INSTITUTO DE ECONOMÍA

TESIS de MAGÍSTER

2018

Natural disasters, violence and crime: evidence from 2017 Chilean megafires

Marcela Arriagada Silva

www.economia.puc.cl

Master in Economics Thesis

"Natural disasters, violence and crime: evidence from 2017 Chilean megafires"

Marcela Arriagada Silva

Advisor Professors: Emilio Depetris-Chauvin - Gert Wagner

December 28, 2018

"Clio Lab Thesis Commission"

Natural disasters, violence and crime: evidence from the 2017 Chilean megafires

Marcela Arriagada Silva*

December 28, 2018

Abstract

We investigate whether individuals' behavior change in the aftermath of a natural disaster: the 2017 Chilean megafires. Exploiting geographical variation in the intensive and extensive margin of fires in a municipality-level panel data setting, we estimate the impact of the megafires on crime and domestic violence. Our estimates suggest that megafires caused a substantial increase in domestic violence, whereas we find no such statistical pattern in the case of violent crime and property crime. We find suggestive evidence on the underlying mechanism for our reduced-form results: A negative shock on the income of people whose main source of revenue was related to agricultural and forestry activities, as well as a negative psychological shock that generates high levels of stress, altering individuals' behavior.

Key words: *Natural disasters, Crime activity, 2017 Chilean Megafires, Income shocks, Social cohesion, Stress shock, Quasi-experiment, Panel data.*

JEL codes: D74, D91, Q34, Q54.

*Master in Economics student. Pontificia Universidad Católica de Chile. Mail: mbarriagada@uc.cl. Professor Emilio Depetris-Chauvin, from Institute of Economics of Pontificia Universidad Católica de Chile, supported this thesis via Fondecyt Initiation 11160290. I am grateful to him and Gert Wagner for their constant support. I also thank Vannia Ruiz and Francisco de la Barrera for sharing their megafire data. I am also indebted to Clio-Lab commission for helpful comments.

I Introduction

Natural disasters bear adverse consequences and impose difficult conditions on citizens by upsetting their most basic activities (Lemieux 2014). Individuals affected by disaster may experience disruptions in their life, damage or destruction of housing, loss of financial status and challenges to access everyday consumer and health services. In many cases, economic activity simply moves to other parts of the region, which generates structural changes in the territorial units (Brady & Perkins 1984). Consequently, given the disruptive nature of disasters, people may not receive an influx of resources, especially those relating to public safety. Thus, public safety resources are likely to remain relatively fixed, while the absolute numbers of individuals experiencing extraordinary economic and social stressors may increase (Varano et al. 2010).

There is a large literature investigating both the causes and effects of natural disasters on several outcomes. While much research has been done on the direct damage inflicted by the impact of natural disasters and extreme weather on income and employment, relatively little attention has been paid to variation of criminal activity and violent behavior. We aim to fill this gap in the empirical evidence by studying the effects of natural disasters on violence and crime. We do so by exploiting the case of the 2017 Chilean megafires.

The 2017 Chilean megafires were the largest fire catastrophe in the country, affecting seven regions and multiple ecosystems (CONAF 2017). We argue that the megafires provide an ideal natural experiment, since individuals (aggregated at the municipal level in this research) exposed to the experimental and control conditions are determined by nature, but the process governing the exposures arguably resembles a random assignment (see also Sheldon & Sankaran (2017)).

Nevertheless, forest fires often are man-made: higher intensity in forest fires may confound with higher levels of crimes and domestic violence, leading to possible endogeneity concerns. To mitigate these concerns we exploit a multiple period differences in differences approach and high frequency data for our outcomes of interest[1]. This methodology allows us to define treated and control groups similar in characteristics, so we can find a suitable counterfactual for individuals' behavior before the negative shock.

We combine georeferenced fires data at the very fine local level (which allows us to identify the geographic extension and the intensity of the fires) by type of area burned (i.e, forest, prairies, agricultural land, and urban areas) with agricultural census data to account for the potential economic effects of the megafires.[2]

We study the evolution of 3 different categories of events: domestic violence, violent crime (e.g., theft with

[1] To do so, we exploit data from the "Center of Analysis and Crime Studies" (hereinafter CEAD) and "Carabineros de Chile".

[2] As can be seen in Figure 5, most of the burned down areas correspond to forests, prairies and agricultural land. In adittion, Figure 6 shows that a significant percentage of forest exploitations were set on fire (roughly 27% of the forestry holdings in the affected area), as well as agricultural lands, which affects not only the income of the people, but their source of work.

violence, injury, homicide and rape) and property crime (e.g., theft of vehicle and robbery in an inhabited place).

We document that the most afflicted municipalities experienced higher levels of domestic violence in the aftermath of the megafires. In particular, there is a strongly significant increase of 8.6% on domestic violence, effect that lasts for a year after the negative shock. While the impact on property crime is not statistically significant, the associated point estimate is consistent with an economically sizeable effect. It rather may be due to the standard error that explodes.

Few papers exploit, as we do, natural experiments to analyze the impact of a negative shock on criminal activity. Economic theory and causal observation suggest that economic crises may favour criminal activity as they affect the opportunity cost of engaging in crime (Bignon et al. 2017): Physical assets are damaged or lost, which directly affects the production function that generates income (e.g., a field or livestock), and this resulting decline in wealth could increase the value of criminal activities as an alternative source of income.

In particular, literature would suggest important effects from the economic channel, which is usually measured by unemployment, income and poverty levels (Miguel 2005, Mehlum et al. 2006). In adittion, Raphael & Winter-Ebmer (2001) suggest that increasing unemployment contributes to raising property crimes (although the magnitude is not large). Then, negative shocks on wealth may have a positive effect on crime (Bohlken & Sergenti 2010, Sarsons 2011, Blakeslee & Fishman 2013, Iyer & Topalova 2014). Furthermore, the economic decline could undermine the ability of government institutions to monitor and curtail criminal activity, or reduce the ability of people to protect themselves against crime (Iyer & Topalova 2014). In line with this, Miguel et al. (2004) use survey data on contemporary rural Tanzania to show that the killing of "witches" (i.e. old women) increases in times of extreme weather events leading to floods and droughts.

In the same way, a comprehensive review of the crime literature indicates several and often opposing hypotheses of relationships between property crime and socioeconomic conditions such as poverty, business cycle conditions, criminal justice system actions, and family structure (Allen 1996), where benefits include the prospects of profitable loot, and costs include the potential consequences of being caught and punished (Blakeslee & Fishman 2013).

Furthermore, additional mechanisms that explain the variation on criminal activity in the aftermath are suggested in the literature. In particular, Bignon et al. (2017), Gerson & Preston (1979) and Zahran et al. (2009) state that after a negative shock, individuals face higher levels of stress, so they are more prone to self-destructive behaviors. The authors show that alcohol consumption may go up due to a stress shock, and moreover, Bignon et al. (2017) show that alcohol consumption is positively correlated with violent crime rates.

Nevertheless, in opposition to a negative shock that makes criminal activity and violence in general to increase, literature also suggests that people begin to interact in community in the aftermath, which generates a sense of collective union and altruism “social cohesion”. As a result, violent behaviors decrease in individuals and consequently, crime rates are reduced. Authors such as Chang (2010), Lemieux (2014), Chamlin & Cochran (1997) support this idea, which often offsets the effects of income and stress shocks.

Literature on natural disasters and crime turns out to be consistent with our main findings. In fact, examining the effect of the megafires provides suggestive evidence in favour of the Economic Theory of Crime: economic shocks may increase crime rates.

The remainder of this paper is organized as follows. Section II describes literature review, section III describes Chilean megafires, section IV reports the data, Section V presents the empirical framework, section VI resports the findings and section VII concludes.

II Literature review

After a natural disaster, many individuals face the loss of their loved ones, belongings and in many cases their employment, having to restructure their lives completely and start from scratch. This occasionally causes a symptom of stress in people, where the initial response during traumatic events is referred to as acute stress response. It is defined as the emotional, dissociative, and physical reaction during a traumatic event (Benight & Harper 2002). Sometimes, this changes individuals' behavior, making them to incur into unusual attitudes, given that are faced with situations such as sexual assaults, food insecurity, households completely destroyed and limited access to durable shelter (Kolbe et al. 2010). All this accounts for severe consequences and mental stress in people, which offers a unique research opportunity.

Modeling the impact of natural disasters in a comprehensive manner is quite complex, since they differ greatly in their nature, intensity, channels and socio-economic consequences on populations (Baez et al. 2010). More recently, a growing number of studies have suggested that the opportunity cost of committing crime can be altered by various negative shocks such as financial crises, trauma from conflict or violence, and natural disasters (e.g., earthquakes, hurricanes, floods, and tsunamis). However, there is little consensus about the direction in which such negative shocks operate. Past studies find conflicting patterns even within the same domain. For example, many studies find that natural disasters increase criminal activity (Altindag 2012, Blakeslee & Fishman 2013), while others find that crime decreases (Siegel et al. 1999, Lemieux 2014). Moreover, Zahran et al. (2009) find that natural disasters significantly reduce the levels of index, property and violent crimes, but significantly increase the number of reported crimes expected from domestic violence. Furthermore, even if such effects exist, little is known about whether they are transitory or persistent.

