country's exports – has expanded over preserved tropical forests, savannas, and wetlands (Hosonuma et al., 2012). Hence, large-scale fires can create profit opportunities especially for individuals engaging in cattle ranching and soy farming (Schelly, Rausch and Gibbs, 2021). As such, we hypothesize that the local economic dependence on soy and cattle production decreases the positive effect of large-scale fires on support for green political platforms.

We measure the exposure of Brazilian municipalities to large-scale fires based on satellite data that measure the radiative power released by all fire foci detected in the country. Data on fires' radiative power are available from 2018 onward and were sourced from the Brazilian Agency of Space Research (*Instituto Nacional de Pesquisas Espaciais*, INPE).[1] We match these data with municipality-level electoral returns for the main green candidate – Marina Silva – in Brazilian presidential elections.

Assessing the causal impact of fires on political behavior is challenging because fires do not occur completely at random, but are influenced by a complex interaction of environmental and anthropogenic factors. Simple Ordinary Least Squares (OLS) estimates might suffer from omitted variable bias as fire activity is likely influenced by economic and social factors that are also plausible drivers of political behavior. Specifically, because fires are often intentionally set to expand land available for pasture and crops, fire activity might be

[1] Currently, for years before 2018, INPE provides data on the location but not on the intensity of all detected fires foci.

positively correlated with anti-environmental sentiment, possibly producing a negative bias in OLS estimates. We address this concern in multiple ways. First, in all our specifications, we rely on large-scale fires only, which are less likely to be caused solely by anthropogenic factors. Second, we employ different identification strategies that exploit plausibly exogenous variation in the presence and scale of fires.

In our first identification strategy, we employ a difference-in-differences (DiD) design comparing support for the main green candidate in the 2018 presidential election, Marina Silva, in municipalities affected by large-scale fires in the seven days before election day with municipalities where no fires were registered in the six months preceding election day. The choice to consider the presence of large-scale fires only in a short period preceding election day is based on one theoretical and one empirical reason. Theoretically, we expect that events that occur close to election day are relatively more salient in the mind of voters, a phenomenon referred to as the recency effect (Baddeley and Hitch, 1993; Baccini and Leemann, 2021). Empirically, the presence of large-scale fires in a given municipality in a specific short period of time is plausibly less endogenous than long-term averages.

In our second identification strategy, we exploit plausibly exogenous variation in the presence of large-scale fires linked to the impact of weather conditions on fire activity in two instrumental variable (IV) designs (Shikwambana and Kganyago, 2021). Specifically, we instrument fire activity in the week before the 2018 presidential election with either a measure of fire risk constructed by INPE or measures of temperature and wind in the same period. Aware of the challenges of using weather instruments in the social sciences, we follow the recent literature and rely on short-term variation in weather conditions, while controlling for longer-term weather patterns as well as rainfall on election day. By doing so, we account for the effects of both long-term weather patterns and weather on election day on electoral behavior through channels other then fires (Mellon, 2021). Our measures of short- and long-term weather patterns are built based on high-resolution, gridded raster data sourced from INPE and Copernicus.

To test our key argument that the impact of natural disasters on voting behavior is conditional on the their distributive implications, we employ our DiD and IV designs to evaluate the effect of large-scale fires conditional on economic dependence on cattle ranching and soy production, which we measure as the share of workers employed in these two industries in 2017, that is, one year before treatment. This measure is constructed based on administrative records that the Brazilian Ministry of the Economy made available.

We find robust evidence across research designs and specifications that exposure to large-scale fires increases support for the green political agenda, as measured by vote shares to Marina Silva, the presidential candidate with the most advanced pro-environment political platform in the country. In line with our expectations, we find that this positive effect is only present in municipalities with low levels of employment in soy and cattle production. In fact, in municipalities with high levels of employment in these industries, fires decrease vote shares for Marina Silva. In a series of robustness checks, we find that other theoretically motivated moderators (such as the ideological leaning of municipalities) are not driving our results.

We further examine underlying mechanisms by relying on individual-level survey data collected by the Technology and Society Institute of Rio de Janeiro (ITS-RIO) and its partners. By matching these survey data with fire activity data based on the municipality where respondents reside, we provide suggestive evidence that employment in soy production and cattle ranching moderate how large-scale fires impact individuals' perception of the tradeoff between environmental protection and economic growth.

Our paper's main contribution is showing that the documented effects of natural disasters on support for green policies and candidates can be conditional on their distributive implications. While previous research focusing on developed countries showed that first-hand experience of natural disasters increased support for green candidates in advanced democracies (e.g., Hazlett and Mildenberger, 2020; Baccini and Leemann, 2021; Hoffmann et al., 2022; Garside and Zhai, 2022; Valentim, 2021), our results provide a more nuanced picture. On the one hand, we find that large-scale fires increase support for green political platforms where their effects are unambiguously negative. On the other hand, we show that when voters can reap profits from natural disasters due to the type of economic activities with which they engage, the political implications might actually be the opposite: a decrease in support for green policies. By doing so, we highlight the importance of taking into account how local economic structures shape the lived experiences of environmental degradation and how such experiences shape public opinion and behavior. Although we focus on a Global South example, where reliance on agricultural commodities and ranching implies that the destruction of natural vegetation creates opportunities for economic benefit, our results highlight lessons for developed countries as well. Also in these contexts, economic and social structures shape how individuals experience climate change and environmental degradation; for example, in the United States, access to private house insurance moderates how voters respond to hurricanes (Pahontu, 2020).

The present paper is also closely related to the literature on the extent to which material self-interest shapes views on climate mitigation and adaptation policies. By showing how a similar logic applies to natural disasters, we extend previous work mostly focused on developed countries showing that, when evaluating green policies, voters consider related costs and benefits to their employment perspectives and consumer habits (Bechtel, Genovese and Scheve, 2019; Bush and Clayton, 2022; Colantone et al., 2022; Gaikwad, Genovese and Tingley, 2022; Bolet, Green and Gonzalez-Eguino, 2023). Finally, we contribute to the literature on Latin American politics. In a context dominated by pork and clientelism (Roberts, 2013; Singer and Tafoya, 2020; Zucco and Power, 2021), we show that natural disasters might lead at least some voters to support programmatic parties.

2 Natural Disasters and Material Self-Interest

A growing body of research studies how natural disasters affect political behavior. Early work has drawn on the retrospective voting literature by considering natural disasters as a particular case of a negative shock (see Healy and Malhotra, 2013, for a review). Overall, these studies have shown that natural hazards decrease support for incumbents among the affected populations, but this effect can be offset by disaster relief policies (Healy and Malhotra, 2009; Bechtel and Hainmueller, 2011; Gasper and Reeves, 2011; Cooperman, 2022).

More recently, a growing scholarship focused on developed countries has examined how natural disasters shape support for green political agendas. For example, Hazlett and Mildenberger (2020) and Baccini and Leemann (2021), analyzed referendum data from California and Switzerland, respectively, and showed that natural disasters increased support for green policies. Other work focused on electoral returns showed that floods in Germany (Garside and Zhai, 2022; Hilbig and Riaz, Forthcoming) and bushfires in Australia (McAllister and bin Oslan, 2021) increased support for green parties. Furthermore, several studies have shown that weather anomalies increased climate change concern and support for green parties as measured by survey data from Europe and the United States (e.g., Egan and Mullin, 2012; Hoffmann et al., 2022; Valentim, 2021; Weber, 2016; Bergquist and Warshaw, 2019; Howe et al., 2019). Overall, the message is that natural disasters and abnormal weather events provide voters with accessible information about the environmental risks to which they are exposed. Consequently, voters become more concerned about climate change, support more green policies, and vote more for green candidates.

Yet, questions remain as to under which conditions natural disasters actually increase support for green political platforms. Hazlett and Mildenberger (2020), Baccini and Leemann (2021), and McAllister and bin Oslan (2021) provided evidence that most of the positive effects of natural disasters on support for green political agendas are driven by left-leaning regions. In the present paper, we argue that natural disasters increase support for green political agendas only when voters perceive the related damages to be greater than the economic opportunities.

Our argument builds on a related body of literature that has examined how distributive concerns shape support for climate adaptation and mitigation policies. For example, Bechtel, Genovese and Scheve (2019) showed that support for climate mitigation policies in developed countries was higher among workers employed in industries with low emission levels of greenhouse gases. Bush and Clayton (2022) showed that individuals that have more polluting consumption habits (typically men in developed countries) are more likely to oppose climate mitigation policies due to the higher costs these policies involve for them. Studying a ban on polluting cars in Milan, Colantone et al. (2022) showed that voters whose pocketbooks were negatively affected by the ban, voted more for Lega – the party who opposed the ban's introduction. Gaikwad, Genovese and Tingley (2022) showed that climate policy preferences were shaped by both physical vulnerability to climate change impacts and economic vulnerability to climate policy. We extend this literature by considering how natural disasters interact with material self-interest in shaping support for green political platforms.

By focusing on developed countries, the literature on the electoral consequences of natural disasters has considered, to date, natural disasters as producing exclusively adverse consequences. Instead, we argue that in developing countries and emerging markets, where the primary sector and extractive industries are relatively more important, large-scale fires may produce economic benefits in certain regions. As such, like green policies, natural disasters may create winners and losers, and such distributive implications are consequential to how natural hazards shape political attitudes and behaviors.

3 Fires and Their Distributive Implications in Brazil

Fires in Brazil's natural areas – especially in the Amazon region – have made international headlines in the last few years (e.g., Landau and Phillips, 2020). The drivers of large-scale fires in Brazil vary depending on the type of land coverage and land use. In Southern Brazil, fires have been associated with low rainfall and air humidity accompanied by increased atmospheric pressure and wind speed (de Andrade et al., 2020). In the Brazilian Pantanal (the world's largest tropical wetland), located mostly in the center-west region of the country, dry spells and high temperatures combined with extensive agriculture have been associated with higher frequency and severity of fires (de Oliveira-Junior et al., 2020; Libonati et al., 2020). In the Brazilian Amazon, located mostly in the Northern region, large-scale fires are often the unintended consequences of land management practices. It is common that ranchers employ fires in previously deforested areas, mainly pastures, to rid the area of weeds and prevent shrub encroachment (Malhi et al., 2008; Cano-Crespo et al., 2015). Depending on weather conditions, fires can burn uncontrolled and enter forested areas (Eloy et al., 2019).

While fires can be an important land management tool, including for indigenous and traditional communities (Mistry et al., 2005), fires that get out of control can cause significant damage to the environment and the human population. For example, large-scale fires in the Amazon forest release greenhouse gases and aerosols that impact the regional and global climate (Correia et al., 2021). Moreover, fires can harm public health. It is well-documented that exposure to wildfire smoke increases the incidence of respiratory and cardiovascular diseases (Requia et al., 2021). In addition, large-scale fires have economic costs, especially for indigenous communities. For example, de Oliveira et al. (2019) provided evidence that fires in the Amazon reduced the economic returns of sustainable logging production. Bowman, Amacher and Merry (2008), in turn, studied how economic variables correlated with the extent to which households in traditional forest communities engaged with fire prevention in the Amazon. They showed that the propensity to engage in fire prevention was associated with households' reliance on standing forest resources. For example, households that hunted in surrounding forest reserves burned less land area and used fire prevention tactics to a higher extent.

However, by destroying natural vegetation and "clearing" land, large-scale fires can increase opportunities for some individuals to reap economic profit. In Brazil, vast areas, mostly covered by forest and natural vegetation, are subject to land grabbing. Land grabbing is an illegal but common practice that consists of individuals simulating, often through falsified or unofficial documents, that they are the legal owners of public land or private property that belongs to third parties. Acquiring unofficial property rights over land involves a series of illegal practices, one of which entails dislodging forest communities by using force or false documents (Boekhout van Solinge, 2010) and converting forest into pasture (Faminow et al., 1998; Hoelle, 2015). These practices allow individuals to profit from land grabbing in two ways. First, they may profit from using the land for ranching and agricultural production, mostly in the form of cattle ranching and soy monocultures (Faminow et al., 1998). Second, the existence of an irregular market of land in rural areas in Brazil, including the Amazon region, makes land grabbing a profitable business through real estate speculation. Fires, including large-scale fires that grow out of control, can facilitate land grabbing by making it easier to convert forest into pasture and agricultural fields, which is a necessary step to claim ownership over land (Barona et al., 2010). This reality influences how natural vegetation and cultivated land are perceived in these areas. Areas covered by cattle ranching and soy production are often perceived as providing more economic security and profitability than land covered by natural vegetation. As a result, areas covered by cattle ranching and soy crop production are often associated with hard work and progress, whereas areas covered by natural vegetation are associated with laziness and backwardness (Hoelle, 2018).

