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AN EXPLORATORY STUDY ON THE ECONOMIC IMPACTS OF WILDFIRES IN PORTUGAL

Joana Filipa Henriques e Sousa

Dissertation presented as partial requirement for obtaining the Master's degree in Statistics and Information Management, with specialization in Risk Analysis and Management

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Abstract

Wildfires are natural disasters that can be highly destructive, affecting communities and economies all over the world. The Mediterranean region has been severely affected by these events and Portugal is no exception: the rural areas have been affected by demographic and socioeconomic changes throughout the decades, and the conditions for fire ignition and propagation have led Portugal to be one of the European countries with the highest ignition density and relative burnt area.

In this work, we analyse the economic effects of catastrophic wildfires on the municipalities of Portugal. To achieve this, we estimated the impacts of these events on the consumption of electric energy, which can be used as a proxy for the level of economic activity. This study is based on the estimation of impulse response functions (IRFs) using the local projections (LPs) approach of Jordà, 2005, which allows us to analyse the effects on a temporal level and therefore estimate both immediate and longer term effects. For measuring the occurrence of disasters, we considered yearly levels of burnt area over 25%, 33.3% and 50%.

Findings show that catastrophic wildfires have a negative effect on the economic activity of a municipality, up to the year after an event occurs. For 33.3% and 50% of burnt area, negative impacts are immediate and can reach 1.4% and 2.5%, in comparison to the level of economic activity of the previous year; for over 50%, the effect worsens in the following year, indicating the presence of a 3% negative impact on the economic activity. These results indicate that larger levels of burnt area are responsible for more severe and longer-lasting negative effects.

Our conclusions support the idea that wildfires can have severe economic consequences, at a short and longer term. This work contributes to improve the understanding of wildfire economic impacts for the municipalities of Portugal, and hopes to serve as a motivation for future investments in reinforcing wildfire mitigation measures.

Keywords: Wildfires; economic impacts; Portugal; Natural disaster; Local Projections ...

Resumo

Os incêndios são desastres naturais com grande capacidade de destruíção, afetando comunidades e economias em todo o mundo. A região do Mediterrâneo tem sido severamente afetada por estes eventos e Portugal não é exceção: as zonas rurais têm vindo a ser afetadas por alterações demográficas e socioeconómicas ao longo das décadas, e as condições para ignição e propagação do fogo fizeram com que Portugal seja um dos países europeus com maior densidade de ignição e área ardida relativa.

Neste trabalho, analisamos os efeitos económicos de incêndios catastróficos nos municípios de Portugal. Para tal, estimámos of impactos destes eventos no consumo de energia elétrica, que pode ser usado como um *proxy* para o nível de atividade económica. Este estudo é baseado na estimação de impulse response functions (IRFs), usando a abordagem de local projections (LPs) de Jordà, 2005, que nos permite analisar os efeitos numa escala temporal e, assim, estimar tanto efeitos imediatos como efeitos a médio/longo prazo. Para registar a ocorrência de desastres, consideramos os níveis de área ardida acima de 25%, 33.3% e 50%.

Os resultados mostram que incêndios catastróficos têm um efeito negativo sobre a atividade económica de um município, até ao ano após a ocorrência de um evento. Para áreas ardidas de 33.3% e 50%, os impactos negativos são imediatos e podem chegar a 1.4% e 2.5% relativamente ao nível de atividade económica do ano anterior; para acima de 50%, o efeito piora no ano seguinte, indicando a presença de um efeito negativo de 3% sobre a atividade económica. Estes resultados demonstram que maiores níveis de área ardida são responsáveis por efeitos negativos mais severos e mais duradouros.

As nossas conclusões apoiam a ideia de que os incêndios podem ter severas consequências económicas, a curto e longo prazo. Este trabalho contribui para melhorar o conhecimento sobre os impactos dos incêndios nos municípios de Portugal, e esperemos que sirva de motivação para futuros investimentos em reforço de medidas de mitigação de incêndios.

Palavras-chave: Incêndios; impactos económicos; Portugal; Desastre natural; Local Projections ...

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1

Introduction

Every year, millions of people are affected by the occurrence of natural disasters, all around the world. Natural disasters play a significant role in determining the quality of life of communities, especially in the most vulnerable and affected areas, where damages are greater and more frequent. These events can strongly affect households and generate great financial losses for businesses and governments.