According to the standard economic model of crime (Becker 1968), individuals choose between criminal and legal activities on the basis of the expected utility. In this framework, returns to legal activity are determined by market earnings (wages for salaried workers and profits for the self-employed), whereas returns to illegal activity depend on the potential pay-off of crime and the expected sanctions imposed by the criminal justice system (Bignon et al. 2017). Expected sanctions are an increasing function of the probability of getting caught and of legal punishment if caught.

In adittion, literature suggests that after a negative shock, there is a restructuring of the social order, causing crime rates to vary. In this way, at least three different mechanisms may be at work.

Firstly, Wong & Brown (2011) state that while all human beings are vulnerable to natural disasters, the poor seems to be affected most, as well as developing countries and smaller economies. They face much larger output declines following a disaster of similar relative magnitude than developed countries or larger economies do (Noy 2009). In adittion, aggregate income shocks may increase both the costs and the benefits of criminal activity. On the one hand, individuals with higher non-criminal income have more "to lose" if caught, but the returns from predatory activity are also likely to be higher, so there is more "to gain". The Economic Theory of Crime suggests, therefore, that in principle, negative aggregate income shocks might increase crime rates (Becker 1968).

The impact of negative income shocks on crime rates has been demonstrated by several authors. For example, Miguel (2005) finds that negative weather shocks increase murder rates, while Bohlken & Sergenti (2010) and Sarsons (2011) find an association between negative rainfall shocks and the incidence of riots. A related literature shows civil conflict can also arise as a result of weather related income shocks (e.g. Miguel et al. (2004)). However, Brady & Perkins (1984) argue that the effects of a natural disaster at the macroeconomic level could be less visible, given that the magnitude is local and therefore the effects are dissipated in the long term. On the other hand, a positive wealth shock like favorable labor market conditions have a significant negative effect on property crime rates (Doyle et al. 1999).

In the same way, Altindag (2012) finds that unemployment has a positive influence on property crimes, while Raphael & Winter-Ebmer (2001) suggest that a substantial portion of the decline in property crime rates during the 1990's is attributable to the decline in the unemployment. All this denotes that in principle, there is a positive correlation between unemployment and property crime.

On the other hand, literature suggests another mechanism that is related to the change in behavior when people is faced with a situation of stress and lack of control. It is the stress channel, which can be measured in different ways.

First of all, health clinicians recognize that exposure to trauma can have complex and lasting effects on mental and physical health, with additional consequences for socioeconomic outcomes (Callen et al. 2014). Consequently, it is important to study the economic effects of trauma both for the design of policy and for delivering greater insight into decision making given the volume of trauma-affected individuals.

Furthermore, literature suggests another channel based in “Social Disorganization Theory”[3]. The main idea is that people begin to interact in community in the aftermath, which generates a sense of collective union and altruism labelled “social cohesion”. It is a concept of social solidarity and refers to the degree to which people are connected with one another within the social system (Sweet 1998). This type of altruism generates a decrease in crime rates during the event and is more substantial in the contiguous than in the distant regions (Lemieux 2014).

Authors like Chamlin & Cochran (1997) also support this idea and find that altruism is inversely related to property crimes and violent crime rates. In adittion, many authors argue that severity of exposure to a natural disaster does not make a contribution to traumatic stress or victimization (Siegel et al. 1999), and contrary to what is expected, the effects of natural disasters could be modest in crime outcomes (Varano et al. 2010). Therefore, if social cohesion predominates, we should expect criminal activity to decrease. As stated by Depetris-Chauvin et al. (2018), when the feeling of national unity arises, sometimes differences and tensions can be reduced between groups in conflict, reducing violence rates.

Regarding the impact of forest fires, the economic literature suggests that these left important economic and health costs (Rittmaster et al. 2006). However, socio-economic characteristics could influence the occurrence of man-made forest fires, serving as a source of endogeneity. In adittion, fires caused by children and the burning of debris are more likely in densely populated areas, while those caused by smoking are more common in areas with high rates of unemployment and large proportions of people below the poverty line (Grala et al. 2017).

Besides, climate changes also affect the ocurrence of forest fires (Urrutia-Jalabert et al. 2018) and what’s more, hot weather and violence go hand in hand (Anderson et al. 2000).

To solve the endogeneity concerns, Sheldon & Sankaran (2017) propose a methodology that helps to find an exogenous variation on fires distribution, allowing them to be conceived as a quasi-experiment. For example,

[3] Theory that links crime rates to neighborhood ecological characteristics; a core principle of social disorganization theory is that place matters. In other words, a person’s residential location is a substantial factor shaping the likelihood that that person will become involved in illegal activities. The theory suggests that, among determinants of a person’s later illegal activity, residential location is as significant as or more significant than the person’s individual characteristics (e.g., age, gender, or race).

by stratifying in different areas, fires resembles a random assignment within a certain geographical area.

III Chilean megafires, summer 2017

On January 2017, the biggest fire catastrophe in the history of Chile took place. The wave of megafires occurred between Coquimbo (IV) and La Araucanía (IX) regions. The main fire focus was concentrated between January 9th-29th, with 687 simultaneous fires in seven regions of the country. At least 78 municipalities were affected and more than 500.000 land hectares were set on fire. According to CONAF (2017), forest fires are one of the greatest degradation agents of the existing ecosystems in the world, and megafires duration extends until February 2017.

Roughly 60% of the burned down hectares correspond to environments with some degree of anthropic use (CONAF 2017). The distribution of the fires is shown in Figure 1 and Figure 2, where the largest events were concentrated in the southern-central area of the country.

The 2017 megafires are relevant given their unusual severity. Especially since January 18th[4], when they changed the global scale of fire measurement, reaching the "sixth generation" in terms of intensity. In adittion, the destruction had a total cost of $17.404 million of chilean pesos, namely, 0.012% of the total 2017 GDP[5]. Despite the magnitude of the disaster, remarkably little is known about the short and long-term ramifications for its victims.

CONAF (2017) state that different fire focus had an unprecedented extension, which would be explained by the convergence of a high wind speed, high temperatures, low humidity and the difficult geography of the affected sectors. Figure 3 shows fires spread. The fourth week was the largest registered fire source (January 16th-22nd), where more than 60% of the total hectares were set on fire, which coincides with the "Firestorm". In adittion, after the fifth week (January 23th-29th) there is a decrease in the spread of fires.

The fire called "Las Máquinas" affected Empedrado, Constitución and Cauquenes municipalities in Maule region, and it is considered the largest fire recorded in the history of Chile with 183.946 hectares consumed.

Figure 4 and Figure 5 represent the regional distribution of the burned down hectares by land use. As can be seen, the region with the largest area affected by the fires is Maule (7) with 54.1% of the total area consumed by the megafires, followed by Biobío (8) and O'Higgins (6) with 19.2% and 17.4% respectively. Official statistics indicate that forest plantations were the most affected, followed by native forest and prairies.

[4]On January 18th 2017, the area affected by fires increased abruptly in 16.494 hectares in just 24 hours.

[5]2017 Chilean GDP was 147,530 thousands millions of chilean pesos ($147.530.000.000.000) and per capita GDP $8.394.786 considering a population of 17.574.003 inhabitants based on data from the 2017 Chilean Census.

However, it is worthy to note that fires that affect land for economic use (i.e. forest or agricultural exploitations) probably have a different effect on individuals' behavior than land without economic activity. In fact, the effect of fires on agricultural land or forest exploitations has an economic value, which directly affects the wealth of people.

Table 1 gives us relevant information regarding the land use of the burning down hectares. Roughly 7% of the burned area corresponds to agricultural lands and urban zones. While 74% of the affected area corresponds to forests and 18% to prairies, which also may affect the economic activity. To a lesser extent water zones, wet lands and zones without vegetation. Specifically, 27% of the forest exploitations in the area were burned down. Therefore, fires may have affected people's agricultural and forest income (see Figure 6).

Finally, for the purposes of this research and following CONAF (2017), the severity of megafires will be understood as the loss of organic matter above and below the ground due to a fire, which was developed only at the level of satellite analysis.

IV Data description

1 Main dependent variables

We collected data on criminal activity at monthly frequency during the period 2015-2018. To construct the crime panel, data was drawn from "Carabineros de Chile" and "Center of Analysis and Crime Studies" (CEAD). It is available at individual and municipal level. In this paper, crimes are segregated into three categories: " Violent Crimes " (violence theft, intimidation theft, surprise theft, injury, homicide and rape); " Property Crime" (theft of a motor vehicle, theft of vehicle accessories, robbery in an inhabited place, robbery in an uninhabited place, other robberies with force and theft) and domestic violence.

To test potential mechanisms related to a negative shock to poverty, income and unemployment rates, we use National Socioeconomic Characterization survey (hereinafter CASEN) from 2015 to 2017 years. We use as main measure of income, the income from work. To estimate unemployment and poverty we run a linear probability model using a dummy for the status of individuals: if they are employed/unemployed, or if they are poor/not-poor.

To test social cohesion channel, we use "Latinobarómetro survey[6]" from 2016 to 2017 years, by means of testing *trust in people* and *trust in institutions* (especially Government) following Sandoval (2011).

[6] It is an annual public opinion survey that involves some 20.000 interviews in 18 Latin American countries, representing more than 600 million people. It observes the development of democracies, economies and societies, using indicators of attitude, opinion and behavior.

We follow Zuromski et al. (2018) to test stress channel. We analyze what happens with high frecuency suicide rates after the megafires. Data was drawn from the Legal Medical Service from 2016 to 2018 years.