Therefore, we hypothesize that large-scale fires shape support for green political platforms differently depending on how fires interact with the underlying local economic structure. For communities with low reliance on soy and cattle production for income, large-scale fires bring no benefits. In fact, they bring a series of direct and indirect costs such as heightened environmental damages, adverse health effects, and economic losses for those who rely on forest resources for income and subsistence. Among these communities, we expect that large-scale fires increase support for green political platforms. By contrast, we expect communities that suffer some negative consequences of fires (such as adverse health effect) but at the same time can reap some profits from the resulting cleared land may behave differently. More specifically, we expect that the positive effect of large-scale fires on support for green political platforms decreases as local communities rely more heavily on cattle ranching and soy production for income; hence, land grabbing is more likely to be widespread.

4 Environmental Politics in Brazil

Brazil has a presidential political system with a highly fragmented and personalistic party system. Such fragmentation does not always reflect political cleavages or programmatic differences (Zucco and Power, 2019). Indeed, few parties are programmatic. The Workers' Party (*Partido dos Trabalhadores*, PT) and the Sustainability Network (*Rede Sustentabilitade*, REDE) are exceptions in this respect. The first is associated with a social-democratic agenda (Samuels and Zucco, 2018) and the second advances a markedly pro-environmental political platform.

Marina Silva, REDE's co-founder and presidential candidate in multiple elections, has always been at the forefront of the Brazilian environmental movement. She was a member of the PT from the aftermath of Brazil's re-democratization until 2009. She gained more public prominence when she served as the Minister of the Environment during President Lula's (PT) first and second terms. Due to disagreements regarding environmental and energy policy, Silva left the government in 2008 and the PT shortly thereafter. As one of the most prominent public figures within the environmental movement, Silva ran for president to promote an environmental political agenda under the banners of different parties in 2010 and 2014. Ultimately, she and other members of the environmental movement in Brazil came together to found REDE, which was officially registered in 2015. In Appendix A we provide descriptive evidence that Silva and REDE are markedly more associated with a progressive environmental political agenda than other prominent candidates and parties in the country.

Due to data limitations, which we discuss in the next section, our analysis focuses on the 2018 presidential election. In this election, Silva ran as presidential candidate for REDE and the Partido Verde, advancing a marked pro-environmental platform. Jair Bolsonaro ran as the presidential candidate of the *Partido Social Liberal* (PSL), embracing a nationalist and economically liberal platform. Fernando Haddad ran for the PT, while former President Lula was incarcerated following a trial that was later nullified. Bolsonaro and Haddad received the most votes in the first round of the elections, and Bolsonaro was then elected president in the second round.

5 Data

5.1 Fire Data

We employ data on fire activity in Brazil made available by the *Queimadas* database, maintained by INPE. This database provides information on the location and intensity of all fire foci detected by satellites in Brazil (INPE, 2022). Fire intensity is measured as fire radiative power (FRP), which is defined as the radiant energy released per time unit by burning vegetation. We employ the *Queimadas* data to construct a dataset including different measures of fire activity. Because fire radiative power data is available only since 2018, our analyses are restricted to the 2018 presidential election.

Our main independent variable is a binary variable indicating whether the municipality experienced a fire with radiative power above the yearly national median in the week before the 2018 presidential election. We focus on more sizable fires, which are more likely to be visible and to produce significant damage, excluding those with a negligible radiative power. In the Appendix, we report a series of robustness checks employing different fire activity variables developed using different measures and different temporal cutoffs.

5.2 Weather data

To build variables to use as controls and as instruments in our IV strategy, we employ daily high-resolution gridded observational data on temperature and precipitation made available by INPE, and high-resolution data on wind made available by Copernicus. We employ these raster data to create a daily municipality level dataset of temperature, precipitation, and wind speed. We use these data to compute aggregate measures (i.e., maximum values) of temperature and wind speed in the week before election day, that we employ as instrumental variables in our IV analyses. We also construct different variables measuring long-term weather patterns (temperature and precipitation), that we employ as controls in the IV analyses to prevent possible violations of the exclusion restriction due to the impact of long-term weather patterns on voting behavior through a channel different from fires. We also compute similar measures based on a second temporal cutoff, which we use in our robustness checks. We provide more details on these variables in the "Empirical Strategy" section.

5.3 Fire Risk Data

We also employ a measure of fire risk as instrument in one of our IV specifications. We rely on daily high-resolution gridded data made available by INPE to create a daily municipality level fire risk dataset. The measure of fire risk developed by INPE is based mainly on the consideration of rain patterns in the previous 120 days, with more recent precipitation receiving greater weight. The measure also considers temperature, relative humidity, vegetation type, the occurrence of fire in the area, as well as topographic elevation and latitude (see Setzer, Sismanoglu and Martins dos Santos, 2019, for more details). We compute the maximum municipality level fire risk in the week before election day, which we employ as one of our instrumental variables. We also compute a similar measure based on a second temporal cutoff, which we use in our robustness checks.

5.4 Electoral Data

We use Brazilian electoral data made available by the Superior Electoral Court (*Tribunal Superior Eleitoral*, TSE). In Brazil, federal elections occur every four years, generally in October. The president is elected through a two-round system, with the first round generally being held on the first Sunday of October and the second round being held on the last Sunday of October. We perform our analyses focusing on the 2018 presidential election. Our outcome variable is Marina Silva's vote shares in the first round of the 2018 presidential elections. One advantage of focusing on the first round is that voters vote more sincerely in this stage than in runoffs (Fujiwara et al., 2011). In our difference-in-differences design, we also use data from the 2010 and 2014 presidential elections. Marina Silva ran for president in 2010, 2014, and 2018, but each time with a different party. In 2010, she ran with the Green Party (PV), in 2014 with the Brazilian Socialist Party (PSB), and in 2018 with the Sustainability Network (REDE) and the PV. Given the level of fluidity and personalism of the Brazilian party system (see discussion in the "Environmental Politics in Brazil" section), we focus on the vote share for Silva in each election, regardless of the party with which she ran.

5.5 Labor Market Data

We hypothesize that the effect of fires on vote choice will depend on the potential damages and opportunities for economic profit stemming from fires. As we previously argued, the soy and cattle sectors tend to benefit from the clearance of land due to fires. We therefore expect voters in municipalities that do not depend on those sectors for employment to be more supportive of environmentalist political platforms in response to fires. We employ the *Relação Anual de Informações Sociais* (RAIS) dataset to compute the share of jobs in the soy and cattle farming sectors in each municipality in 2017 (one year before the 2018 election). RAIS is an administrative dataset collected annually by the Brazilian Ministry of the Economy. It contains information on the universe of formal contracts in Brazil, including a detailed sectoral classification. The de-identified data is publicly available on the website of the Ministry of the Economy.[2]

6 Empirical Strategy

Contrary to other extreme events, fires are not completely exogenous to human activity and might be correlated with social and political factors that also affect voting behavior. This implies that simple OLS estimates of the impact of fires on voting behavior might suffer from omitted variable bias. Therefore, to estimate the causal impact of fires on voting behavior, we employ two different identification strategies. First, we use a difference-in-differences strategy to estimate the effect of fires in municipalities affected by large-scale fires in the days immediately preceding the election. Second, we use an instrumental variable strategy that exploits short-term variation in weather conditions, while controlling for long-term weather patterns.

In our main specifications, we build on evidence of a strong recency effect in the literature on the political impacts of extreme weather events. In doing so, we examine the short-term effect of fires on voting behavior by looking at the impact of fires in the week before the elections (Baddeley and Hitch, 1993; Baccini and Leemann, 2021). In the Appendix, we report results for a different temporal cutoff.

6.1 Difference-in-Differences Strategy

We first examine the impact of fires on the vote share of Marina Silva, the main green candidate in the 2018 Brazilian presidential election, using a difference-in-differences design. We compare municipalities that were affected by large-scale fires in the week before the first round of the 2018 presidential election (i.e., treated municipalities) with municipalities that were not affected by any fires in the 180 days before election day (i.e., control municipalities). The identification assumption is that the trends in Silva's vote share in the treated and the

[2]The website (ftp://ftp.mtps.gov.br/) is accessible only from Brazil.

control municipalities would be parallel absent any large-scale fires in treated municipalities. Following standard practice, we assess the plausibility of this assumption by looking at dynamic effects of being exposed to large-scale fires in a two-way fixed effects (TWFE) event study. The model estimates the effect of being a treated municipality in each election in which Silva ran before and after the period immediately before the 2018 presidential election (i.e., the time when treatment takes place), taking the 2010 election – the first election in which Silva ran for president – as the reference point. Our main specification is as follows:

$$Y_{jt} = \alpha_{st} + \beta \text{Fire}_{j,2018} \times \mathbb{1}[t \neq 2010] + \delta_j + \omega_t + \varepsilon_{jt}, \tag{1}$$

where j, s and, t index municipalities, states and election-years, respectively. Y_{jt} is the vote share for Marina Silva in the first round of the presidential election in year t and municipality j. $\text{Fire}_{j,2018}$ equals one if in municipality j registered fires with aggregate radiative power above the national median in the seven days preceding the first round of the 2018 presidential elections and zero if there were no fires in the 180 days preceding election day. We exclude from our analyses municipalities that experienced any fire between 8 and 180 days before election day, because including these municipalities would mean that some municipalities in our control group were actually treated in a period relatively close to the election. Hence, including these municipalities could bias our results toward zero. To control for municipality specific, time-invariant, unobserved factors and for time-specific, unobserved factors, we include municipality fixed effects, δ_j, and year fixed effects, ω_t, respectively. We also include state-year fixed effects, α_{st}, to account for state-specific time trends that can be linked, for example, to state-level policies. We cluster standard errors at the municipality level. In Table C.1 in the Appendix, we show results with different specifications in which our treatment dummy is defined using other radiative power cutoffs. In Table C.2 in the Appendix, we show that our results are robust when using a different temporal cutoff when defining our treatment dummy or using spatial auto-correlation robust standard errors.

As we argue previously, large-scale fires are usually fires initiated by human activity that grow out of control due to weather conditions. Therefore, focusing on large-scale fires alleviates the concern that treated municipalities are selecting into treatment. Yet, the variation we are exploiting in our DiD design might include some variation driven by anthropogenic factors, even if plausibly to a small extent. To address this concern, we rely on two instrumental-variable (IV) designs that exploit short-term variation in weather conditions while controlling for long-term weather patterns. In the next section, we explain our IV designs in detail.

6.2 Instrumental Variables Strategy

Our IV strategy exploits variation in fire activity produced by short-term weather conditions. Specifically, we instrument municipality level fire activity in the week before the elections with (1) a municipality level measure of fire risk in the week before the 2018 election day or (2) municipality level measures of temperature and wind in the week before the election. INPE constructed the fire risk measure, which is mostly defined by precipitation levels in the 120 preceding days. For more information about this measure, see the "Data" section.

Our IV strategies rely on two assumptions. First, our instrumental variables need to be exogenous to our outcome variable. Second, they should not influence voting behavior through channels other than fires (i.e., they should not violate the exclusion restriction). Several studies have shown that long-term weather patterns impact local economic conditions, which could influence voting behavior (e.g., Gasper and Reeves, 2011). Hence, there might be a risk of an exclusion restriction violation due to the impact of *long-term* weather conditions on voting behavior through channels other than fires. We address this issue in two complementary ways. First, we exploit only *short-term* variation in our instrumental variables (employing data on temperature and wind, or fire risk, in the same period as our fire treatment period, that is, the seven days before the election, which plausibly does not impact voting behavior through channels other than fires). Second, we control for longer-term weather patterns, which might impact voting behavior through channels other than fires. Moreover, as precipitation on election day has been shown to influence voting behavior, especially turnout (Gomez, Hansford and Krause, 2007), we also control for rainfall on election day. The overall idea is that, when longer-term weather patterns and weather on election day are controlled for, weather conditions and fire risk in the seven days before the election are not only as-good-as-random, but are also unlikely to impact voting behavior through channels other than the actual occurrence of fires in the same period.