Often linked to climate change, the frequency and severity of climate-related hazards have been increasing for several decades. According to EM-DAT (2020), from 1900 to 2012, natural disasters were responsible for 2.8 million deaths and affected [1] around 6.1 billion people (some more than once), having resulted in estimated losses of at least US$ 2.46 trillion. From 1974 to 2012, the average number of recorded disasters per year almost quadruplicated and, in fact, more than 86% of the registered events occurred in this period. Nevertheless, this can also be explained by the scarce disaster data that is available for 1900-1960.

Amongst climate-related hazards, wildfires are one type of natural event that can strongly affect local economies and communities, especially in rural areas, where populations are more dependent on agricultural activities and firefighting is not so effective. Wildfires may be highly destructive and originate large financial losses as well as substantial landscape modifications. Portugal is highly affected by the occurrence of these events, which are one of the most relevant types of disaster in the country; they occur frequently in the summer seasons (Nunes, 2012) and often take on large dimensions.

As Portugal is severely affected by wildfires, the high number of ignitions and the quantity of flammable biomass in the forests need to be addressed, along with increasing awareness to the impacts that these events can have throughout the country, where socioeconomic, meteorological and natural conditions differ. More particularly, a study at the municipality level can be relevant for allowing municipalities to better understand the impacts of these events at this scale and thus better manage mitigation strategies and recovery measures.

[1] EM-DAT considers the people affected by a natural disaster as the "people requiring immediate assistance during an emergency situation".

This study aims to contribute to the literature on the economic effects of extreme events by focusing on large-scale wildfires in Portugal. Our research is focused on assessing the effects of a shock – more exactly, a catastrophic natural event i.e. large wildfires – on the level of economic activity, at municipality level. For obtaining estimations for the impacts on the level of economic activity, we analysed the consumption of electric energy, which is a proper indicator to measure this index, as we can further see in chapter 2. Furthermore, we consider the dynamic aspect of the effects, which can persist years after a shock takes place. In this sense, results allow us to see the temporal evolution of the effects, for a time span of five years.

With this dissertation, we aim to increase the knowledge on wildfire impacts in Portugal, which can possibly lead governments to increase its investment in proper strategies that can prevent the occurrence of large wildfires and mitigate their possible consequences for the local economy.

The rest of the dissertation is organised as follows. Sections 2.1 and 2.2 of chapter 2 analyse the literature review on wildfire occurrences and socioeconomic effects, at a global and national scale, respectively. Chapter 3 describes the methodology adopted to conduct the estimations and chapter 4 contains a brief summary of our dataset. Finally, chapter 5 presents the estimates obtained from the regressions and chapter 6 presents the conclusions we can retrieve from our results.

2

Literature Review

2.1 Natural disasters

The socioeconomic impacts of a natural disaster can be classified as direct and indirect. Direct impacts comprise the physical destruction caused by the event, responsible for costs of repair and replacement. This involves damage to the built environment and networks, such as transportation and lifelines [1] (Okuyama, 2007). Indirect impacts appear as a consequence of damaged assets and they are strongly felt by businesses through business interruption and decreased production and consumption. (Okuyama, 2007).

At a macroeconomic scale, effects can be observed in indicators such as GDP, employment rate, inflation, and external debt stock (Sahin, 2015) and, when occurring frequently, negative impacts can be felt in long-term development and poverty (Benson & Clay, 2004; Loayza et al., 2012). However, it has been suggested that countries can even experience long-run economic growth (Loayza et al., 2012; Sahin, 2015) as a consequence of natural disasters, due to investment in infrastructure and sanitary conditions; while the outflows of people from the affected area can be diminished by the investment in recovery and reconstruction measures in the affected area (Mendoza & Schwarze, 2019). Extreme natural disasters can also be associated to health conditions like physical injuries, systemic illnesses and psychopathologies i.e. depression or anxiety (Cook et al., 2008).

Impacts of disasters can also be felt at a smaller scale. In fact, Rodriguez-Oreggia et al. (2013) analysed the effects of natural disasters on the municipalities in Mexico and they found that both human development index (HDI) and poverty levels are negatively affected by different types of disasters, especially floods and droughts. Findings show that, on average, the impacts on the HDI were comparable to going back two years in human development, while poverty levels increased between 1.5% and 3.7%.