In adittion, to test balance in pre-treatment characteristics, data on fertility, mortality and marriages was obtained from the "Department of Health Statistics and Information" (DEIS). For socioeconomic variables, data was drawn from the "National Institute of Statistics" (INE) and the "National Municipal Information System" (SINIM). Data on municipal elections was drawn from the "Electoral Service of Chile" (SERVEL).

2 Main independent variables

The degree of negative shocks differs significantly, depending on location (Hanaoka et al. 2018). As our interest is to understand how violence and crime are affected by natural disasters, an ideal explanatory variable would be one that captures the wide variation of negative shocks for people who suffered most severely to people who are not affected at all.

In order to exploit the geospatial nature of the fires, we use geographic information systems, where shape files are obtained from CONAF website. The implied data set contains information on the burned down hectares, the affected land use[7] and the fire severity, measured by the NBR index[8]. By means of a combination of infrared bands, the NBR index allows to identify burned down areas and degrees of severity. It detects areas of high, medium-high, medium-low and low severity of fire, in adittion, previously burnt areas that show signs of high and low regeneration (De la Barrera & Ruiz 2017). This measure is constructed by CONAF and data is at the municipality level.

Moreover, database of the 2007 Agricultural Census was drawn in order to quantify the hectares of forest and agricultural exploitations. It is worthy to note that more than 10 years have passed since the Census was carried out. Consequently, it makes sense to think that since 2007 there have been changes in forestry and agricultural economic lands nationwide. Therefore, we could be incorporating measurement error into the data. We will explain how to deal with it in the next section.

[7]Land use is classified in urban areas, forest, agricultural land, prairies, wetlands, water zones and areas without vegetation.

[8]The Normalized Burn Ratio (NBR) was designed to highlight burned areas and estimate fire severity. For a given area, NBR is calculated from an image just prior to the burn and a second NBR is calculated for an image immediately following the burn. Burn extent and severity is judged by taking the difference between these two index layers.

V Empirical framework

Estimating the impact of natural disasters requires finding a credible comparison group to serve as a counterfactual for the experiences of treatment group in the absence of the catastrophe. In this line, Hanaoka et al. (2018) use a differences-in-differences approach based on the 2011 Great East Japan Earthquake to estimate whether individuals' risk preferences change after experiencing a negative shock. Treatment and control groups are based on the perceived degree of intensity of the earthquake.

In adittion, natural disasters often bring about general equilibrium effects, given the displacement of the population and the restructuring in the aftermath.

The persistence of criminal activity is well documented. Jacob et al. (2007) state that serial correlation may be not only evidence of social interactions in the production of crime, but also due to the persistence of unobserved determinants of crime. For example, individuals that have experienced severe natural disasters in the past, might form different attitudes toward crime in the present. Therefore, such differences in the baseline level may bias the coefficients if we estimate an OLS model with cross sectional data, ignoring the unobserved fixed effect.

To the extent that these differences are correlated with individuals' behavior, a simple comparison among those who did and did not set on fire would be biased due, for instance, to reverse causality. In line with this, Mehlum et al. (2006) state that higher crime rates are likely to have a negative impact on economic conditions, as the prevalence of crime in an area discourages business. Thus, negative income shocks may trigger a vicious circle between deteriorating economic conditions and crime (Bignon et al. 2017).

Authors such as Miguel et al. (2004), Mehlum et al. (2006) and Iyer & Topalova (2014) use the instrumental variable approach in order to deal with endogeneity issues, while Coffman & Noy (2012) use synthetic controls.

In this paper, we exploit panel data variation, wich allows to isolate the effects of the exogenous treatment by comparing the differences before and after the event across municipalities that experienced different levels of intensity of megafires. Indeed, we exploit the variation in intensity of the exogenous treatment and the unit of analysis are municipalities.

We aim to capture the economic value of the burned down hectares, in order to estimate the effect of megafires on crime and violence. Table 1 shows the burned down hectares according to land use. We can appreciate that 74% of the affected land corresponds to forest, and to a lesser extent, grasslands and agricultural land. Consequently, we use as the treatment the share of forest burned down hectares over the total forest exploitations in each municipality (see Figure 7 and Figure 8).

Table 2 shows the summary statistics of the burned down hectares by municipality and the treatment. We can notice that of the 78 affected municipalities, the mean is 6668 burned down hectares and the maximum is 69555. In addition, the least value is 38.79 burned down hectares. On the other hand, share variable represents the burned area within a municipality over its total area (see Figure 9). The highest value is 92% (for "Empedrado" municipality, VII region). Moreover, we can notice that in Maule, Biobio and O'higgins regions are the most affected municipalities, with the highest percentage of burned down hectares on average. Also, we can see the descriptive statistics of the treatment. In the first instance, the treatment statistics are shown without restricting it, where the mean is 0.98 and the highest value is 28.62. We deal with the potential measurement error coming from the 2007 Agricultural Census data by restricting the maximum value of the sample to 1 (i.e., this means that the forest exploitations are completely burned down), in order to not have extreme values or spurious correlations. Instead, we will obtain a share of burned down forest exploitations in each municipality. The descriptive statistics for the censored treatment show a mean of 0.33 and a standard deviation of 0.37, which are much lower than the uncensored treatment, given that now the extreme values are not biasing the statistics.

Moreover, megafires are not controlled in the traditional sense of a randomized experiment. Consequently, the causal effect is hard to determine due to selection biases that arise from the non-random fashion in which fires are distributed. To mitigate this concern, we define a sampling of treatment and control group based on proximity, where all the burned down municipalities[9] correspond to the treatment group, while those that did not, in the same region, are the control group. The sampling we use of 7 affected regions (from IV to IX regions including Metropolitana region) corresponds to 254 municipalities, where 78 are treated and 176 controls.

We show by means of a balance check in pre-treatment characteristics that in general, burned down regions are not identical to thoses that did not[10]. Table 3 and Table 4 represent the balance extensive and the intensive margin, respectively. As can be seen, column 1 considers the dependent variable. In column 3 we compare burned down municipalities with the rest of the country, where it can be seen unbalance in some variables (i.e., p-value lesser than 0.1). This is especially in the area and income levels. In column 4 we incorporate regional fixed effects into the model, and we show that the sample is now balanced, except for the share of male population, which shows a small unbalance of 1%. Moreover, in column 7 we restrict the sample to treatment and controls based on proximity in order to not to compare municipalities in extreme regions

[9] The municipality that had the smallest affected area was "Maipu" (Metropolitana region) with a total of 38.79 burned down hectares and the largest "Constitución" (VII region) with 69555.68 burned down hectares. See Table 2.

[10] It is verified through the p-value at which the null hypothesis is rejected, at least 10%.

of the country. Thus, we argue that the megafires provide an ideal natural experiment, since individuals exposed to the experimental conditions are determined by nature, but the process governing the exposures arguably resembles a random assignment.

Table 5 shows the descriptive statistics by type of crime and also the suicide cases for monthly panel data. The sampling used is the treatment based on proximity (i.e., 254 municipalities) and the period analyzed is from January 2016 to January 2018 (i.e., 25 months in total). Domestic violence has a mean of 30.09, where the maximum value is 439 at the overall variation. On the other hand, property crime has a mean of 103, with a maximum of 1900 cases, while violent crime has a mean of 50.86 and a maximum of 1284. In the case of suicide, the mean is much lower, of 0.29 cases per month, since the data contains many zeros. The maximum value is 9 suicide cases per month in the entire period of 2 years.

In order to analyze the type of industry of the workers in the affected municipalities, we made a graph using the 2015 Casen survey. Figure 10 shows that the income of the burned down municipalities comes mainly from agricultural and forestry activity (21.2%), followed by activities related to commerce and services (16.5%). To a lesser extent, mining and manufacturing industries.

1 Identification strategy

Our empirical strategy is a differences in differences model with fixed effects. It exploits the variation in the intensity of the megafires, while controlling for time-invariant municipal characteristics. More formally, the basic model to test whether the megafires influence individuals' behavior can be written as follows:

$$\ln(y_{it}) = \alpha_i + \beta_t + \gamma fire_i \times post_t + \phi X_{it} + \varepsilon_{it} \tag{1}$$

where i and t denote respectively municipality and period. The variables are explained below:

- y_{it}: Crime/violence outcome of municipality i at time t.
- α_i: Municipality i fixed effect.
- β_t: Time fixed effect.
- $fire_i$: Intensity of the fire, treatment status (intensive or extensive margin).
- $post_t$: Dummy that is 1 if the time period is after the megafires and 0 otherwise.
- X_{it}: Set of time-varying covariates at the municipality level.

- ε_{it}: Error term, allowed to be correlated within municipalities and time.

The γ coefficient corresponds to the difference in difference estimator, which is the interaction of the treatment variable with that of time period. γ represents the variation on criminal activity of both treated and controls municipalities before and after the megafires. Thus, this coefficient corresponds the causal effect of megafires on criminal activity. In adittion, standard errors are clustered at the municipal and monthly level to allow for correlation across individuals within municipalities and within municipalities over time. The logarithm of crime is the dependent variable, since it allows to obtain semi-elasticities and more simple estimators to interpret.

In adittion, as mentioned before, we aim to capture the economic value of the burned down hectares by the megafires. We do so by defining a continuous treatment based on the share of burned down forest hectares over the total forest exploitations by municipality, measured in hectares. Nevertheless, given the distribution of the treatment, it arises the need to restrict extreme values to avoid spurious effects. We censor extreme values to 1 (i.e., so we have a share of forest exploitations) in order to deal with this concern, changing the value of the treatment for 12 municipalities in this case.