Our main explanatory variable is a binary variable indicating whether a municipality was exposed to fires with an above-median level of radiative power in the week before the election. In Appendix D, we show that our results are robust to constructing our main explanatory variable differently. In the 2SLS specifications, we instrument the variable measuring fire exposure in the week before the elections with either (1) the average fire risk in the week before the election or (2) the maximum wind speed and the maximum temperature in the week before election day, excluding the election day itself. We estimate using the following first-stage equation:

$$\mathrm{Fires}_{jk} = \beta \mathrm{Z}_{jk} + \gamma \mathbf{X}_{jk} + \phi_k + \varepsilon_{jk}, \tag{2}$$

and the following second-stage equation:

$$\mathrm{Y}_{jk} = \pi \widehat{\mathrm{Fires}}_{jk} + \tau \mathbf{X}_{jk} + \omega_k + \nu_{jk}, \tag{3}$$

where j indexes municipalities in microregion k. Microregions are territorial units defined for statistical purposes by the Brazilian Institute of Geography and Statistics (*Instituto Brasileiro de Geografia e Estatística*, IBGE), defined based on spatial patterns of economic activities and natural features. In 2018, Brazil was divided into 5,570 municipalities clustered into 558 microregions. Y_{jk} represents the vote share of Marina Silva in municipality j in microregion k in the first round of the presidential elections. Fires_{jk} denotes whether municipality j experienced a fire with an above-median radiative power in the week before the election.

In our first IV specification, which is just-identified, Z_{jk} is a measure of average fire risk in the week preceding the election in municipality j. In our second IV specification, which is over-identified, Z_{jk} includes both the maximum wind speed and the maximum temperature in the week preceding the election in municipality j. $\mathbf{X}$ is a vector of four control variables included to prevent possible violations of the exclusion restriction. The first two controls measure the mean temperature and the mean precipitation in municipality j in the five years before the week before the election (excluding the seven days before the election). The third control measures deviations in precipitation levels in the year before the election with respect to the average in the 5 years preceding the election. This last control is meant to account for any recent abnormal dry spells that may influence vote choice.[3] These three variables allow us to control for possible violations of the exclusion restriction due to the impact of long-term weather patterns on electoral results through channels other than fires in the week before elections. To control for the possible direct impact of election day's weather on voting behavior, specifically turnout, we include precipitation on election day as a further control variable. Finally, we include fixed effects at the microregional level, (ω_k), to control for microregion-level time-invariant factors that might confound our estimates. These might include, for example, different levels of media coverage of natural disasters in different regional and state television channels produced by the occurrence of fires in one state or region. Standard errors are clustered at the microregion level [4]

[3] Following Hazlett and Mildenberger (2020), this variable is defined as the difference between mean precipitation in the last year before the elections and mean precipitation in the last five years, divided by the 5-year mean.

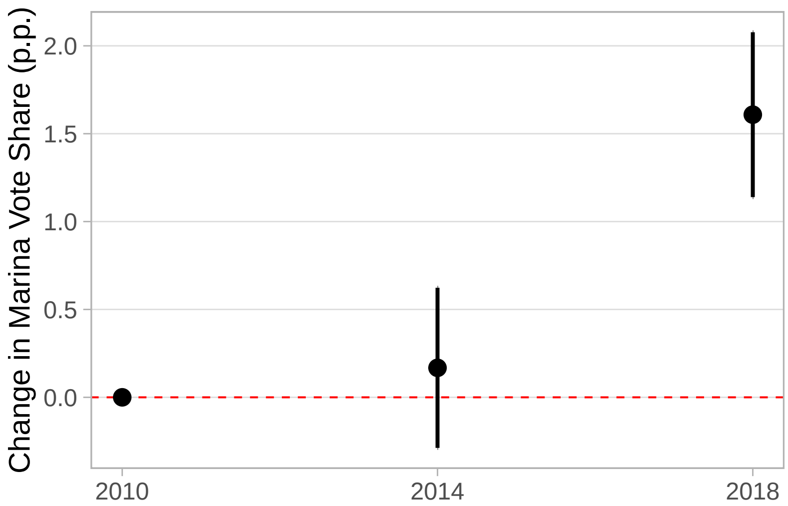
[4] We are aware that clustering at the microregional level does not completely account for spatial correlation. Ideally, as Cooperman (2017) proposed, we would have used a randomization inference method to estimate uncertainty around our estimates by employing historical patterns in the past decades, but we are unfortunately constrained by data availability, as data on fire radiative power are available only from 2018.

7 Average Treatment Effect

In Figure 1, we present the dynamic treatment effects plot from Equation 1. Under the standard DiD assumptions (for a review, see Xu, 2023), the point estimate for 2018 can be interpreted as the causal effect of recent exposure to large-scale fires (which we define as fires with above-median levels of radiative power) on the electoral returns of Silva – the candidate with the most progressive and salient pro-environment political platform in Brazil. We find that exposure to large-scale fires in the seven days before the 2018 election increased Silva's vote share by 1.6 percentage points. Considering that Silva's average vote share in the period between 2010 and 2018 was 8 percent (with a standard deviation of 8.17), this is a sizable effect. Furthermore, the results in Figure 1 indicate that control and treated municipalities followed statistically indistinguishable trends in electoral support for Silva in the pre-treatment period, that is, in the 2010 and 2014 elections. These results land credibility to our identification assumption, namely that absent exposure to large-scale fires in the days before the 2018 election, treated and control units would continue to follow parallel trends in vote shares for Silva.

In Appendix C, we conduct a series of additional tests to examine the robustness of our results. First, we construct our treatment dummy using other radiative power cutoffs. Columns (1) and (3) in Table C.1 show the results. Overall, point estimates are larger in magnitude when we apply higher radiative power cutoffs. This suggests that our results are driven by large fires that become unmanageable, are visible, and cause significant damage. Second, in Table C.2, we show that our results are robust to applying different temporal cutoffs when constructing our treatment dummy or to using standard errors robust to spatial auto-correlation.

Figure 1: Estimated Effect of Fire on Vote Share for M. Silva from DiD design



***Notes*:** The dots represent coefficients from TWFE specifications (see Equation 1) with 95 percent confidence intervals. Standard errors are clustered at the municipality level. Column (2) in Table C.1 in Appendix C presents the full set of coefficients.

In our IV strategies, we rely on short-term weather variation to assess the impact of large-scale fires that occurred in the seven days before the election day on Silva's vote share in the first round of the 2018 presidential election. The intuition behind this strategy is to exploit exogenous variation in large-scale fires coming from short-term variation in weather patterns while controlling for long-term weather patterns. Table 1 displays the results of the IV specifications from equation 3. Column (2) reports the results of 2SLS specification, where the fire variable is instrumented with maximum fire risk in the seven days before election day. Column (3) reports the results of the 2SLS regressions where the fires variable is instrumented using maximum temperature and wind in the five days before election day. The results in columns (2) and (3) indicate that exposure to large-scale fires in the week before the elections increased Silva's vote share by more than 0.7 percentage points. In both columns (2) and (3), the F-statistics are above the critical value of 10. Following Sun (2018) and Andrews, Stock and Sun (2019), we also report 95 percent confidence intervals that provide correct coverage regardless of the strength of the instrument. We find that the effects estimated using weak-IV robust coefficients point to the same direction.

Following standard practice, column (1) reports the results of the OLS specification. The results of the OLS regression yield coefficients smaller in magnitude than their 2SLS counterparts and are also statistically indistinguishable from zero at conventional confidence levels. The contrast between our OLS and IV estimates might be explained by the fact that regions where more fires are initiated are likely to be the same ones with higher levels of anti-environmentalist sentiment, possibly leading OLS estimates to suffer from a bias toward zero.

Table 1: The Effect of Fire Exposure on the Vote Share of Marina Silva (IV Design)

	DV: Marina Silva's Vote Share		
	(1)	(2)	(3)
Fires	0.016	0.756**	0.763***
	(0.016)	(0.328)	(0.144)
Weak IV Robust 95% CI		[.26854, 1.82714]	[.633648, 1.18059]
Controls	✓	✓	✓
Microregion Fixed Effects	✓	✓	✓
StandardErrors	Cl. Microreg	Cl. Microreg	Cl. Microreg
Observations	5561	5557	5559
F-statistic		14.250	31.920
Model	OLS	IV Fire Risk	IV Temp & Wind

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: "Fires" is a dummy variable that is equal to one if a municipality was hit by a fire with an above-median radiative power in the seven days before the election, and zero otherwise. The outcome variable is Silva's municipality level vote share. All regressions include controls for municipality level precipitation and temperature in the five years before the week preceding the election; the municipality level deviation of precipitation in the year before the election with respect to the average in the five years preceding the election; and municipality level precipitation on election day. For the IV specifications, we also report weak-IV robust 95 percent confidence intervals computed following the recommendations by Andrews, Stock and Sun (2019) for non-homoskesdastic models with clustered standard errors, following the procedure developed by Sun (2018) which applies as well to cases with multiple endogenous regressors and multiple instruments. Standard errors clustered at the microregion level are reported in parentheses. Results with the full set of coefficients can be found in Table D.1. Results with first-stage results can be found in Table D.2.

In Appendix D, we report a series of tests for the robustness of our IV results. In Table D.3, we examine the robustness of our results to other cutoffs of fire radiative power when defining our treatment dummy, i.e., "$Fire_{jk}$" in Equation 2. In Table D.4, we replace our treatment dummy with a continuous measure of fires, which equals to the sum the radiative power of all fires detected in the seven days before the election. To analyze the robustness of our results to different temporal cutoffs, we run a similar specification where we define our treatment dummy based on a 30-day cutoff instead of 7-day cutoff (Table D.5). Finally, we assess the robustness of our results to account for spatial auto-correlation.[5] Overall, our robustness checks confirm our main results. In Table G.1, we report and discuss equivalent analyses to the reported in Table 1, but where the dependent variable is vote shares for Jair Bolsonaro in 2018, whose political platform, albeit focused on other issues, was considerably anti-environment.[6]

So far, we have established that exposure to large-scale fires, on average, increased the electoral support for the main green candidate, Marina Silva, in the 2018 Brazilian presidential election. In the next section, we examine whether this effect is moderated by underlying economic structures that can facilitate turning the land cleared by large-scale fires into a source of profit for local populations.

8 Heterogeneity by Share of Employment in Cattle Ranching and Soy Farming

In the section "Natural Disasters and Material Self-Interest", we hypothesized that natural disasters drive up the vote shares of green candidates only when the costs of such disasters outweigh their benefits. In the section "Fires and Their Distributive Implications in Brazil", we discussed the costs and benefits of fires in Brazil for different groups. Specifically, we argued that fires generate both health and economic costs for most of the affected populations.

[5] Due to space constraints, these results are not included in the Appendix and tables can be provided upon request.

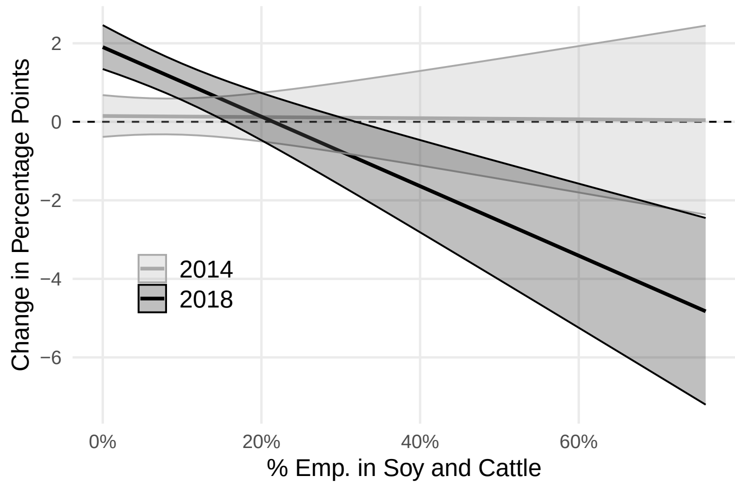
[6] Because Jair Bolsonaro ran for president for the first time in 2018, we cannot analyze the effect of large-scale fires on his electoral returns using our DiD design.

An exception is individuals who work in soy farming and cattle ranching. As fires destroy natural vegetation, they facilitate land grabbing, which is done through the transformation of unoccupied land in soy fields and especially pasture. In this section, we show that the average positive effect of fire exposure on support for Marina Silva is conditional on pre-treatment levels of employment in cattle ranching and soy farming using our DiD and IV designs. To do that, we interact our treatment dummy in both the DiD and IV designs with the share of employment in cattle ranching and soy farming at the municipality-level in 2017.

Figure 2 displays heterogeneous treatment effect results for the DiD design. It plots the marginal effects of exposure to large-scale fires in 2018 on the electoral returns of Marina Silva in 2014 (light gray) and 2018 (dark gray) conditional the share of the population employed in the soy farming and cattle ranching. The figure shows that, as expected, fire exposure in 2018 is not correlated with Marina Silva's vote share in the 2014 election across all levels of employment in cattle ranching and soy production. In 2018, the positive effect of large-scale fire exposure on Silva's electoral returns decreases with an increase in the share of employment in cattle and soy production and even becomes negative for extreme values of employment in these sectors. In Appendix E, we also examine the common support and the linearity assumption of our interaction term (see Table E.2 and Figure E.1). Overall, these additional tests confirm the main conclusion we draw from the results presented in the main text.[7]

[7] We also conducted robustness checks where we apply different radiative power and temporal cutoffs in constructing our treatment dummy and account for spatial auto-correlation. Due to space constraints, these results are available upon request.