The degree of hazard damage and socioeconomic impacts can be influenced by

[1] Lifelines are structures that are crucial for the functioning of a community (i.e. roadways, pipelines or power lines) (USGS, n.d.).

many factors like the hazard characteristics – its nature and intensity – but also the socioeconomic conditions of the affected area and the mitigation strategies conducted by governments and institutions. Some measures of hazard mitigation consist in establishing good construction and emergency practices, which are crucial for lowering the overall impacts of a disaster, but also establishing proper land use (Lindell & Prater, 2003) which plays an important role in wildfire mitigation (Tedim et al., 2013).

Previous studies showed that socioeconomic conditions can be related to disaster vulnerability. Formetta and Feyen (2019) found that there is a clear negative relation between income and vulnerability, due to a bigger investment from wealthier countries in protection measures, warning systems and management strategies, which makes them more protected and therefore less vulnerable to disasters. However, income can depend on other factors like education, which was found to play a role in disaster controllability (Ho et al., 2008). Regarding long-term impacts, poverty remains the main risk factor (Guha-Sapir et al., 2013). Moreover, macroeconomic vulnerability can also be lower in more developed economies since they have a considerable share of assets held by the private sector insured against disasters (Benson & Clay, 2004). Within the hazard area, the spatial distribution of damages can be influenced by elements like economic inter-connections of productive systems, which can be responsible for propagation of losses within certain areas (Marin & Modica, 2017), and heterogeneity in the density of constructions (Jongman et al., 2012).

Wildfires are one type of disaster that is able to significantly transform the landscapes and their impacts can be felt by both population and the economy. The direct impacts of these events comprise the destruction of crops and vegetation; loss of wildlife and livestock; damage to machinery and infrastructure, like water pipes and telephone lines (Tedim et al., 2013); and, in some cases, loss of lives (Lourenço, 2004; Molina-Terrén et al., 2019). Wildfires can also have indirect consequences for livelihoods since farming activities can be extremely affected by the destruction. This may lead families to require financial compensation, usually in the form of a subsidies or food supplies for the household or animals (Tedim et al., 2013). Indirect economic losses usually entail insurance losses, business and tourism interruption, decrease in family income and loss of soil productivity (Tedim et al., 2013). Lastly, wildfires can be responsible for non-socioeconomic effects, since they damage ecosystem services like the carbon sequestration, due to a decrease in the quantity of biomass (Román et al., 2013).

2.2 Wildfires in Portugal

Having a Mediterranean climate, Portugal is recurrently affected by wildfires. The occurrence of these events has had significant impacts for the population: in the 21st century, 9 large fires affected 155,301 people and were responsible for 153 losses of lives and total damages of US$ 4,269,000 (EM-DAT, 2020). In 2003 and 2005, the wildfire seasons were particularly severe in terms of burnt area and, in fact, up to 2012, 12 of the 20 largest wildfires registered in Portugal occurred in the year of 2003 (Leite et al., 2012). More recently, in 2017, a combination of meteorological conditions led to a catastrophic wildfire season, which resulted in a total of 112 deaths. Amongst these events, one large fire that flared in the area of Pedrógão Grande resulted in 64 deaths (EM-DAT, 2020).

In 2016, Portugal had the highest ignition density and relative burnt area amongst southern European countries (Nunes et al., 2016) and the number of occurrences has been increasing over the years. Nunes (2012) analyses forest fire ignitions and burnt areas in mainland Portugal for the period from 1980-2009 and her findings show that, in this period, Portugal registered over a million ignitions and a total burnt area of approximately 3,236,890 ha — about more than a third of its total area. Moreover, the annual average burnt area in the 2000s (148,000 ha) was 45% higher than in the 1990s (102,720 ha); the 2000s registered a yearly average of 26,000 forest fires while the 1990s registered a yearly average of 22,250 occurrences.