We also discretized this treatment in order to evaluate the extensive margin of the effects of the megafires on crime and violence.

The treatment is described as follows:

- *Share of forest exploitations set on fire:* It corresponds to the ratio of burned down forest hectares over forest exploitations (in hectares) by municipality. This treatment captures more accurately the economic value of the burned down hectares given the losses in income that comes from people's forestry activities.

- *Discrete treatment:* To evaluate the extensive margin we use as discrete treatment a dummy that takes the value of 1 if the share of burned forest exploitations is greater than 0.3 and 0 otherwise. We base on the distribution of the sample[11], where there are 31 municipalities that have a value of 1 and 47 of 0.

One potencial concern with this strategy is that treatment based on proximity does not consider that adjacent municipalities could have been contaminated by the effect of megafires. This could be possible since the effects of the fires expand and people migrate from one municipality to another. In adittion, people who work in a different municipality to which they live may have burned down their workplace. Thus, they received the

[11] 40% of the 78 burned down municipalities will be 1 while the remaining 60% will be 0.

impact of megafires indirectly, so the point estimates may be donward biased. Sheldon & Sankaran (2017) also support this idea since they study the impact of the Indonesian forest fires on air quality and health outcomes in Singapore, which gets contaminated due to Indonesian fires.

2 Channels

The economic literature suggests at least three possible mechanisms that operate in the variation of criminal activity after natural disasters. These are the economic channel, social cohesion and stress.

Wong & Brown (2011) investigate the link between household's poverty and vulnerability resulting from natural disasters. In this study, "vulnerability" refers to reductions in the distribution of household consumption. They find that households with a high degree of exposure to smoke from the fires are more vulnerable than households with lower exposure.

In adittion, when unemployment, crime and fear are high, individuals do not develop a strong sense of attachment to the community and are more likely to behave destructively when the opportunity cost of incurring on criminal activity decreases (Raphael & Winter-Ebmer 2001). The drop in income may affect individual decisions regarding property crimes through different channels. First, it is likely to have reduced the expected return to legal activities either because of an increase in the probability of being unemployed or by means of the loss of the people's workplaces. If unemployment increase after the catastrophe, Raphael & Winter-Ebmer (2001) suggest that the time allocation of individuals is likely to have been modified in favour of income-generating criminal activities, and they find that an increase in unemployment raises property crime. Evidence from contemporary data suggests that property crime also responds to decreases in unskilled worker's wages since they reduce the expected return on legal activities (Bignon et al. 2017).

On the other hand, Zuromski et al. (2018) suggest that suicide rates increase after a natural disaster, but individuals who have a history of prior interpersonal violence may be particularly vulnerable following experience of additional traumatic events and that for suicide risk in the aftermath.

In adittion, to test social cohesion channel we follow Sandoval (2011), who states that trust (especially in people and institutions) builds social relationships and is strongly associated with social cohesion. Since people rationalize the trust that is bestowed on others, it can be seen as a state of mind of men which indicates security and optimism in his relationship with his environment.

To examine whether the impact of natural disasters on crime rates is mediated through income channel, we estimate regressions, specifically Equation 1, for the income, unemployment and poverty status, for intensive and extensive margin. If individuals' wealth is the main driving force behind megafires and crime, we should expect to see the implied elasticity of crime to poverty and unemployment to be roughly similar when using these two disparate sources of income fluctuations. The same will be done for social cohesion and stress channels, measured by trust in people and institutions; and by suicide rates.

VI Results

1 Main results

This section presents the main results, with an analysis of the mechanisms that operate behind the variation on criminal activity and violence in general.

Table 6 shows the differences in differences results, considering a time horizon from January 2016 to June 2018 (i.e., 25 months). We use a symmetric horizon of one year before and after the megafires, in order to have an extended period of time and see if the effect is persistent. In addition, this allows us to rule out problems such as seasonality in the data.

We clustered standard errors at municipal and month level in order to allow for correlation within municipalities over time. Post variable is 1 from March 2017 onwards, since the fires occurred the first two months of the 2017 year. This allows us to fully capture the effect of the megafires. In adittion, all the regressions have municipal and month fixed effects to absorb municipal invariant characteristics and also time-varying characteristics. The sampling we use is the treatment based on proximity (i.e., 254 muncipalities).

It can be seen that in the parametric form of our strategy there are no significant effects of the megafires neither on property crime nor violent crime. Although the magnitude of the point estimate is large in both the intensive and the extensive margin (5.2 percentage points and 7.2 logaritmic points, respectively) for property crime. We argue that this may be due to an explosion of standard error. In the case of violent crime, we have small coefficients in magnitude and not statistically significant.

Nevertheless, we note a positive significant effect on domestic violence. In the intensive margin there is an increase of 11.7 percentage points on domestic violence at 90% confidence, while at the extensive margin there is an increase of 8.6% after the megafires at 95% confidence.

Nevertheless, although we find significant effects, their magnitude is not as large as compared to other authors in the economic literature, such as Mehlum et al. (2006), Raphael & Winter-Ebmer (2001) or Bignon et al. (2017).

Furthermore, when using a differences in differences model it is necessary to argue the compliance of the key assumption (i.e., parallel trends). Even though such an assumption is not directly testable, we can investigate whether the pre-trend is similar for both the treatment and control group. In particular, we estimate the same specification as our main specification (1) using data before the megafires for each type of crime, from January to December 2016. Post variable is 1 from July to December 2016. Table 7 shows that we find no discernable pre-trend before the megafires, since no significant effects are found. In addition, small effects can be seen compared to our main specification of the differences in differences model. Therefore, we may assume that treatment and control groups share parallel trends before the shock. In fact, this allows us to assume that we find a suitable counterfactual for the treatment group.

2 Robustness checks

In the previous section, we provided novel evidence that the megafires were associated with an increase in domestic violence.

In order to support our previous results, we run a placebo test, assigning a false treatment period of two years before the megafires, from January 2015 to January 2017. The specification is the same as Equation 1.

Table 8 shows regressions for each type of crime. Standard errors are clustered at municipal and month level. In the same way that previous regressions, it contains municipal and monthly fixed effects, in addition to a linear trend. Post period is 1 from January 2016 onwards, since it is a fictitious period of treatment right in the middle of the time horizon. As can be seen, there are no signifficant effects in any type of crime. This verifies the robustness of the results found in the previous section.

3 Mechanisms

Under the routine activities perspective, three elements must converge in time and space for crime to occur: a motivated offender, suitable target, and lack of capable guardianship (Zahran et al. 2009). In order to find the variables that make crime rates to vary, diverse regressions are carried out to see if significant effects are found in the previously described mechanisms. For all channels, we estimate a differences in differences fixed-effect model (as Equation 1).

On the one hand, we test whether individuals' income and wealth levels vary before and after the megafires. For this purpose, we use three measures: income from work (natural logarithm), unemployment and poverty status. By means of regressions at individual level, we test if income is the main driving force behind the variation on criminal activity. We append two Casen survey for 2015 and 2017 years. Post variable is 0 for 2015 and 1 for 2017 year. In adittion, we use the Casen expansion factor as analytical weights in order to let the sample to be representative of the entire population. We use linear trend and municipal and year fixed effects.

Table 9 shows regressions for the income channel. We can notice that the levels of income vary negatively after the megafires. In particular, there is a strongly signifficant decrease of 6.1 logarithmic points of the income level, while the extensive margin shows a decrease of 16.9 percentage points at 90% confidence. Although unemployment levels do not show a significant effect, very large coefficients can be seen. Therefore, it can not be said in the first instance that these coefficients are zero, but that it could be that the standard error explodes. In adittion, we have high poverty levels after the megafires, which are demonstrated by means of large and highly significant point estimates.

Based on the literature, which suggests a positive effect of stress on crime, we test by means of suicide rates the stress channel. Since the variation on suicide cases is not high, it is necessary to use a counting method that allows us to work more adequately the large number of zeros in the data. For this purpose, we run zero-inflated poisson regressions. It is a type of discrete probability distribution of the number of events, allowing to estimate more accurately the effect of fires on suicide. Table 10 shows these results. We can see coefficients large in magnitude, although they are not statistically significant. The extensive and intensive margin show coefficients of 0.517 and 0.818. That means an increase of 1.68 and 2.27 times in the number of suicide cases, respectively. As a result, it seems that suicide rates increased in the municipalities treated after the megafires.

Finally, we test social cohesion channel by means of a linear probability model. It is measured as "trust in people" and "trust in institutions" (in particular, Government), before and after the megafires. We test whether individuals interact more in community before the shock by means of Latinobarómetro survey for 2016 and 2017 years. Post variable is 0 for 2016 and 1 for 2017 year. Table 11 shows that trust in people has a strongly signifficant increase of 64.6 percentage points in the intensive margin, while the extensive margin shows an increase of 47.7 percentage points at 95% confidence. Moreover, trust in institutions also increase. In particular, *trust in Government* increase by 80.7 and 78.0 percentage points in the intensive and extensive margin, respectively. The explanation of this may be due to individuals feel more secure and optimism in his relationship with the current Government and others. Individuals became more altruistic and consequently there is more interaction between communities. Moreover, trust in the institutions that are in charge of collective matters would achieve good levels of social cohesion (Sandoval 2011).

Therefore, we have maintained that the main channel driving these results is a negative shock on the income of people whose main source of revenue was related to a large percentage of agricultural and forestry activities (see Figure 10 for more details), as well as a negative psychological shock that generates high levels of stress, altering individuals' behavior.