Figure 2: Marginal Effect of Large-Scale Fire, Conditional on Municipality Share of Cattle and Soy Employment (DiD)



Notes**:** The figure presents the marginal effect of the presence of large-scale fires in the seven days prior to the 2018 election in the vote share for Marina Silva in the 2014 and 2018 presidential elections at different levels of employment in the soy and cattle sectors with 95 percent confidence intervals. Table E.1 in Appendix E reports the full set of coefficients.

Table 2 reports the results of the heterogeneous treatment effects with the IV designs. As in the DiD design, the measure of fire activity is interacted with a measure of the share of employees working in soy and cattle production. Columns (2) and (3) in Table 2 show that as the share of employees working in the soy and cattle sectors increases, the positive effect of fire exposure on Marina Silva's vote share decreases. Our IV estimates confirm that exposure to large-scale fires increased Silva's vote shares only in municipalities with low levels of employment in cattle ranching and soy farming. To address the potential concern of F-statistics below the critical value of 10 for our IV regression that relies on fire risk (column 2), we also report weak-IV robust confidence intervals, which provide correct lower and upper bound estimates of the effects regardless of the strength of the instrument (Sun, 2018; Andrews, Stock and Sun, 2019). The results confirm that as the share of jobs in cattle and soy increase, the positive effect of large-scale fires on support for Silva progressively decreases. In Table G.2, we report equivalent analyses testing the heterogenous effects of fire exposure on the vote share for Jair Bolsonaro, who ran in 2018 with a markedly antienviromentalist platform.

Table 2: Heterogeneous Effects of Fire Exposure on the Vote Share of Marina Silva

	DV: Marina Silva Vote's Share		
	(1)	(2)	(3)
Fires	0.036**	0.965**	0.715***
	(0.017)	(0.387)	(0.147)
Weak IV Robust 95% CI		[0.649, 2.225]	[0.595, 1.192]
Cattle & Soy	-0.459***	-0.277*	-0.424***
	(0.114)	(0.147)	(0.122)
Fires * Cattle & Soy	-0.170	-1.573**	-0.866*
	(0.155)	(0.743)	(0.467)
Weak IV Robust 95% CI		[-3.390,-0.362]	[-1.991,-0.491]
Controls	✓	✓	✓
Microregion Fixed Effects	✓	✓	✓
StandardErrors	Cl. Microreg.	Cl. Microreg.	Cl. Microreg.
Observations	5561	5557	5559
F-statistic		6.905	20.103
Model	OLS	IV Fire Risk	IV Temp & Wind

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: "Fires" is a dummy variable that equals one if a municipality was hit by a fire with an above-median radiative power in the seven days before the election, and equal to zero otherwise. All regressions include controls for municipality level precipitation and temperature in the five years before the week before the election; the municipality level deviation of precipitation in the year before the elections with respect to the average in the five years before elections; and municipality level precipitation on election day. Standard errors clustered at the microregional level are reported in parentheses. For the IV specifications, we also report for the endogenous regressors weak-IV robust 95 percent confidence intervals. These confidence intervals are computed following recommendations by Andrews, Stock and Sun (2019) for non-homoskesdastic models with clustered standard errors. To adapt Andrews, Stock and Sun (2019)'s method to cases with multiple endogenous regressors and instruments (such as in the case where we instrument fire radiative power with wind and temperature measures), we follow a procedure developed by Sun (2018). In Appendix F, we report results with the full set of coefficients (Table F.1) and first-stage results (Table F.2).

Overall, our results are consistent with our argument that natural disasters increase the electoral returns of green candidates and parties only when the damages outweigh the opportunities for economic profit. In the next section, we discuss alternative explanations and related tests.

9 Ruling out Alternative Explanations

In the literature, one of the most prominent moderators of the effects of natural disasters on support for the green political agenda is political ideology (e.g., Hazlett and Mildenberger, 2020). If the pretreatment ideology of a municipality is correlated with the pretreatment share of employment in cattle ranching and soy production, our heterogeneous treatment effects results might be picking the effect of ideology rather than the effect of profit opportunities that large-scale fires might generate in areas with higher levels of employment in cattle ranching and soy farming. We attempt to rule out this possibility by regressing the share of jobs in soy farming and cattle ranching in 2017 on a municipality level measure of political ideology computed based on the results of the 2014 general election. Intuitively, the residuals of that regression contain the variation of employment in cattle and soy in Brazil "net" of the ideological leaning of municipalities. In our heterogeneous treatment effects analyses, we replace the share of jobs in soy farming and cattle ranching with the residuals of this regression. In Appendices E and F, we provide more details on this procedure. We report the results for these analyses in Figure E.2 for the DiD design and, in Table F.6 for the IV design. Overall, the results of these analyses indicate that the results we present in section "Heterogeneity by Share of Employment in Cattle Ranching and Soy Farming" are not driven by the pretreatment ideology in municipalities.

The share of jobs in soy farming and cattle ranching might also be correlated with other socio-demographic moderators of the effect of natural disasters on political behavior that are less explored in the literature. To check whether the results reported in the Section "Heterogeneity by Share of Employment in Cattle Ranching and Soy Farming" are capturing the effect of other potentially relevant socio-demographic variables, we regress the share of employment in cattle ranching and soy production on municipality-level measures of: education, the share of population living in rural areas, the prevalence of people living in extreme poverty and the Human Development Index. We then use the residuals of this regression as our moderator in our DiD and IV strategies. We report the results in Figure

E.3 for the DiD design and in Table F.7 for the IV design. These results suggest that these variables are not confounding the moderation effect of share of jobs in cattle ranching and soy production that we find in the previous section.

10 Exploring Individual-level Mechanisms

The literature points to two types of individual-level mechanisms that explain the causal relationship between natural disasters and support for green political platforms. On the one hand, large-scale fires and other extreme natural events provide information about the costs of climate change and environmental degradation. In this sense, large-scale fires can provide information about the tradeoff between the health and environmental costs of environmental degradation and the economic costs of preserving natural areas, where economic activities are restricted. We refer to this channel as the *cost-benefit mechanism*. On the other hand, experiencing natural disasters might change environmental attitudes and behaviors through *psychological mechanisms*. This could include affect activation: the activation of emotions and feelings about specific objects, ideas, or images (in this case, environmental degradation) or a decrease in psychological distance: the perception of how far an event or issue (including environmental degradation) is from an individual's current experience, both in terms of time and space (Leiserowitz, 2006; Spence, Poortinga and Pidgeon, 2012). Natural disasters might also increase the salience of environmental issues, leading individuals to weight environmental considerations more when casting their votes (Sisco, 2021; Bromley-Trujillo and Poe, 2020). While we do not deny that psychological mechanisms, such as affect activation and reduction of psychological distance, play an important role in shaping how people respond to natural disasters, we argue that the cost-benefit mechanism contributes to explaining, at least in part, the impact of large-scale fires on support for the green candidate, Marina Silva.

We provide municipality level evidence for the cost-benefit mechanism in section "Heterogeneity by Share of Employment in Cattle Ranching and Soy Farming." In this section, we leverage individual-level data to better examine the cost-benefit mechanism. We rely on survey data collected for the study "Climate Change According to the Perception of Brazilian Citizens," a project by the ITS-RIO (*Instituto de Tecnologia e Sociedade*) and the Yale Program on Climate Change Communication. The data were collected between September 28 and November 1, 2021. The sample includes 2,600 Brazilians above 18 years old. The data was collected following census-based quotas of geographic region, education, gender, and age groups. Importantly, the database includes information about the municipality where respondents live. Among the available survey items, one is closely related to the *cost-benefit mechanism*. This item measures the extent to which respondents agree that "fires in the Amazon are necessary for economic growth."[8] Although this item does not directly measure perceived personal costs and benefits associated with fires, it reflects the tradeoff between a specific type of economic development and forest preservation.

We hypothesize that direct experience with large-scale fires decreases the perception of fires' contribution to economic growth in areas with low levels of employment in soy farming and cattle ranching. These are the areas where we expect that fewer individuals can reap profits from recently cleared land. To test our hypothesis, we merge the aforementioned geo-coded survey data with a measure of aggregate fire radiative power at the municipality level. Because the survey data does not include information on the specific days of the interviews, we look at large-scale fires in the month before the data collection started, that is, between August 27 and September 27, 2021. We construct the following specification:

$$\begin{aligned} \mathrm{Y}_{isjt} = \alpha + \mathrm{FRP}_{sjt-1} + \beta \text{Cattle \& Soy}_{sjt-2} + \gamma \mathrm{FRP}_{sjt-1} \times \text{Cattle \& Soy}_{sjt-2} \\ + \delta \mathbf{X}_{isjt} + \zeta \mathbf{K}_{sjt-2} + \omega_s + \varepsilon_{isjt}, \end{aligned} \tag{4}$$

where i indexes individuals, s states, j municipalities and t time; t indicates the data collection period, $t-1$ the treatment period (the month before the data collection) and $t-2$

[8] Unfortunately, among the available survey items, none is appropriate to test other mechanisms such as affect activation, psychological distance, and issue salience.

indicates the pretreatment years in which municipality level controls were collected. Y_{isjt} is the dependent variable, “Fires in the Amazon are necessary for economic growth,” which is measured with the following scale: Disagree (1), Do not agree nor disagree (2), Agree (3). FRP_{sjt-1} is the sum of the radiative power of fires above the national median at the municipality level in the month before the survey data collection started. Cattle & Soy_{sjt-2} is the (pretreatment) share of employment in soy and cattle production in 2017. $\mathbf{X}_{isjt}$ are individual-level controls that are plausibly unaffected by fires (gender, age and, education). $\mathbf{K}_{sjt-2}$ are pretreatment municipality level controls, including per capita GDP (2010), log population (2010), the share of the population employed in agriculture (2010), and the share of the municipality area covered by forests (2017). The specific year of the control variables depends on data availability. ω_s are state fixed effects and, ε_{isjt} are standard errors clustered at the mricroregion level.

The results presented in figure 3 suggests that large-scale fires decrease the perception that “Fires in the Amazon are necessary for economic growth” among communities that we expect to be unlikely to reap economic gains from fires, that is, municipalities with low levels of employment in soy production and cattle ranching. By contrast, in municipalities with high levels of employment in the soy and cattle sectors, the presence of large-scale fires is associated with higher agreement with the statement “fires in the Amazon are necessary for economic growth.” These results suggest that experiencing large-scale fires interacts with the underlying local economic structure to inform respondents’ perception of the tradeoff between economic benefits and environmental preservation. Overall, these individual-level results provide suggestive evidence that the *cost-benefit mechanism* explains at least in part the effects of large-scale fires on support for green political platforms that we document in the previous sections of the paper.

One potential issue with our estimates is that areas where more fire occur might be more likely to economically benefit from fires. While relying on large-scale fires that took place in the month before data collection started alleviates this concern, it does not completely solve

Figure 3: Effect of Fires on Agreement with "Fires in the Amazon are Necessary for Economic Growth"

***Notes*:** The figure presents coefficients with 95 percent confidence intervals of the effects of large-scale fires in the month prior to the period when the survey data was collected on agreement with the statement "Fires in the Amazon are necessary for economic growth" conditional on level of employment in soy and cattle at the municipality level. As indicated in equation 4, the regression includes pretreatment municipality-level controls and individual level covariates that are unlikely to be affected by treatment. Column (1) in Table H.1 in Appendix H reports the full set of coefficients. The regression includes sampling weights.

this problem. Hence, in column (2) of Table H.1 (Appendix H), we conduct an additional test in which we control for long-term patterns in large-scale fire activity (2018-2020) interacted with our measure of employment in cattle ranching and soy farming. We show that our findings are robust to this different specification and conclude that long-term patterns of fire intensity are unlikely to be driving our results.

11 Conclusion

The consequences of environmental degradation and climate change are increasingly dire, particularly in Global South countries (IPCC, 2021). As such, it is critical to understand which factors can impact politicians' incentives to implement ambitious environmental policies. In democracies, an important part of such incentives comes from how citizens express their demands at the ballot box. As a result, a growing body of literature, mostly focused on advanced democracies, examines the determinants of voting for parties with progressive environmental platforms.