According to Nunes (2012), from 1980 to 2009, the region that registered the highest number of ignitions was the district of Porto (around 4000 per year). On the other hand, the lowest number of forest fires was registered in the more southern regions of Beja, Évora and Portalegre. In fact, fire ignition was considerably higher in more urban and suburban districts as opposed to rural areas. However, due to a more effective firefighting, fires are more easily extinct in urban areas than in the rural ones, which explains the large number of small fires in Porto, Braga, Lisbon and Setúbal, but also the large burnt areas in Guarda, Viana do Castelo, Coimbra, Viseu and Vila Real, which are regions that are not so urban as the previous. Overall, findings show that the northern and central regions were the ones more affected: Guarda, with a yearly average burnt area of 18,000 ha, was the area most affected followed by Castelo Branco, Viseu, Coimbra and Vila Real. The northern and central Portugal is also where wildfires are the most fatal (Molina-Terrén et al., 2019).

In Portugal, megafires [2] are defined as fires in which the burnt area surpasses 100ha (Leite et al., 2012). Tedim et al. (2013) investigated the occurrence of megafires in Portugal and suggested that not only climate change and socioeconomic preconditions are significant drivers of these events, but land use also has an important role on the

[2] There are three factors that can determine a megafire: fire behavior (intensity and spread rate) (McRae & Sharples, 2011), resistance to control efforts and fire severity (size, fatalities, economic losses etc) (Williams et al., 2005).

prevention against fire damages. In the 1960s, Portugal suffered some megafires in Leiria (1961) (Leite et al., 2012) but also in Viana do Castelo (1962), Boticas (1964), and Sintra (1966) (APIF & ISA, 2005). In the following decades, megafires have been occurring more frequently, with the 100ha threshold being more easily surpassed.

At a smaller scale, Oliveira et al. (2017) analysed wildfire impacts on the Portuguese civil parishes (which, in Portuguese, are "freguesias") with regard to socioeconomic and demographic parameters. Results show that parishes with higher fire density also have a higher population density, young and educated people and overcrowded buildings whereas parishes with higher levels of burnt area are less populated, more aged and more agriculture-dependent – which supports, again, the idea that wildfires are more frequent in urban areas but more severe in rural ones.

Several factors can be responsible for the severity of wildfires in the country. For example, meteorological variables are proven to be associated with the amount of burnt area. Lourenço (1991) concluded that fire hazard indexes – based on levels of temperature and humidity – are correlated with fire frequency and level of burnt area, whilst Viegas and Viegas (1994) also show that there is an exponential and negative relationship between rainfall and burnt area. Moreover, areas with steeper slopes, higher levels of precipitation and lower temperatures are the ones with the highest levels of burnt area, which can be attributed to the quantity of biomass in these areas (Nunes et al., 2013).

With the rural exodus that started in the 1950s, poor existing conditions for agriculture, lack of alternative employment and the aging of farmers, agriculture may no longer be self-sustainable. Therefore, the landscape has been intensely altered throughout the decades because it is no longer being used (Nunes, 2012). This promotes the increase of biomass fuel in non-populated agricultural land and, thus, facilitating the propagation of fires. Moreover, 55% of the forest area is composed by highly inflammable matter like maritime pine and eucalyptus (Nunes, 2012). The combination of these conditions have made the landscape prone to big proportion fires, with wildfires easily turning into megafires (Leite et al., 2012).

Besides its importance for the ecossystem, the Portuguese forest has a significant economic value, as it generates large economic profits every year. In 2021, Mendes (2021) estimated that the Portuguese forest produces an equivalent of about 1.8 billion euros a year, with nearly half of it accounting for ecosystem services such as biodiversity protection and carbon sequestration. This economic value includes a significant amount of the country's goods exportation, representing 8.6% of its total value in 2019 (INE, 2021). The impact of wildfires on the forest tree's profit can vary with the affected species but it is estimated that maritime pine and eucalyptus are the ones that suffer the biggest yearly percentage losses of its potential profit – about 24% and 25%, respectively (Lopes & Cunha-e-Sá, 2014).

3

Empirical Strategy

To estimate the socioeconomic impacts of wildfires, we focused on analysing the response of the level of economic activity to these events. More specifically, we want to estimate the effects that these catastrophic events have on the yearly consumption of electric energy of a municipality, which can be a proper indicator of the level of economic activity [1].