In general, there are two opposite effects that are generated after the negative shock of the megafires. On the one hand, there is more interaction and altruism in individuals after the shock, which make people less prone to commit crime. On the other hand, there is also a negative shock that generates a decrease in the income of people, the loss of employment and increases poverty levels. Additionally, stress levels also increase in the aftermath. Therefore, individuals have a lower opportunity cost to commit crime and they have less altruistic and more self-destructive behaviors, so they are more prone to incur on criminal activity.

Given that the channels are opposed, the increase on domestic violence is explained since the income and stress effect predominates (i.e., people may be more altruistic in community, but maintain or worsen levels of stress in the home). On the other hand, for property crime and violent crime the effect is netted.

VII Conclusion

This article studies the effects of a negative shock using a dataset based on violent crime, property crime and domestic violence at the municipal level. The case study of this research focuses on the 2017 Chilean megafires, which caused a series of massive destruction and thousands of people lost their homes and jobs. In other words, megafires were a negative shock to the Chilean economy, since they affected the areas where income was mainly coming from agricultural and forestry activity.

To shed light on the research question, we test whether experience of megafires alters individuals' behavior by means of a differences in differences approach and high frecuency crime data. We provide novel evidence on the effects of the spread of the megafires on the levels of wealth, stress and social cohesion.

Our results show that megafires generated a strong increase on domestic violence, plausibly driven by the impact of a stress shock and the negative economic conditions of those living in the affected areas, which is consistent with Becker's Economic Crime Theory and the findings of Zahran et al. (2009).

Nevertheless, we find no significant effects neither on property crime nor violent crime. Although the point estimate is large in magnitude in the case of property crime . We argue that this may be due to an explosion of standard error. Consequently, we can not rule out that there was a positive effect.

In the case of violent crime, we have small coefficients in magnitude and not statistically significant.

In general, there are two opposite effects that are generated after the negative shock of the megafires. On the one hand, there is more interaction and altruism in individuals after the shock, which make people less prone to commit criminal activities. On the other hand, the negative shock decreases the wealth of individuals and makes the stress levels to increase. Therefore, individuals have a lower opportunity cost to commit crime and they have less altruistic and more self-destructive behaviors, so they are more prone to incur on criminal activity.

Our results suggest that social cohesion is also a mechanism that operates behind the variation on criminal activity. This led to greater social interaction among individuals from different communities. Furthermore, due to the interaction of the Government with individuals, they feel more in confidence with institutions after the negative shock.

We argue that the increase in domestic violence is explained by the income and stress effects, which predominate to social cohesion. While social cohesion operates in community and social interactions, our results suggests that the stress causes individuals to become more violent in their homes, increasing the levels of domestic violence.

On the other hand, for property crime and violent crime the effect seems to be netted.

In addition, it should be taken into account that there was a social restructuring after the natural disaster, where many people had to migrate to other municipalities due to the total loss of their assets.

Therefore, we have maintained that the main channel driving these results is a negative shock on the income of people whose main source of revenue was related to a large percentage of agricultural and forestry activities, as well as a negative psychological shock that generates high levels of stress, altering individuals' behavior.

We must to highlight that this research has some limitations. It would be ideal to carry out the study at the individual level, which in this case is not possible since there is no tracking data of the people directly affected by the fires. The fire intensity measure we use indeed capture the degree of shock by municipality, but a municipal panel could add noise to the estimates. Secondly, spillovers may imply that we may downward bias the effect of megafires, since the localities adjacent to the burned ones are treated to a certain manner.

Third, we cannot fully understand the mechanism of how experience of high intensity of the megafires alters individuals' behavior. While we provide suggestive evidence of income, stress and social cohesion channel, it is difficult to state that these are the only three mechanisms that operate after the variation on criminal activity.

Moreover, the long-term persistence of these effects remains for future research, since it has been a short time since the megafires occurred. These questions are beyond the scope of this study but clearly remain as an avenue for future research.

References

Allen, R. C. (1996), 'Socioeconomic conditions and property crime: A comprehensive review and test of the professional literature', *American Journal of Economics and Sociology* **55**(3), 293–308.

Altindag, D. T. (2012), 'Crime and unemployment: Evidence from europe', *International review of Law and Economics* **32**(1), 145–157.

Anderson, C. A., Anderson, K. B., Dorr, N., DeNeve, K. M. & Flanagan, M. (2000), Temperature and aggression, *in* 'Advances in experimental social psychology', Vol. 32, Elsevier, pp. 63–133.

Baez, J., De la Fuente, A. & Santos, I. V. (2010), 'Do natural disasters affect human capital? an assessment based on existing empirical evidence', *Working Paper - IZA Discussion Paper No. 5164* .

Becker, G. S. (1968), Crime and punishment: An economic approach, *in* 'The economic dimensions of crime', Springer, pp. 13–68.

Benight, C. C. & Harper, M. L. (2002), 'Coping self-efficacy perceptions as a mediator between acute stress response and long-term distress following natural disasters', *Journal of Traumatic Stress: Official Publication of The International Society for Traumatic Stress Studies* **15**(3), 177–186.

Bignon, V., Caroli, E. & Galbiati, R. (2017), 'Stealing to survive? crime and income shocks in nineteenth century france', *The Economic Journal* **127**(599), 19–49.

Blakeslee, D. & Fishman, R. (2013), 'Rainfall shocks and property crimes in agrarian societies: Evidence from india', *SSRN Electronic Journal. Available at SSRN: https://ssrn.com/abstract=2208292* .

Bohlken, A. T. & Sergenti, E. J. (2010), 'Economic growth and ethnic violence: An empirical investigation of hindu-muslim riots in india', *Journal of Peace research* **47**(5), 589–600.

Brady, R. J. & Perkins, J. B. (1984), 'Macroeconomic effects of the earthquake', *US Geological Survey professional paper* p. 3.

Callen, M., Isaqzadeh, M., Long, J. D. & Sprenger, C. (2014), 'Violence and risk preference: Experimental evidence from afghanistan', *American Economic Review* **104**(1), 123–48.

Chamlin, M. B. & Cochran, J. K. (1997), 'Social altruism and crime', *Criminology* **35**(2), 203–226.

Chang, K. (2010), 'Community cohesion after a natural disaster: insights from a carlisle flood', *Disasters* **34**(2), 289–302.

Coffman, M. & Noy, I. (2012), 'Hurricane iniki: measuring the long-term economic impact of a natural disaster using synthetic control', *Environment and Development Economics* **17**(2), 187–205.

CONAF (2017), 'Análisis de la afectación y severidad de los incendios forestales ocurridos en enero y febrero de 2017 sobre los usos de suelo y los ecosistemas naturales presentes entre las regiones de coquimbo y los ríos de chile', *Corporacion Nacional Forestal. Informe Técnico. 56 p. Santiago, Chile* .

De la Barrera, F. & Ruiz, V. (2017), 'Evaluación del impacto de los incendios de chile centro-sur en el verano del año 2017', *Primera entrega. IALE-Chile* .

Depetris-Chauvin, E., Durante, R. & Campante, F. R. (2018), 'Building nations through shared experiences: Evidence from african football', *National Bureau of Economic Research, Working Paper No. 24666* .

Doyle, J. M., Ahmed, E. & Horn, R. N. (1999), 'The effects of labor markets and income inequality on crime: evidence from panel data', *Southern Economic Journal* pp. 717–738.

Gerson, L. W. & Preston, D. A. (1979), 'Alcohol consumption and the incidence of violent crime.', *Journal of Studies on Alcohol* **40**(3), 307–312.

Grala, K., Grala, R. K., Hussain, A., Cooke, W. H. & Varner, J. M. (2017), 'Impact of human factors on wildfire occurrence in mississippi, united states', *Forest policy and economics* **81**, 38–47.

Hanaoka, C., Shigeoka, H. & Watanabe, Y. (2018), 'Do risk preferences change? evidence from the great east japan earthquake', *American Economic Journal: Applied Economics* **10**(2), 298–330.

Iyer, L. & Topalova, P. (2014), 'Poverty and crime: evidence from rainfall and trade shocks in india', *HBS Working Paper Number: 14-067* .

Jacob, B., Lefgren, L. & Moretti, E. (2007), 'The dynamics of criminal behavior evidence from weather shocks', *Journal of Human resources* **42**(3), 489–527.

Kolbe, A. R., Hutson, R. A., Shannon, H., Trzcinski, E., Miles, B., Levitz, N., Puccio, M., James, L., Noel, J. R. & Muggah, R. (2010), 'Mortality, crime and access to basic needs before and after the haiti earthquake: a random survey of port-au-prince households', *Medicine, conflict and survival* **26**(4), 281–297.

Lemieux, F. (2014), 'The impact of a natural disaster on altruistic behaviour and crime', *Disasters* **38**(3), 483–499.

Mehlum, H., Miguel, E. & Torvik, R. (2006), 'Poverty and crime in 19th century germany', *Journal of Urban Economics* **59**(3), 370–388.

Miguel, E. (2005), 'Poverty and witch killing', *The Review of Economic Studies* **72**(4), 1153–1172.

Miguel, E., Satyanath, S. & Sergenti, E. (2004), 'Economic shocks and civil conflict: An instrumental variables approach', *Journal of political Economy* **112**(4), 725–753.