In this paper, we investigate how first-hand experiences of large-scale fires shape support for green candidates in Brazil. We argue that the effect of exposure to large-scale fires on voting behavior is conditional on the balance between the damages and profit opportunities they generate. Employing both difference-in-differences and instrumental variable strategies, we show that large-scale fires increased the vote shares of Marina Silva, the presidential candidate with the most advanced pro-environmental platform in the 2018 presidential election, but only in municipalities with a low probability of reaping economic benefits from land newly cleared by fires. In short, we show that environmental concern and material self-interest closely interact, especially when economies rely on primary or extractive sectors, which are more likely to directly benefit from the distruction of the natural environment. We further employ survey data to provide suggestive evidence that first-hand experiences with large-scale fires change the perceptions of the costs and benefits of environmental degradation.

While a burgeoning literature, mostly focused on advanced democracies, provides evidence that natural disasters can increase the salience of environmental issues and support for green parties and candidates (e.g., Hazlett and Mildenberger, 2020; Hoffmann et al., 2022), our findings highlight the importance of taking into account the distributive consequences of environmental shocks, which might vary significantly depending on the underlying economic, institutional, and social structures. As the effects of climate change are expected to be particularly adverse in the Global South, our study highlights the importance of bringing more evidence on how citizens perceive green political agendas in these contexts. Promising avenues for future research include systematically assessing different political and distributive consequences of various types of natural disasters, such as floods and hurricanes, and investigating how different groups, including economic elites, benefit from or are damaged by natural disasters.

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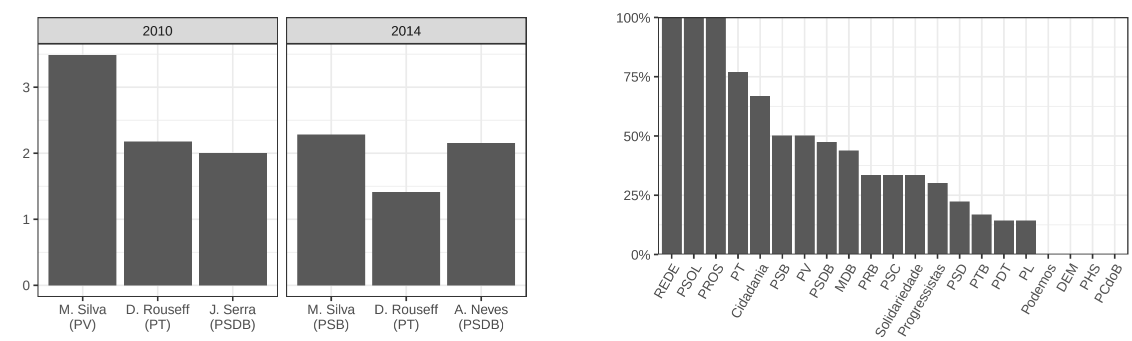
Online Appendix for "Global Harms, Local Profits: How the Uneven Costs of Natural Disasters Affect Support for Green Political Platforms"

Silvia Pianta & Paula Rettl

Table of Contents

A Environmentalism among Parties and Candidates

Figure A.1 shows the level of environmentalism among parties and candidates. Panel (a) shows the level of environmentalism among the three most voted Presidential candidates in 2010 and 2014. Data are sourced from the Comparative Manifesto Project (CMP). We use the method by Lowe et al. (2011) to create an environmentalism index that combines candidates' scores on the following categories: economic growth, anti-growth economy, sustainability and environmental protection. Panel (b) shows the level of environmentalism among members of parliament by party. Data is sourced from the Brazilian Legislative Survey (BLS) 2017 edition. Our measure of environmentalism in this case is the percentage of members of congress by party who declared in the survey that environmental protection should take precedence over economic development and job creation. On Panel (a) we observe that Marina Silva is, by far, the candidate with the most pro-environmental manifesto in 2010. In 2014, she is still the most pro-environment candidate (score: 2.28), although closely followed by Aecio Neves (PSDB) (score: 2.16). On panel (b), it is clear that the party founded by Silva – the Network Sustainability (REDE) – scores much higher in environmentalism than the Brazilian Social Democracy Party (PSDB), which is the party with which Neves has been affiliated since 1988. Although PSOL and PROS score similarly as REDE in our measure of environmentalism in panel (b), these small far-left parties tend to focus on economic and identitarian issues and much less on the environmental issues. Taken together, these descriptive statistics suggest that Silva has issue ownership over environmental issues in Brazil, much more so than her competitors in presidential elections.



(a) Environmentalism in Presidential Candidates' Manifestos

(b) Percentage of Pro-Environment Members of Congress in 2017 by Party (BLS)

Figure A.1: Environmentalism in Candidates and Parties

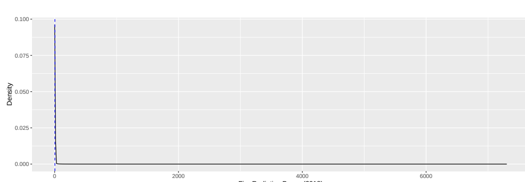
Note: Panel (a) displays the level of environmentalism among the three most voted presidential candidates in the 2010 and 2014 elections according to the Comparative Manifesto Project. Panel (b) shows the percentage of members of congress that agree that environmental protection should take precedence over economic development and job creation.

B Details about the Data and Descriptive Statistics

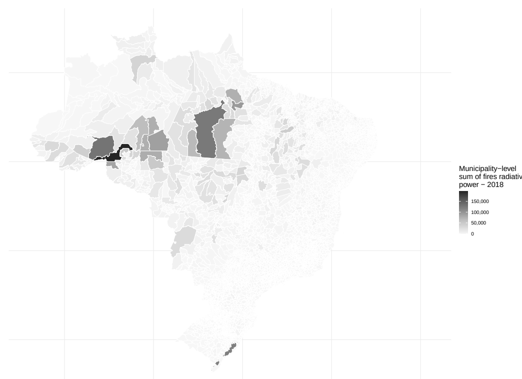
Fire activity data

We construct our variables measuring municipality level fire activity employing the *Queimadas* database, which is made available by the Brazilian Agency of Space Research (*Instituto Nacional de Pesquisas Espaciais*, INPE). The dataset provides information on the location of all fire foci detected in Brazil. For the years 2018 onward, the dataset also reports the radiative power (FRP), defined as the radiant energy released per time unit by burning vegetation, of all the detected fires.

We employ the Queimadas dataset to create a daily municipality level dataset that includes different measures of fire activity. As there is a very high number of very small fires, the distribution of the fire radiative power variable is extremely skewed (see panel (a) in Figure B.1 and Table B.1). As we want to focus on non-negligible fires that are likely to be noticed by citizens, in our main analyses reported in the main body of the paper, we focus on fires with a radiative power (FRP) that is above the yearly median (which is equal to 25 for the year 2018). Our main independent variable is a binary variable which is equal to 1 if a municipality experienced a fire with an above-median level of radiative power in the week before the first round of the 2018 Brazilian national elections, and 0 otherwise. Our dataset also includes other measures of fire activity that we employ in the analyses reported in the following sections of the Appendix. We provide details on such measures alongside the analyses below.



(a) Distribution of fire radiative power of all detected fires in 2018



(b) Municipality level yearly sum of fire radiative power in 2018

Figure B.1: Fire Radiative Power: Descriptive Figures

Table B.1: Descriptive Statistics of the fire radiative power of all detected fires in 2018

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 50	Pctl. 75	Max
Fire Radiative Power	132870	51	104	0	14	25	51	7303

Electoral data

Table B.2: Percentage votes for M. Silva (descriptive statistics)

Year	Observations	Mean	Std. dev.	Min.	Max.
2010	5565	10.365	6.151	0.935	42.473
2014	5565	13.240	8.565	0.637	74.192
2018	5565	0.508	0.359	0.000	4.528

Instruments

Table B.3: Descriptive Statistics of Municipality Level Instrumental Variables

	Source	Obs.	Mean	Std. dev.	Min	Max
Fire risk	INPE	5,560	0.680	0.382	0.000	1.000
Temperature	Copernicus	5,564	303.297	4.530	290.243	312.129
Wind	Copernicus	5,562	2.466	1.179	0.490	8.723

Note: Data sources: INPE (*Instituto Nacional de Pesquisas Espaciais*); Copernicus (Copernicus Satellite Images)

Co-variates at the municipality level

Table B.4: Descriptive Statistics of Co-variates at the Municipality Level

	Source	Year	Obs.	Mean	Std. dev.	Min.	Max.
Share of jobs in cattle and soy	RAIS	2017	5565	0.047	0.08	0.000	0.764
Extreme poverty (%)	UN	2010	5565	11.341	11.764	0.000	69.670
Share of rural population	UN	2010	5565	0.362	0.220	0.000	0.958
Education index	UN	2010	5565	0.397	0.106	0.120	0.800
HDI	UN	2010	5565	0.659	0.072	0.418	0.862
Ideology	BLS	2014	5565	-0.234	0.128	-0.472	0.131

Note: data sources: RAIS (*Relação Anual de Informações Sociais, 2017*); UN (United Nations Atlas of Human Development in Brazil, 2010); BLS (Brazilian Legislative Survey aggregated and inputed by Power and Rodrigues-Silveira (2019), combined with Electoral Returns from the *Tribunal Superior Eleitoral*, TSE) in Brazil.

Survey data

Table B.5: Descriptive Statistics for Variables Used in the Survey Data Analysis

	Obs.	Mean	Std. Dev.	Min.	Max.
	Individual-level variables				
DV	2457	1.399	0.758	1.000	3.000
Female	2457	0.501	0.500	0.000	1.000
Age categories	2457	4.171	1.339	2.000	6.000
Education	2457	3.469	1.410	1.000	5.000
	Municipality level variables				
Fires (standardized)	786	-0.023	1.380	-0.190	35.828
Jobs in cattle and soy (%)	786	3.094	6.728	0.000	56.260
Employed (%)	786	20.792	17.859	0.180	75.480
Income per capita	786	620.710	292.288	149.190	2000.290
Area covered by forest	786	0.350	0.235	0.000	1.000
Population (log)	786	10.818	1.377	7.425	16.236

Note: data sources for individual-level survey data is from the project "Climate Change According to the Perception of Brazilian Citizens" by ITS-RIO (*Instituto de Tecnologia e Sociedade do Rio de Janeiro* and partners. DV refers to the dependent variable (i.e., item asking the extent to which respondent agrees that "Fires in the Amazon are necessary for economic growth"). The variable was reverse coded so that higher values indicate more agreement with the statement. Fires refer to fire radiative power in the month before the survey data started to be collected. The data source for fire radiative power is INPE. Area covered by forest is computed using 2017 data Map Biomas (https://brasil.mapbiomas.org/en/). Log population is computed using data from the United Nations Atlas of Human Development in Brazil (2010).

C Average Effects - DiD Design

Baseline Specification and Alternative Treatments

Column (2) of table C.1 reports the results plotted in Figure 1. Columns (1) and (3) report results for similar specifications, where the treatment variable is defined based on other cutoffs of fire radiative power. In column (1), municipalities exposed to fires of any level of radiative power in the seven days before the 2018 election are considered treated. In column (3), municipalities exposed to an aggregate level of fire radiative power equal or above 50 in the seven days before the 2018 election are considered treated. In column (1), we observe that the coefficient for being assigned to the treatment group (i.e., being exposed to any fire in the days before the 2018 election) is associated with higher levels of vote share for Silva in 2014 at the 95% confidence level. However, we do not observe statistically significant pretrends in electoral support for Silva when the treatment group is defined based on exposure to larger fires. In line with our argument in section "Empirical Strategy", these results suggest that small fires are endogenous to political behavior at the municipality level, but large fires are not.

Table C.1: Average Effect of Fire Exposure on the Vote Share of Marina Silva (DiD)

	DV: Marina Silva's Vote Share		
	(1)	(2)	(3)
FRP $> 0 \times$ Year$_{2014}$	0.432*		
	(0.242)		
FRP $> 0 \times$ Year$_{2018}$	0.953***		
	(0.259)		
FRP $> 25 \times$ Year$_{2014}$		0.168	
		(0.232)	
FRP $> 25 \times$ Year$_{2018}$		1.608***	
		(0.239)	
FRP $> 50 \times$ Year$_{2014}$			0.118
			(0.257)
FRP $> 50 \times$ Year$_{2018}$			1.669***
			(0.253)
Observations	9141	11847	13110
R-squared	0.866	0.870	0.875
Municipality FE	✓	✓	✓
Year FE	✓	✓	✓
State × Year FE	✓	✓	✓

Standard errors clustered by municipality in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Different Temporal Cutoffs and Spatial Autocorrelation

In this section, we present robustness checks for the estimates presented in Figure 1. In columns (1) and (2) of Table C.2, we present results for a different temporal cutoff in defining our treatment variable. In column (1), we define the treatment dummy as equal to one if municipality j registered a fire with a radiative power above the national median in the thirty days preceding the first round of the 2018 presidential election and zero if there were no fires in the 180 days preceding election day. In an alternative specification not presented here due to space constraints, we define out temporal cutoff as fourteen days before the election day. Our results suggest that the longer the time frame considered to define the treatment dummy, the smaller is the effect, which is in line with recency theory (i.e., the idea that recent events matter more to define public opinion and behavior) (Baddeley and Hitch, 1993). Columns (2), (3) and (4) present results of spatial autocorrelation robustness checks. Column (2) clusters standard errors at the microrregion-level. Microregions are similar to commuting zones in the US and are defined by the Brazilian Institute of Geography and Statistics based on natural and economic similarities. In columns (3) and (4), standard errors are clustered based on a radius of 100 and 200km, respectively.