Noy, I. (2009), 'The macroeconomic consequences of disasters', *Journal of Development Economics* **88**(2), 221–231.

Raphael, S. & Winter-Ebmer, R. (2001), 'Identifying the effect of unemployment on crime', *The Journal of Law and Economics* **44**(1), 259–283.

Rittmaster, R., Adamowicz, W., Amiro, B. & Pelletier, R. (2006), 'Economic analysis of health effects from forest fires', *Canadian Journal of Forest Research* **36**(4), 868–877.

Sandoval, M. (2011), 'La confianza de los jóvenes chilenos y su relación con la cohesión social', *Ultima década* **19**(34), 139–165.

Sarsons, H. (2011), Rainfall and conflict, *in* 'Manuscript. http://www. econ. yale. edu/conference/neudc11/papers/paper_199. pdf', Citeseer.

Sheldon, T. L. & Sankaran, C. (2017), 'The impact of indonesian forest fires on singaporean pollution and health', *American Economic Review* **107**(5), 526–29.

Siegel, J. M., Bourque, L. B. & Shoaf, K. I. (1999), 'Victimization after a natural disaster: Social disorganization or community cohesion?', *International Journal of Mass Emergencies and Disasters* **17**(3), 265–294.

Sweet, S. (1998), 'The effect of a natural disaster on social cohesion: A longitudinal study', *International Journal of Mass Emergencies and Disasters* **16**(3), 321–331.

Urrutia-Jalabert, R., González, M. E., González-Reyes, Á., Lara, A. & Garreaud, R. (2018), 'Climate variability and forest fires in central and south-central chile', *Ecosphere* **9**(4).

Varano, S. P., Schafer, J. A., Cancino, J. M., Decker, S. H. & Greene, J. R. (2010), 'A tale of three cities: Crime and displacement after hurricane katrina', *Journal of Criminal Justice* **38**(1), 42–50.

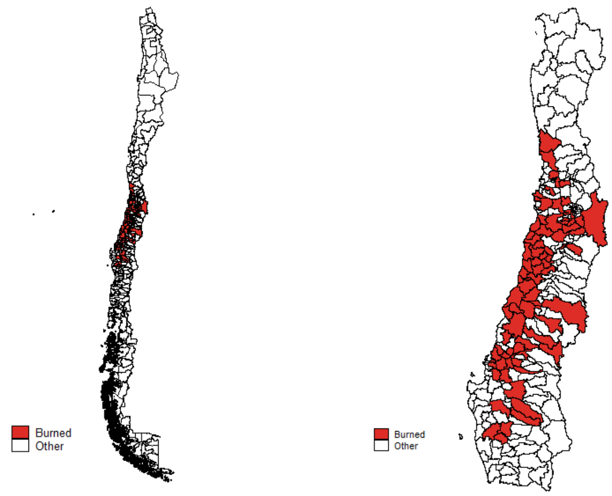
Wong, P. Y. & Brown, P. H. (2011), 'Natural disasters and vulnerability: Evidence from the 1997 forest fires in indonesia', *The BE Journal of Economic Analysis & Policy* **11**(1).

Zahran, S., Shelley, T. O., Peek, L. & Brody, S. D. (2009), 'Natural disasters and social order: Modeling crime outcomes in florida', *International Journal of Mass Emergencies and Disasters* **27**(1), 26–52.

Zuromski, K. L., Resnick, H., Price, M., Galea, S., Kilpatrick, D. G. & Ruggiero, K. (2018), 'Suicidal ideation among adolescents following natural disaster: The role of prior interpersonal violence.', *Psychological trauma: theory, research, practice and policy* .

VIII Tables and figures

Figure 1: National map of the area affected by the 2017 megafires.



The figure plots the 346 municipalities in Chile. 78 were burned down, which are in red. 7 regions were affected in the southern-central area of the country. The fire intensity is measured by the NBR ratio.

Figure 2: Distribution of 2017 Chilean megafires, southern-central area of Chile. Source: De la Barrera & Ruiz (2017).

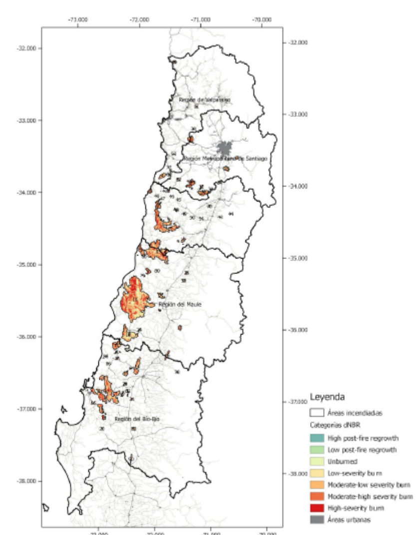
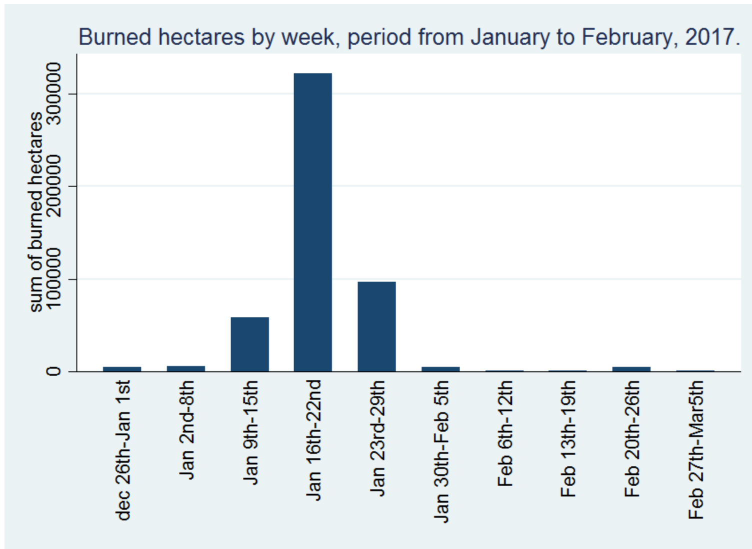


Figure 3: Weekly distribution of 2017 Chilean megafires.



Spread of the burned down hectares in weeks. The third week corresponds to the "Firestorm", which is the largest forest fire in the history of the country.

Figure 4: Regional distribution of burned down hectares, by land use.

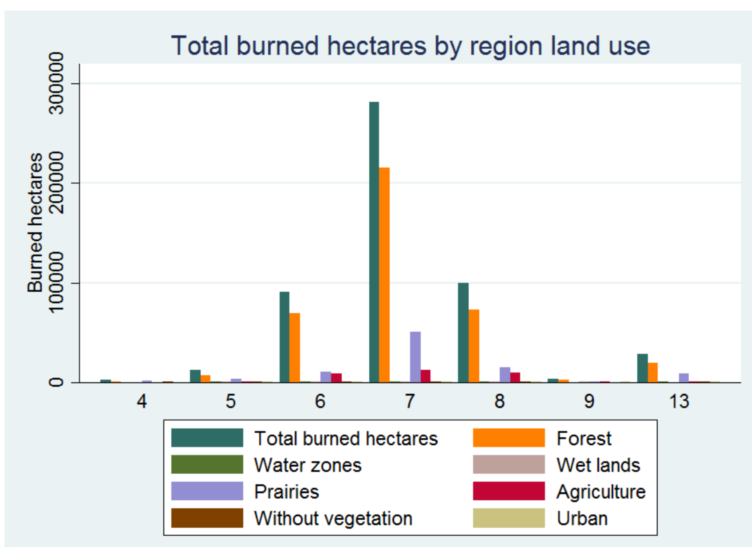


Figure 5: Percentage of burned down hectares over land use, by region.

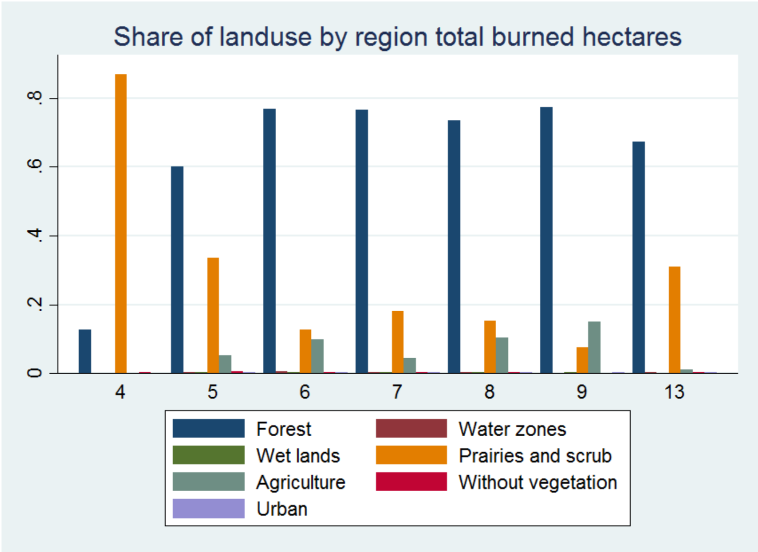


Figure 6: Share of burned down hectares over agricultural and forest exploitations, by region.

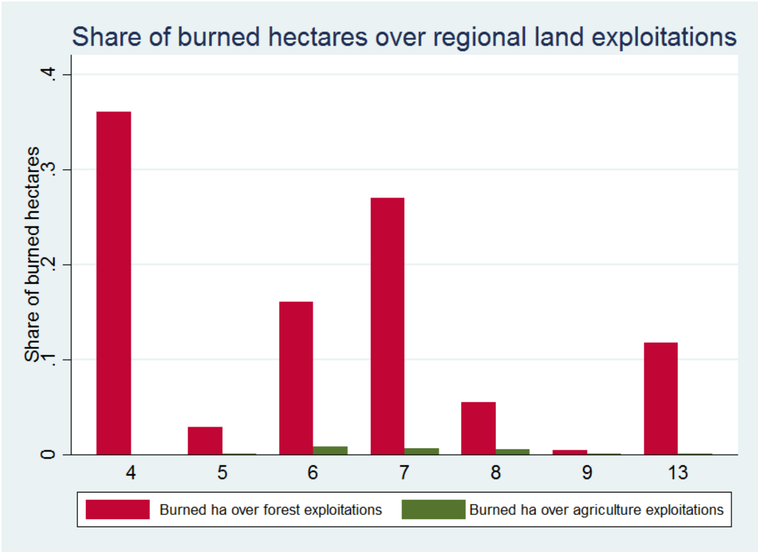
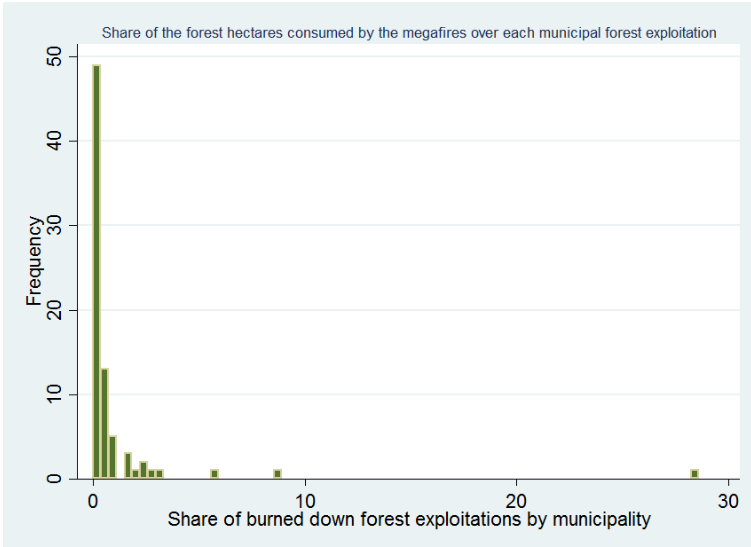
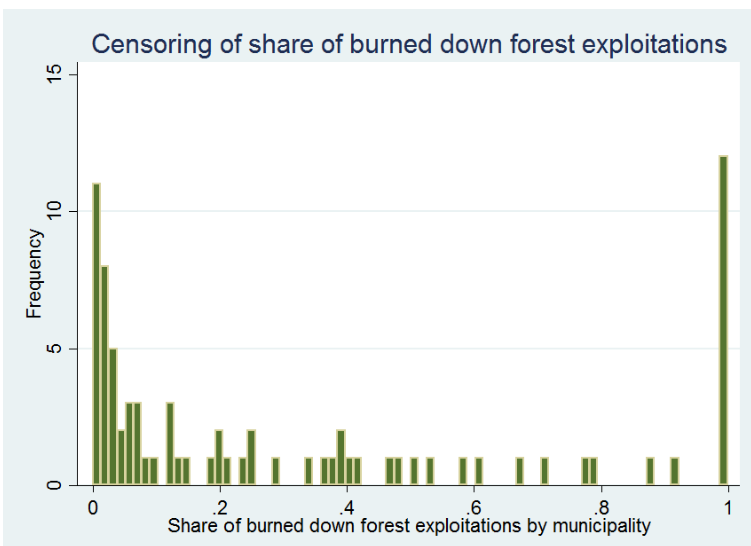


Figure 7: Distribution of the share of burned down forest exploitations by municipality, between January and February 2017.



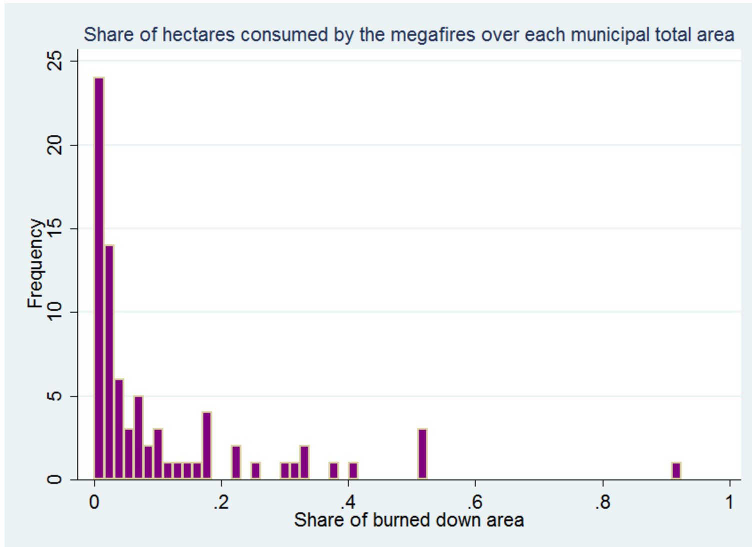
Share forest is the treatment that evaluates the intensive margin of the effects of megafires on crime. It is measured as the percentage of forest burned down hectares over hectares of forestry exploitations. This ratio is based on the 2007 Agricultural Census.

Figure 8: Censored distribution of the share of burned down forest exploitations by municipality, between January and February 2017.



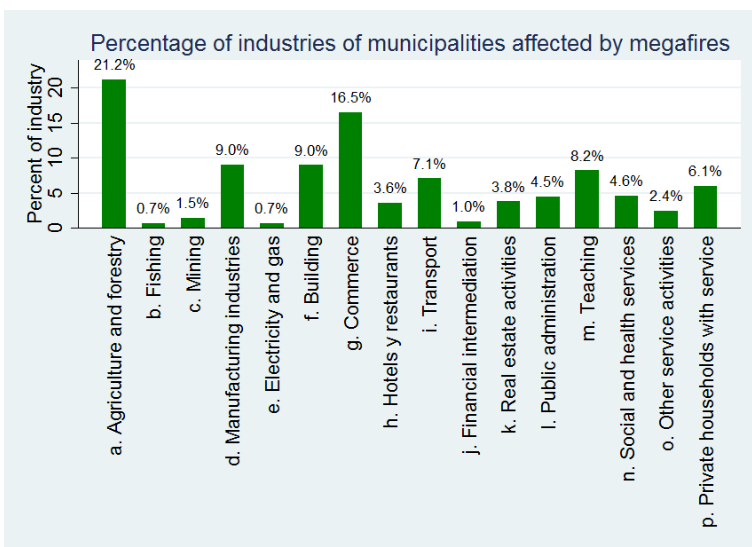
By means of censoring the maximum value to 1, we reduce the effect of possibly spurious outliers. 12 municipalities modified the value of their treatment due to censorship. Share forest is the treatment that evaluates the intensive margin of the effects of megafires on crime. It is measured as the percentage of forest burned down hectares over hectares of forestry exploitations. This ratio is based on the 2007 Agricultural Census.

Figure 9: Percentage of burned down area by municipality.



Distribution of the percentage of hectares consumed by megafires over each municipal total area, between January and February 2017. The largest burned down area by municipality corresponds to the Empedrado municipality, VII region.

Figure 10: Percentage of individuals working by type of industry.



Percentage of individuals working according to type of industry in the 78 municipalities affected by the 2017 megafires. Analysis according to 2015 Casen survey data.

Table 1: Total burned down hectares, by land use.

	Total burned down hectares	Share of burned down hectares
Without vegetation	659.78	0.0013
Urban areas	822.93	0.0016
Forest	388851.59	0.74
Water zones	1799.81	0.003
Wetlands	541.57	0.001
Prairies	93926.99	0.18
Agricultural land	33528.03	0.07
Total	520,130	1

Note: Megafires total burned hectares, classified according to land use. Period from January to February, 2017.

Table 2: Summary statistics: treatment

Treatment	Observations	mean	sd	min	max
Share forest	78	0.98	3.43	0.00	28.62
Share forest (censored)	78	0.33	0.37	0.00	1.00
Burned down hectares					
Total burned down hectares	78	6668.34	12786.06	38.79	69555.68
Share of burned down hectares	78	0.11	0.16	0.00	0.93
Coquimbo (IV) region share	1	0.02	.	0.02	0.02
Valparaíso (V) region share	9	0.03	0.03	0.00	0.11
O'higgins (VI) region share	16	0.11	0.12	0.00	0.41
Maule (VII) region share	14	0.24	0.27	0.00	0.93
Bio-bío (VIII) region share	19	0.12	0.14	0.00	0.52
Araucanía (IX) region share	5	0.01	0.01	0.00	0.02
Metropolitana (XIII) region share	14	0.04	0.03	0.00	0.11

Table 3: Balance check in pre-treatment characteristics. Extensive margin.