Table C.2: Average Effect of Fire Exposure on the Vote Share of Marina Silva (DiD): Robustness for Different Temporal Cutoffs and Spatial Autocorrelation

	DV: Marina Silva's Vote Shares			
	(1)	(2)	(3)	(4)
$\text{Fires}_{30d} \times \text{Year}_{2014}$	0.193			
	(0.162)			
$\text{Fires}_{30d} \times \text{Year}_{2018}$	0.533^{***}			
	(0.172)			
$\text{Fires} \times \text{Year}_{2014}$		0.168	0.168	0.168
		(0.275)	(0.329)	(0.364)
$\text{Fires} \times \text{Year}_{2018}$		1.608^{***}	1.608^{***}	1.608^{***}
		(0.356)	(0.444)	(0.539)
Observations	14331	11847	11847	11847
R-squared	0.871	0.870	0.00461	0.00461
Municipality FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
State × Year FE	✓	✓	✓	✓
Std. Err.	Mun.	Micror.	100km	200km

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

D Average Effects - IV Design

Details on the Baseline Specification

Table D.1 reports the results presented in Table 1 in the main text, but also showing the coefficients of all control variables. As in in Table 1, the outcome variable is the municipality level vote share of Marina Silva in the first round of the 2018 presidential elections. "Fires" is a dummy variable that is equal to 1 if a municipality was hit by a fire with an above-median radiative power in the seven days before the election, and equal to 0 otherwise. "5 Year Precipitation" and "5 Year Temperature" are the average municipality level precipitation and temperature in the five years before the week before the election; "Precipitation Deviation" is the municipality level deviation of precipitation in the year before the elections with respect to the average in the five years before the week before the elections; "Precipitation Election Day" is the municipality level precipitation on the election day. Model (1) reports results of the OLS specification, Model (2) reports results of the IV specification employing the maximum municipality level fire risk in the week before the elections as instrumental variable, and Model (3) reports results of the IV specification employing the municipality level maximum temperature and maximum wind speed in the week before the elections as instruments. Standard errors clustered at the microregional level are reported in parentheses.

Table D.2 reports the first stage results of the IV estimates presented in Table 1 alongside the second stage estimates presented there.

Table D.1: Effect of Fire Exposure on the Vote Share of Marina Silva
Table Reporting the Full Set of Coefficients

	DV: Marina Silva's Vote Share		
	(1)	(2)	(3)
Fires	0.016	0.756**	0.763***
	(0.016)	(0.328)	(0.144)
5 Year Precipitation	0.039**	0.077***	0.078***
	(0.017)	(0.028)	(0.022)
5 Year Temperature	-0.014**	-0.029**	-0.029***
	(0.007)	(0.011)	(0.009)
Precipitation Election Day	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
Precipitation Deviation	-0.071	0.058	0.058
	(0.071)	(0.119)	(0.105)
Microregion Fixed Effects	✓	✓	✓
StandardErrors	Cl. Microreg	Cl. Microreg	Cl. Microreg
Observations	5561	5557	5559
F-statistic		14.250	31.920
Model	OLS	IV Fire Risk	IV Temp & Wind

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.2: Effect of Fire Exposure on the Vote Share of Marina Silva
Table With First Stage of IV Specifications

	(1) Fires	(2) Marina Silva Share	(3) Fires	(4) Marina Silva Share
Fires		0.756**		0.763***
		(0.328)		(0.144)
Fire Risk 7 days	0.162***			
	(0.043)			
Temperature 7 days			0.065***	
			(0.009)	
Wind 7 days			0.034***	
			(0.011)	
Prec 5 years	-0.040**	0.077***	-0.041**	0.078***
	(0.019)	(0.028)	(0.018)	(0.022)
Temp 5 years	0.018**	-0.029**	-0.043***	-0.029***
	(0.007)	(0.011)	(0.011)	(0.009)
Precip election day	0.000	-0.001	0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Precip Deviation	-0.142*	0.058	-0.181**	0.058
	(0.085)	(0.119)	(0.080)	(0.105)
Microregion Fixed Effects	✓	✓	✓	✓
StandardErrors	Cl. Microreg	Cl. Microreg	Cl. Microreg	Cl. Microreg
Observations	5557	5557	5559	5559
F-statistic	14.250	14.250	31.920	31.920
Model	IV Fire Risk	IV Fire Risk	V Temp & Wind	IV Temp & Wind

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Alternative Treatment Variable: Binary Treatment Based on Any Fires

Table D.3 reports analyses similar to those presented in Table 1 in the main text, but here 'Fires" is a dummy variable that is equal to 1 if a municipality was hit by *any fire* in the seven days before the election, and equal to 0 otherwise. Column (1) reports results of the OLS specification, column (2) reports results of the IV specification employing the maximum municipality level fire risk in the week before the elections as instrument, and column (3) reports results of the IV specification employing the municipality level maximum temperature and maximum wind speed in the week before the elections as instruments. Overall, our estimates are slightly smaller in magnitude when we consider any fires instead of only large-scale fires. Overall, our estimates are slightly smaller in magnitude when we consider any fires instead of only large-scale fires.

Table D.3: Effect of Fire Exposure on the Vote Share of Marina Silva
Binary Treatment – Any Fires

	DV: Marina Silva's Vote Share		
	(1)	(2)	(3)
Fires	0.026*	0.592**	0.656***
	(0.015)	(0.240)	(0.122)
Controls	✓	✓	✓
Microregion Fixed Effects	✓	✓	✓
StandardErrors	Cl. Microreg	Cl. Microreg	Cl. Microreg
Observations	5561	5557	5559
F-statistic		16.911	37.448
Model	OLS	IV Fire Risk	IV Temp & Wind

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Alternative Treatment Variable: Continuous Variable Measuring the Sum of the Radiative Power of All Detected Fires

Table D.4 reports analyses with a similar specifications presented in Table 1 in the main text, but the treatment is a continuous variable measuring the *sum of the radiative power of all fires* detected in the seven days before the election in each municipality. Column (1) reports results of the OLS specification, column (2) reports results of the IV specification employing the maximum municipality-level fire risk in the week before the elections as instrument, and column (3) reports results of the IV specification employing the municipality level maximum temperature and maximum wind speed in the week before the elections as instruments. Standard errors clustered at the microregional level are reported in parentheses. The coefficients have the same direction and comparable significance levels a those reported in Table 1 in the main text. The lower magnitude and lower relevance of the instrumental variables in Table D.4 is likely due to the distribution of the non-transformed fire activity variable, which is extremely skewed towards zero. In our main specification, we focus on large-scale fires, which are more visible and less likely to be endogenous, and we employ a binary variable because the interpretation of its coefficient is more straightforward with respect to the interpretation of the continuous variable measuring fire radiative power.

Table D.4: Effect of Fire Exposure on the Vote Share of Marina Silva
Continuous Treatment: Fire Radiative Power Variable

	DV: Marina Silva's Vote Share		
	(1)	(2)	(3)
Fires	-0.000	0.001*	0.001***
	(0.000)	(0.000)	(0.000)
Controls	✓	✓	✓
Microregion Fixed Effects	✓	✓	✓
StandardErrors	Cl. Microreg	Cl. Microreg	Cl. Microreg
Observations	5560	5556	5558
F-statistic		8.746	8.578
Model	OLS	IV Fire Risk	IV Temp & Wind

Alternative Treatment Variable: Binary Treatment Based on Above-median Fires in the Month Before Elections

Table D.5 reports analyses with a similar specification as the one presented in Table 1 in the main text, but here "Fires" is a dummy variable that is equal to 1 if a municipality was hit by a fire with an above-median radiative power in the *30 days* before the election, and equal to 0 otherwise. Column (1) reports results of the OLS specification, column (2) reports results of the IV specification employing the maximum municipality-level fire risk in the month before the elections as instrumental variable, and column (3) reports results of the IV specification employing the municipality level maximum temperature and maximum wind speed in the month before the elections as instruments. Standard errors clustered at the microregional level are reported in parentheses. The impact of fires in the month before elections on the vote share of Silva is positive and significant, and approximately half in size with respect to the impact of fires in the week before elections presented in Table 1 in the main text.

Table D.5: The Effect of Fire Exposure on the Vote Share of Marina Silva
The Impact of Fires in the Month Before the Elections

	DV: Marina Silva's Vote Share		
	(1)	(2)	(3)
Fires	0.035***	0.439***	0.380***
	(0.011)	(0.143)	(0.066)
Controls	✓	✓	✓
Microregion Fixed Effects	✓	✓	✓
StandardErrors	Cl. Microreg	Cl. Microreg	Cl. Microreg
Observations	5561	5557	5559
F-statistic		31.448	65.062

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

E Heterogeneous Treatment Effects - DiD Design

Baseline Specification and Alternative Treatments

Column (2) of Table E.1 shows the full set of coefficients for Figure 2. Column (1) and (3) show the results for a similar specification in which the treatment indicator is defined based on other fire radiative power cutoffs. Specifically, in column (1) we define the treatment group as municipalities exposed to fires of any level of radiative power in the seven days before the 2018 election day and; in column (3) as municipalities exposed to fires with aggregate level of radiative power above 50 in the same period.

Other Functional Forms and Linearity of the Interaction

One potential issue with our heterogeneous effects analysis is the distribution of municipalities in the treatment and control groups with different levels of employment in cattle and soy production. As shown in Table E.2, this distribution is left-skewed and, as a result, most municipalities have low levels (i.e., below 25%) of employment in cattle and soy. We address this issue in two ways. First, we run the same specification as in Figure 2 and column 2 in Table E.1 but using the inverse hyperbolic sine (IHS) transformation of the share of employment in cattle and soy. Similarly to the log transformation, the IHS transformation smooths the distribution. As a result, municipalities with extreme levels of employment in cattle ranching and soy production receive lower weight. In Figure E.1b we observe that the negative slope of the interaction between fires and employment in cattle or soy persists in 2018 when we employ the IHS transformation. Second, in Figure E.1c, we run a similar model with a categorical transformation of the continuous measure of employment in soy or cattle. We observe that for municipalities with less than 25% of employment in the soy and cattle sectors, the effect of fire exposure is positive; for municipalities with intermediate levels (i.e., 25-50%), the effect is null and; for municipalities with high levels (i.e., 50-75%), the effect

Table E.1: Heterogeneous Treatment Effect of Fire Exposure on the Vote Share of Marina Silva by Level of Employment in Cattle or Soy (DiD)

	DV: Marina Silva's Vote Share		
	(1)	(2)	(3)
FRP > 0 × Year_{2014}	0.395		
	(0.277)		
FRP > 0 × Year_{2018}	1.130***		
	(0.295)		
FRP > 0 × Year_{2014} × % Jobs cattle or soy	0.841		
	(1.982)		
FRP > 0 × Year_{2018} × % Jobs cattle or soy	-6.690***		
	(2.146)		
Year_{2014} × % Jobs cattle or soy	-0.532	1.161	0.847
	(1.733)	(1.318)	(1.102)
Year_{2018} × % Jobs cattle or soy	11.43***	12.64***	12.15***
	(1.911)	(1.389)	(1.260)
Fires *times* Year_{2014}		0.148	
		(0.271)	
Fires *times* Year_{2018}		1.902***	
		(0.285)	
Fires *times* Year_{2014} × % Jobs cattle or soy		-0.139	
		(1.770)	
Fires *times* Year_{2018} × % Jobs cattle or soy		-8.854***	
		(1.775)	
FRP > 50 × Year_{2014}			0.0480
			(0.312)
FRP > 50 × Year_{2018}			2.004***
			(0.313)
FRP > 50 × Year_{2014} × % Jobs cattle or soy			0.520
			(1.834)
FRP > 50 × Year_{2018} × % Jobs cattle or soy			-8.683***
			(1.986)
Constant	7.490***	7.629***	7.802***
	(0.0493)	(0.0322)	(0.0261)
Observations	9141	11847	13110
R-squared	0.867	0.871	0.876
Municipality FE	✓	✓	✓
Year FE	✓	✓	✓
State × year FE	✓	✓	✓

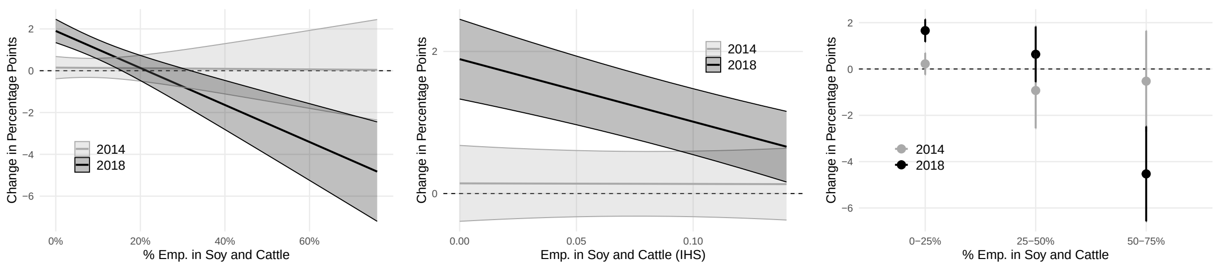
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table E.2: Distribution of municipalities by control group (2010) and treatment groups (2014 and 2018) by level of employment in soy and cattle

Jobs in doy and cattle (%)	0-25	25-50	50-75
Control group	3310	36	3
Treatment group	534	52	13

is negative. Overall, these results confirm the findings we show in the main text. Finally, in Figure E.1a, we show the results for a quadratic form of the interaction between fire exposure and employment in cattle and soy. Overall, the functional form of the interaction seems to be unaffected by the inclusion of the quadratic term.