	Treatment	p-value	Treatment	p-value	Treatment	p-value
Rural	1.65	0.750	2.31	0.660	2.31	0.660
Area (k^2)	-1642.33	0.025	-83.41	0.448	-83.41	0.445
Population	-0.02	0.463	-0.02	0.479	-0.02	0.476
Income tax	-0.01	0.792	-0.00	0.923	-0.00	0.922
Income transfers	-0.04	0.008	-0.02	0.186	-0.02	0.183
Own income	-0.02	0.429	-0.01	0.526	-0.01	0.523
Total net income	-0.02	0.397	-0.01	0.458	-0.01	0.454
Poverty	0.01	0.741	0.01	0.851	0.01	0.850
Multidimensional poverty	0.01	0.670	0.01	0.497	0.01	0.494
Crime	-0.28	0.531	-0.17	0.688	-0.17	0.686
Domestic violence	-0.22	0.594	-0.13	0.723	-0.13	0.721
Share "Nueva Mayoria"	-0.02	0.713	-0.04	0.303	-0.04	0.300
Herfindahl index	-0.03	0.387	-0.04	0.219	-0.04	0.216
Marriages	-0.04	0.504	-0.04	0.499	-0.04	0.496
Born alive	-0.03	0.514	-0.03	0.540	-0.03	0.537
Mortality	0.02	0.955	-0.01	0.969	-0.01	0.968
Infant mortality	0.29	0.644	0.28	0.666	0.28	0.664
Men	0.00	0.281	0.01	0.044	0.01	0.043
Regional fixed effects	No		Yes		Yes	
N	346		346		254	
Sample	All		All		7 regions affected	

Note: Balance check in pre-treatment characteristics, extensive margin. Independent variable is the discrete treatment: 1 if share forest is greater than 0.3 and 0 otherwise. Dependents variables are represented in column 1. Columns 2 and 3 consider a sample of the whole country, without fixed effects. Column 4 and 5 add regional fixed effects, for the 346 municipalities of Chile. Columns 6 and 7 consider a 7 regions sample, from the IV (Coquimbo) to the IX (Araucanía) regions, including Metropolitana region.

Table 4: Balance check in pre-treatment characteristics. Intensive margin.

	Share forest	p-value	Share forest	p-value	Share forest	p-value
Rural	-1.52	0.806	0.53	0.935	0.53	0.935
Area (k^2)	-2173.16	0.028	-49.03	0.717	-49.03	0.715
Population	-0.03	0.474	-0.02	0.548	-0.02	0.545
Income tax	-0.01	0.827	0.00	0.999	0.00	0.999
Income transfers	-0.04	0.032	-0.02	0.365	-0.02	0.361
Own income	-0.02	0.429	-0.01	0.585	-0.01	0.583
Total net income	-0.02	0.392	-0.02	0.510	-0.02	0.506
Poverty	0.02	0.662	0.01	0.778	0.01	0.776
Multidimensional poverty	0.01	0.780	0.01	0.588	0.01	0.585
Crime	-0.31	0.584	-0.14	0.797	-0.14	0.796
Domestic violence	-0.26	0.596	-0.13	0.779	-0.13	0.777
Share "Nueva Mayoria"	-0.01	0.866	-0.04	0.420	-0.04	0.417
Herfindahl index	-0.04	0.267	-0.05	0.106	-0.05	0.104
Marriages	-0.05	0.527	-0.04	0.577	-0.04	0.574
Born alive	-0.04	0.532	-0.03	0.628	-0.03	0.626
Mortality	0.07	0.863	-0.00	0.988	-0.00	0.988
Infant mortality	0.63	0.409	0.64	0.429	0.64	0.425
Men	0.00	0.321	0.01	0.053	0.01	0.051
Regional fixed effects	No		Yes		Yes	
N	346		346		254	
Sample	All		All		7 regions affected	

Note: Balance check in pre-treatment characteristics, intensive margin. Independent variable is the share of burned down forest hectares over municipal forest exploitations with winsorizing (Figure 6). Dependents variables are represented in column 1. Columns 2 and 3 consider a sample of the whole country, without fixed effects. Column 4 and 5 add regional fixed effects, for the 346 municipalities of Chile. Columns 6 and 7 consider a 7 regions sample, from the IV (Coquimbo) to the IX (Araucanía) regions, including Metropolitana region.

Table 5: Summary statistics: crime

Variable	Category	Mean	Sd	Min	Max	Observations
Domestic violence	overall	30.09	44.46076	0	439	N=6350
	between		43.78939	.8	367.68	n=254
	within		8.154548	-38.18835	116.4917	T=25
Property crime	overall	103.30	199.6719	0	1900	N=6350
	between		198.7502	.4	1609.16	n=254
	within		22.72706	-133.8643	449.1357	T=25
Violent crime	overall	50.86	103.3901	0	1284	N=6350
	between		102.6222	.52	968.6	n=254
	within		14.07135	-152.7379	366.2621	T=25
Suicide cases	overall	.29	.7764524	0	9	N=6350
	between		.4600043	0	3.28	n=254
	within		.6261584	-2.989921	7.050079	T=25

Table 6: Differences in differences, period from January 2016 to January 2018

	Domestic violence		Property crime		Violent crime	
	(1)	(2)	(3)	(4)	(5)	(6)
Share forest×post	0.117*		0.052		-0.018	
	(0.061)		(0.061)		(0.138)	
High intensity×post		0.086**		0.072		-0.010
		(0.037)		(0.061)		(0.095)
N	6350	6350	6350	6350	6350	6350
Municipal fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Linear trend	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors clustered at municipal and monthly level in parentheses. Sample of 25 months from January 2016 to January 2018. Post variable is 1 from March 2017 onwards. Fixed effects at municipal and monthly level. Dependent variable is the (one plus) natural logarithm of crime. Share forest is the percentage of burned forest hectares over each municipal forest exploitations. Discrete treatment is 1 if share forest is greater than 0.3 and 0 otherwise.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 7: Parallel trends. Sample from January to December 2016.

	Domestic violence		Property crime		Violent crime	
	(1)	(2)	(3)	(4)	(5)	(6)
Share forest×post	-0.016		-0.006		0.019	
	(0.017)		(0.016)		(0.019)	
High intensity×post		-0.028		-0.041		0.024
		(0.035)		(0.032)		(0.020)
N	3048	3048	3048	3048	3048	3048
Municipal fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Weights	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors clustered at municipal level in parentheses. Fixed effects at municipal and monthly level. Dependent variable is (one plus) the natural logarithm of crime. Post variable is equal to 0 from January to June 2016, and 1 from July to December 2016. Discrete treatment is 1 if share of forest burned hectares is greater than 0.3 and 0 otherwise.

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

Table 8: Differences in differences placebo, period from January 2015 to January 2017

	Domestic violence		Property crime		Violent crime	
	(1)	(2)	(3)	(4)	(5)	(6)
Share forest×post	-0.043		0.072		0.024	
	(0.060)		(0.051)		(0.093)	
High intensity×post		-0.053		0.073		0.007
		(0.050)		(0.051)		(0.071)
N	6350	6350	6350	6350	6350	6350
Municipal fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Linear trend	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors clustered at municipal and monthly level in parentheses. Sample of 25 months from January 2015 to January 2017. Fixed effects at municipal and monthly level. Dependent variable is the (one plus) natural logarithm of crime. Share forest is the percentage of burned forest hectares over each municipal forest exploitations. Discrete treatment is 1 if share forest is greater than 0.3 and 0 otherwise. Post variable is 1 from January 2016 to January 2017.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 9: Income channel

	Income		Unemployment		Poverty	
	(1)	(2)	(3)	(4)	(5)	(6)
Share forest×post	-0.169**		0.159		0.413***	
	(0.008)		(0.140)		(0.005)	
High intensity×post		-0.061*		0.707		0.245***
		(0.007)		(0.539)		(0.001)
N	144348	144348	156851	156851	156476	156476
Municipal fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Weights	Yes	Yes	Yes	Yes	Yes	Yes
Linear trend	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors clustered at municipal and annual level in parentheses. Fixed effects at municipal and annual level. Dependent variable is the natural logarithm of income for columns 1 and 2; columns 3 and 4 is a dummy for unemployment status; columns 5 and 6 is a dummy for poverty status. Share forest is the percentage of burned forest hectares over each municipal forest exploitations. Discrete treatment is 1 if share forest is greater than 0.3 and 0 otherwise.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 10: Stress channel: Suicide cases

	(1)	(2)
Share forest×post	0.818	
	(0.757)	
High intensity×post		0.517
		(0.631)
N	6350	6350
Municipal fixed effects	Yes	Yes
Month fixed effects	Yes	Yes
Linear trend	Yes	Yes

Zero inflated poisson regressions. Fixed effects at municipal and monthly level. Dependent variable is the number of suicide cases in period from January 2016 to January 2018. Post variable is 1 from March 2017 onwards. Share forest is the percentage of burned forest hectares over each municipal forest exploitations. Discrete treatment is 1 if share forest is greater than 0.3 and 0 otherwise.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 11: Social cohesion channel

	Trust in people		Trust in Government	
	(1)	(2)	(3)	(4)
Share forest×post	0.646***		0.807***	
	(0.126)		(0.138)	
High intensity×post		0.477**		0.780***
		(0.219)		(0.072)
N	2927	2927	2933	2933
Municipal fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Linear trend	Yes	Yes	Yes	Yes

Standard errors clustered at municipal and annual level in parentheses. Fixed effects at municipal and annual level. Dependent variable is a dummy that takes value of 1 if people trust in others and 0 otherwise, for column 1 and 2. Dependent variable for columns 3 and 4 is 1 if people trust in Government and 0 otherwise. Share forest is the percentage of burned forest hectares over each municipal forest exploitations. Discrete treatment is 1 if share forest is greater than 0.3 and 0 otherwise.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$