Figure E.1: Marginal Effect of Fires, Conditional on Municipality Share of Employment in Cattle or Soy (DiD) – Robustness



(a) Quadratic (b) IHS (c) Categorical

Potential Confounders of Employment in Soy and Cattle Sectors

In this section, we consider potential spurious results of our interaction between fires and employment in the cattle and soy sectors. The first concern we address is the possibility that employment in cattle and soy is correlated with previous ideology at the municipality level. This is particularly important as previous work shows that the effect of fires is conditional on previous voting patterns in US counties (Hazlett and Mildenberger, 2020). We control for that by substituting the raw measure of cattle and soy employment by the residuals of a regression where the dependent variable is our measure of employment in cattle and soy in 2017 and the only independent variable is a measure of ideological centers of gravity of municipalities in 2014 (which was the last presidential election before 2018). Ideological centers of gravity are party scores weighted averages, where the weights are vote shares at the municipality level. Specifically, to compute the ideological center of gravity for municipality j, we multiply the position in the left-right scale computed by Power and Rodrigues-Silveira (2019) of a given party p in 2014 by its vote shares in municipality j in the same year. To obtain the ideological center of gravity for municipality j, we aggregate this measure over all parties p. Intuitively, the residuals of that regression contain the variation of employment in cattle and soy in Brazil "net" of the ideological leaning of municipalities. Figure E.2 shows the results for a similar specification as in Figure 2 in the main text, but where employment in cattle and soy is replaced by these residuals. The figure shows that the patterns we observe in Figure 2 are not explained by a potential correlation between employment in cattle and soy and ideology at the municipality level.

Another possible concern is that our measure of employment in cattle and soy is correlated with socio-demographic characteristics that are predictors of voting behavior. We address this concern by residualizing our measure of employment in cattle and soy by the following socio-demographic characteristics at the municipality level: an index of education levels, the rural share of the population, the percentage of the population in extreme poverty and the Human Development Index. Details about these measures and related data can be found in Table B.4 in Appendix B. Figure E.3 presents the results. Overall, the general trend of a decreasing magnitude of the effect of fires before the 2018 election as employment in cattle and soy increases is maintained when we use this residualized version of our cattle and soy measure.

Marginal Effect of Fires, Conditional on Municipality Share of Employment in Cattle or Soy (DiD) – Accounting for Confounders

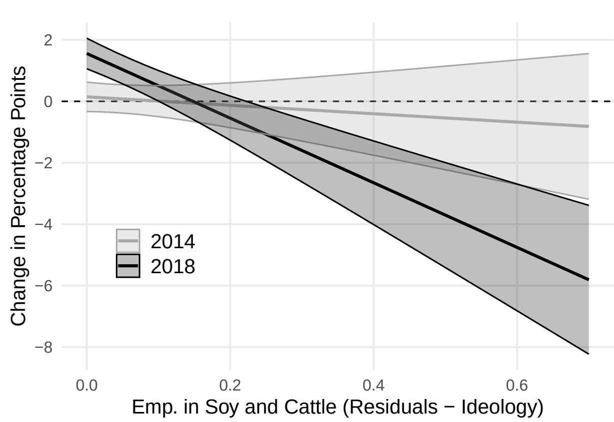


Figure E.2: Residuals - previous ideology

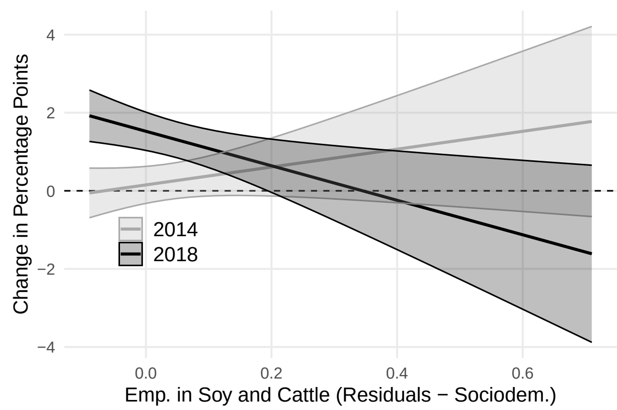


Figure E.3: Residuals - sociodemographic characteristics

F Heterogeneous Treatment Effects - IV Design

The 2SLS specifications of the heterogeneous treatment effects reported in Section 8 of the manuscript mirror the ones we report in Section 6.2 for the direct effects. We report here more details on the 2SLS specifications of the heterogeneous treatment effects. We employ the following equation:

$$\mathrm{Y}_{jk} = \beta\widehat{\mathrm{Fires}}_{jk} + \gamma\mathrm{Cattle\ \&\ Soy}_{jk} + \delta\mathrm{Fires}_{jk} \times \mathrm{Cattle\ \&\ Soy}_{jk} + \zeta\mathbf{X}_{jk} + \phi_k + \varepsilon_{jk} \tag{5}$$

where j indexes municipalities in microregions k. Y_{jk} represents vote share of Marina Silva in municipality j in microregion k in the first round of the 2018 presidential elections. Fires_{jk} denotes whether municipality j experienced a fire with an above-median radiative power in the week before the elections. $\mathbf{X}$ is a vector of four control variables: the first two measure the mean temperature and the mean precipitation in municipality j in the five years before the week before the election; the third measures the difference between mean precipitation in the last year before the elections and mean precipitation in the last five years, divided by the 5-year mean; the fourth measures precipitation on the election day. We include fixed effects at the microregional level, (ϕ_k).

We instrument both the variable measuring fire activity in the week before the elections, Fires_{jk}, and the interaction between fire activity and the share of the population working in the soy and cattle sectors, $\text{Fires}_{jk} \times \text{Cattle \& Soy}_{jk}$. In the first IV specification, we use as instruments the average municipality level fire risk in the week before the elections and the interaction between the latter and the municipality level share of the population working in the soy and cattle sectors. In the second IV specification, we use as instruments the municipality level maximum wind speed and maximum temperature in the week before the election day, as well as the interactions between the latter two and the municipality level share of the population working in the soy and cattle sectors.

Details on the Baseline Specification

Table F.1 reports the same results presented in Table 2 in the main text, also reporting the coefficients of all the control variables. The outcome variable is the municipality level vote share of Marina Silva in the first round of the 2018 presidential elections. "Fires" is a dummy variable that is equal to 1 if a municipality was hit by a fire with an above-median radiative power in the seven days before the election, and equal to 0 otherwise. "Cattle & Soy" is the share of the municipality population that is employed in the soy or cattle sectors. "Fires * Cattle & Soy" is the interaction of the "Fires" variable with the "Cattle & Soy" variable. "5 Year Precipitation" and "5 Year Temperature" are the average municipality-level precipitation and temperature in the five years before the week before the election; "Precipitation Deviation" is the municipality level deviation of precipitation in the year before the elections with respect to the average in the five years before the week before the elections; "Precipitation Election Day" is the municipality level precipitation on the election day. Column (1) reports results of the OLS specification, column (2) reports results of the IV specification employing the maximum municipality level fire risk in the week before the elections as instrument, and column (3) reports results of the IV specification employing the municipality level maximum temperature and maximum wind speed in the week before the elections as instruments. Standard errors clustered at the microregional level are reported in parentheses.

Table F.2 reports the first stage results of the IV estimates presented in Table 2 in the main text, alongside the second stage estimates presented there.

Table F.1: Heterogeneous Effects of Fire Exposure on the Vote, Share of Marina Silva
Table Reporting the Full Set of Coefficients

	DV: Marina Silva's Vote Share		
	(1)	(2)	(3)
Fires	0.036**	0.965**	0.715***
	(0.017)	(0.387)	(0.147)
Cattle & Soy	-0.459***	-0.277*	-0.424***
	(0.114)	(0.147)	(0.122)
Fires * Cattle & Soy	-0.170	-1.573**	-0.866*
	(0.155)	(0.743)	(0.467)
5 Year Temperature	-0.013*	-0.030**	-0.026***
	(0.007)	(0.012)	(0.009)
5 Year Precipitation	0.040**	0.082***	0.073***
	(0.017)	(0.030)	(0.021)
Precipitation Deviation	-0.079	0.051	0.021
	(0.069)	(0.119)	(0.095)
Precipitation Election Day	-0.001	-0.001*	-0.001*
	(0.001)	(0.001)	(0.001)
Microregion Fixed Effects	✓	✓	✓
StandardErrors	Cl. Microreg.	Cl. Microreg.	Cl. Microreg.
Observations	5561	5557	5559
F-statistic		6.905	20.103
Model	OLS	IV Fire Risk	IV Temp & Wind

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table F.2: Heterogeneous Effects of Fire Exposure on the Vote Share of Marina Silva
Table With First Stage of IV Specifications

	Fire Risk Instrument			Temp & Wind Instruments		
	(1)	(2)	(3)	(4)	(5)	(6)
	First stage	First stage		First stage	First stage	
	Fires	Fires * Cattle & Soy	Marina Silva Share	Fires	Fires * Cattle & Soy	Marina Silva Share
Fires			0.965**			0.715***
			(0.387)			(0.147)
Fires * Cattle & Soy			-1.573**			-0.866*
			(0.743)			(0.467)
Fire Risk 7 days	0.110***	-0.022***				
	(0.043)	(0.008)				
Fire Risk 7 days * Cattle & Soy	0.619***	0.488***				
	(0.200)	(0.078)				
Temperature 7 days				0.059***	0.001	
				(0.009)	(0.001)	
Wind 7 days				0.026**	0.001	
				(0.012)	(0.001)	
Temperature 7 days * Cattle & Soy				0.105***	0.069***	
				(0.023)	(0.009)	
Wind 7 days * Cattle & Soy				0.422***	0.070	
				(0.116)	(0.046)	
Cattle & Soy	-0.197**	-0.056	-0.277*	-32.554***	-20.850***	-0.424***
	(0.084)	(0.045)	(0.147)	(7.048)	(2.677)	(0.122)
Temp 5 years	0.017**	0.000	-0.030**	-0.041***	-0.002	-0.026***
	(0.007)	(0.001)	(0.012)	(0.011)	(0.002)	(0.009)
Prec 5 years	-0.040**	-0.004*	0.082***	-0.042**	-0.004*	0.073***
	(0.019)	(0.002)	(0.030)	(0.018)	(0.002)	(0.021)
Precip Deviation	-0.141*	-0.019	0.051	-0.189**	-0.028**	0.021
	(0.083)	(0.012)	(0.119)	(0.076)	(0.011)	(0.095)
Precip election day	0.000	0.000	-0.001*	0.000	0.000	-0.001*
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Microregion Fixed Effects	✓	✓	✓	✓	✓	✓
StandardErrors	Cl. Microreg.	Cl. Microreg.	Cl. Microreg.	Cl. Microreg.	Cl. Microreg.	Cl. Microreg.
Observations	5557	5557	5557	5559	5559	5559
F-statistic	6.905	6.905	6.905	20.103	20.103	20.103
Model	IV Fire Risk	IV Fire Risk	IV Fire Risk	IV Temp & Wind	IV Temp & Wind	IV Temp & Wind

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Alternative Treatment Variable: Binary Treatment Based on Any Fires

Table F.3 reports analyses similar to those presented in Table 2 in the main text, but here "Fires" is a dummy variable that is equal to 1 if a municipality was hit by *any fire* in the seven days before the election, and equal to 0 otherwise. "Cattle & Soy" is the share of the municipality population that is employed in the soy or cattle sectors. "Fires * Cattle & Soy" is the interaction of the "Fires" variable with the "Cattle & Soy" variable. The outcome variable is the municipality level vote share of Marina Silva in the first round of the 2018 presidential elections. All regressions include controls for municipality level precipitation and temperature in the five years before the week before the election; the municipality level deviation of precipitation in the year before the elections with respect to the average in the five years before the elections; and municipality level precipitation on the election day. Column (1) reports results of the OLS specification, column (2) reports results of the IV specification employing the maximum municipality level fire risk in the week before the elections as instrument, and column (3) reports results of the IV specification employing the municipality-level maximum temperature and maximum wind speed in the week before the election as instruments. Standard errors clustered at the microregional level are reported in parentheses

Table F.3: Heterogeneous Effects of Fire Exposure on the Vote Share of Marina Silva Binary Treatment – Any Fires

	DV: Marina Silva's Vote Share		
	(1)	(2)	(3)
Fires	0.037**	0.777***	0.600***
	(0.014)	(0.284)	(0.122)
Cattle & Soy	-0.460***	-0.127	-0.361***
	(0.124)	(0.171)	(0.127)
Fires * Cattle & Soy	-0.125	-1.310**	-0.604
	(0.151)	(0.591)	(0.376)
Controls	✓	✓	✓
Microregion Fixed Effects	✓	✓	✓
StandardErrors	Cl. Microreg.	Cl. Microreg.	Cl. Microreg.
Observations	5561	5557	5559
F-statistic		8.523	23.093
Model	OLS	IV Fire Risk	IV Temp & Wind

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Alternative Treatment Variable: Continuous Variable Measuring the Sum of the Radiative Power of All Detected Fires

Table F.4 reports analyses with the same specifications presented in Table 2 in the main text, but here "Fires" is the *sum of the radiative power of all fires* detected in the seven days before the election. “Cattle & Soy” is the share of the municipality population that is employed in the soy or cattle sectors. “Fires * Cattle & Soy” is the interaction of the “Fires” variable with the “Cattle & Soy” variable. The outcome variable is the municipality level vote share of Marina Silva in the first round of the 2018 presidential elections. All regressions include controls for municipality level precipitation and temperature in the five years before the week before the election; the municipality level deviation of precipitation in the year before the elections with respect to the average in the five years before the elections; and municipality level precipitation on the election day. Model (1) reports results of the OLS specification, Model (2) reports results of the IV specification employing the maximum municipality level fire risk in the week before the elections as instrument, and Model (3) reports results of the IV specification employing the municipality level maximum temperature and maximum wind speed in the week before the elections as instruments. Standard errors clustered at the microregional level are reported in parentheses. The coefficients have the same direction and comparable significance levels a those reported in Table 2 in the main text. The lower magnitude and lower relevance of the instrumental variables in Table F.4 is likely due to the distribution of the non-transformed fire activity variable, which is extremely skewed toward zero.

Table F.4: Heterogeneous Effects of Fire Exposure on the Vote Share of Marina Silva
Continuous Treatment: Fire Radiative Power Variable

	DV: Marina Silva's Vote Share		
	(1)	(2)	(3)
Fires	0.000	0.001**	0.001***
	(0.000)	(0.001)	(0.000)
Cattle & Soy	-0.492***	-0.297**	-0.303***
	(0.095)	(0.120)	(0.114)
Fires * Cattle & Soy	-0.000	-0.002*	-0.002***
	(0.000)	(0.001)	(0.001)
Controls	✓	✓	✓
Microregion Fixed Effects	✓	✓	✓
StandardErrors	Cl. Microreg.	Cl. Microreg.	Cl. Microreg.
Observations	5560	5556	5558
F-statistic		4.502	6.771
Model	OLS	IV Fire Risk	IV Temp & Wind

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Alternative Treatment Variable: Binary Treatment Based on Above-median Fires in the Month Before Elections

Table F.5 reports analyses with the same specifications presented in Table 2 in the main text, but here “Fires” is a dummy variable that is equal to 1 if a municipality was hit by a fire with an above-median radiative power in the *month* before the election, and equal to 0 otherwise. “Cattle & Soy” is the share of the municipality population that is employed in the soy or cattle sectors. "Fires * Cattle & Soy" is the interaction of the "Fires" variable with the "Cattle & Soy" variable. The outcome variable is the municipality level vote share of Marina Silva in the first round of the 2018 presidential elections. All regressions include controls for municipality level precipitation and temperature in the five years before the month before the election; the municipality level deviation of precipitation in the year before the elections with respect to the average in the five years before elections; and municipality level precipitation on the election day. Column (1) reports results of the OLS specification, column (2) reports results of the IV specification employing the maximum municipality level fire risk in the month before the elections as instrumental variable, and column (3) reports results of the IV specification employing the municipality level maximum temperature and maximum wind speed in the month before the elections as instruments. Standard errors clustered at the microregional level are reported in parentheses. The coefficients in Table F.5 have the same direction and significance level and are approximately half the size with respect to the coefficients of the analyses focusing on the week before elections presented in Table 1 in the main text.

Table F.5: Heterogeneous Effects of Fire Exposure on the Vote Share of Marina Silva
The Impact of Fires in the Month Before the Elections

	DV: Marina Silva's Vote Share		
	(1)	(2)	(3)
Fires	0.032***	0.539***	0.375***
	(0.012)	(0.164)	(0.069)
Cattle & Soy	-0.548***	-0.119	-0.448***
	(0.085)	(0.208)	(0.151)
Fires * Cattle & Soy	0.081	-0.798*	-0.172
	(0.117)	(0.453)	(0.294)
Controls	✓	✓	✓
Microregion Fixed Effects	✓	✓	✓
StandardErrors	Cl. Microreg.	Cl. Microreg.	Cl. Microreg.
Observations	5561	5557	5559
F-statistic		15.051	35.090
Model	OLS	IV Fire Risk	IV Temp & Wind

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Potential Confounders of Employment in the Soy and Cattle Sectors

Similarly to what we do in Section E for in our DiD analyses, we run some robustness checks to address potential concerns that the results of our interaction between fires and the employment in cattle and soy are spurious due to the possible correlation of the latter with previous political ideology and sociodemographic characteristics that are predictors of voting behavior. We residualize our measure of employment in cattle and soy by the same measure of ideology and the same sociodemographic caracteristics described in Section E.

Tables F.6 and F.7 show the results for the same specification as in Table 2 in the main text, but where employment in cattle and soy is replaced by the residuals of its regression on the two sets of confounders. Overall, the general trend of decreasing magnitude of the effect of fires before the 2018 election as employment in cattle and soy increases is maintained when we use this residualized version of our cattle and soy measure.

Table F.6: IV HTE Residuals Ideology

	DV: Marina Silva's Vote Share		
	(1)	(2)	(3)
Fires	0.029*	0.895**	0.632***
	(0.015)	(0.364)	(0.133)
Cattle & Soy (res, ideology)	-0.459***	-0.222	-0.382***
	(0.113)	(0.148)	(0.121)
Fires * Cattle & Soy (res, ideology)	-0.170	-1.774**	-0.978**
	(0.159)	(0.753)	(0.474)
Controls	✓	✓	✓
Microregion Fixed Effects	✓	✓	✓
StandardErrors	Cl. Microreg.	Cl. Microreg.	Cl. Microreg.
Observations	5561	5557	5559
F-statistic		6.889	19.943
Model	OLS	IV Fire Risk	IV Temp & Wind

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table F.7: IV HTE Residuals Sociodemographics

	DV: Marina Silva's Vote Share		
	(1)	(2)	(3)
Fires	0.031**	0.979**	0.742***
	(0.015)	(0.379)	(0.144)
Cattle & Soy (res, sociodem.)	-0.262**	0.111	0.058
	(0.111)	(0.168)	(0.131)
Fires * Cattle & Soy (res, sociodem.)	-0.286*	-2.451***	-2.048***
	(0.154)	(0.816)	(0.508)
Controls	✓	✓	✓
Microregion Fixed Effects	✓	✓	✓
StandardErrors	Cl. Microreg.	Cl. Microreg.	Cl. Microreg.
Observations	5525	5521	5523
F-statistic		6.874	18.702
Model	OLS	IV Fire Risk	IV Temp & Wind

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

G Treatment Effects – Jair Bolsonaro

In Tables G.1 and G.2 we assess the impact of fire exposure on the vote share for Jair Bolsonaro in the first round of the 2018 Presidential elections, employing the same IV specifications we use in Tables 1 and 2 in the main text. Table G.1 shows that fires increase the vote share of Jair Bolsonaro, whose platform was markedly anti-environment, suggesting that the increased salience of environmental issues produced by fires might have a polarizing effect, increasing the vote share of candidates with both pro-environmental and anti-environmental platforms. Results in column 3 in Table G.2 shows that fire exposure increased Bolsonaro's vote share more in areas more reliant on soy and cattle production (although results are significant only at the 90% confidence level). This provides additional evidence that in areas where the local population is more likely to reap economic benefits from fires, anti-environmental platforms gain support. However, we do not find similar results in column (2), where we use fire risk as our instrumental variable. This is likely due to the low F-statistics.

Table G.1: The Effect of Fire Exposure on the Vote Share of Jair Bolsonaro

	DV: Jair Bolsonaro's Vote Share		
	(1)	(2)	(3)
Fires	0.901**	31.118***	8.517**
	(0.457)	(11.320)	(3.802)
Controls	✓	✓	✓
Microregion Fixed Effects	✓	✓	✓
StandardErrors	Cl. Microreg	Cl. Microreg	Cl. Microreg
Observations	5561	5557	5559
F-statistic		14.250	31.920
Model	OLS	IV Fire Risk	IV Temp & Wind

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table G.2: Heterogeneous Effects of Fire Exposure on the Vote Share of Jair Bolsonaro

	DV: Jair Bolsonaro's Vote Share		
	(1)	(2)	(3)
Fires	0.652	35.032***	6.312*
	(0.503)	(13.386)	(3.786)
Cattle & Soy	-23.539***	-24.396***	-28.699***
	(2.260)	(5.340)	(3.463)
Fires * Cattle & Soy	6.856**	-19.749	19.272*
	(3.407)	(24.390)	(10.610)
Controls	✓	✓	✓
Microregion Fixed Effects	✓	✓	✓
StandardErrors	Cl. Microreg.	Cl. Microreg.	Cl. Microreg.
Observations	5561	5557	5559
F-statistic		6.905	20.103
Model	OLS	IV Fire Risk	IV Temp & Wind

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

H Individual-Level Analysis: Main Table and Robustness Checks

Table H.1: Individual-Level Estimates: Main Specification and Robustness

	DV: "Fires in the Amazon are necessary for economic growth"	
	(1)	(2)
Fires	-0.0899***	-0.153**
	(0.0337)	(0.0647)
% Jobs cattle or soy	0.00255	0.00458
	(0.00666)	(0.00668)
Fires × % Jobs cattle or soy	0.00508**	0.00754*
	(0.00255)	(0.00424)
Female	0.0809*	0.0799*
	(0.0441)	(0.0443)
Age	-0.00228	-0.00220
	(0.00168)	(0.00171)
$\text{Edu.}_{elementary}$	-0.0144	-0.0229
	(0.121)	(0.122)
$\text{Edu.}_{incomplete\ high\ school}$	-0.118	-0.119
	(0.0815)	(0.0819)
$\text{Edu.}_{complete\ high\ school}$	-0.229***	-0.228***
	(0.0720)	(0.0729)
$\text{Edu.}_{some\ college}$	-0.392***	-0.395***
	(0.0690)	(0.0699)
Rural pop (%)	0.0749	
	(0.222)	
Income per capita	0.0000199	
	(0.000132)	
Forest area (share)	-0.0606	
	(0.138)	
Population (log)	-0.0170	
	(0.0226)	
Fires (2018-2020)		0.0661
		(0.0624)
Fires (2018-2020) × % Jobs cattle or soy		0.000287
		(0.00337)
Constant	0.432*	0.227**
	(0.244)	(0.115)
Observations	2457	2458
N municipalities	786	787
R-squared	0.0332	0.0331
State FE	✓	✓
Std. Errors	Cl. micror.	Cl. micror.

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

References — Appendix

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