The correlation between the electric energy consumption and economic activity has been extensively studied and often is conjectured that electricity use is a coincident indicator of the level of economic activity (Arora et al., 2014; Kasperowicz, 2014; Paper, 2020; Payne, 2010; Santos et al., 2018). Alongside capital and labour, electricity consumption is essential for production processes, as most goods and services are produced using electricity, and is undeniably essential for various sectors like the industrial, agricultural and commercial. The consumption of electricity can be used as a proxy for GPD (Paper, 2020), which is a frequently used indicator for measuring economic activity. Arora et al. (2014) analyse annual US data since 1950 and quarterly data since 1976 and find that the correlation between GDP growth and electricity use can be as high as 90%. They also conclude that during the recessions analysed, annual growth in electricity sales progressed very similarly to annual growth in real GDP. Likewise, Paper (2020) concludes that the elasticity relationship between GDP and electricity consumption is about 1.42. In sum, electric energy consumption is a commonly used index for measuring economic activity and thus it is a good indicator for estimating wildfire economic effects, in order to understand the impact that these events can have on the economic activity.

The methodology we have adopted to conduct our research is based on estimating impulse responses, used to describe how a certain endogenous variable reacts over

[1] Throughout the study, several dependent variables were analysed, like the number of unemployed, the companies' turnover or the Gross Value Added (GVA). However, the availability of data for each variable did not allow us to produce conclusive results, as the number of shocks considered was very scarce for bigger levels of burnt area. Additionally, some variables did not have the municipality's geographic location scope, as is the case of GVA, which is registered for the location of the company's headquarters. On the other hand, the data on electricity consumption is available for a broad period of time and it is associated with the municipality's location, which makes it a convenient variable to analyse.

time to a shock. In our work, we apply this method in order to measure the response of the consumption of electric energy (kWh) of a municipality to a catastrophic wildfire event, represented by a dummy variable that indicates the occurrence of the shock. The usage of this variable allows us to focus on extreme events rather than analysing all events, considering that the great majority of occurrences are of very small scale and therefore do not have significant impacts.

For estimating the impulse response functions (IRFs) we use the local projections (LPs) approach of Jordà (2005). This method is based on the estimation of multiple regressions that are local to each forecast horizon, and has been applied in multiple studies in order to study the effects caused by financial distresses like price shocks or banking crisis on economic variables such as GDP growth, employment rate and output losses (Abbritti et al., 2020; Barnichon & Brownlees, 2019; Furceri & Zdzienicka, 2012; JORDÀ et al., 2013; Romer & Romer, 2017) [2]. The use of LPs brings several advantages such as the estimation being based on simple regression techniques with standard regression packages and the fact that they are more robust to misspecification (Jordà, 2005). The effect of the occurrence of a shock in municipality i and year t on the outcome variable in year $t+h$ is given by the estimation of the following sequential equations:

$$\log(y_{i,t+h-1}) - \log(y_{i,t-1}) = \sum_{s=0}^{2} \delta_s^h D_{i,t-s} + \sum_{s=0}^{2} \boldsymbol{\theta}_s^h \boldsymbol{X}_{i,t-s} + \alpha_i^h + \eta_t^h + u_{i,t+h-1}, \tag{3.1}$$

with $h = 1, ..., H$ and $s = 0, 1, 2$.

In these regressions, the dependent variable is the cumulative growth of y – where y is the yearly electric energy consumption of a municipality – for which the estimated effects are always in relation to its value in $t-1$. D is a dummy variable that represents the occurrence of an extreme natural event, being equal to one if a certain municipality registered a catastrophic degree of burnt area in a certain year, and equal to zero otherwise. In order to estimate the IRFs, we used three different shock variables that are associated with three different yearly levels of burnt area – 25%, 33.3% and 50% of a municipality's total area [3]. The vector $\boldsymbol{X}$ contains a set of control variables. Lagged values of control and explanatory variables are included [4]. For the control variables, we chose socioeconomic variables that could possibly have an influence on the dependent variable's value, in other words, that could potentially make some municipalities more vulnerable to wildfires than others. Considering the literature review, we control our

[2] We used the R package Lpirfs (Adämmer, 2019), namely its function *lp_lin_panel*, which estimates linear impulse responses for a panel data structure.

[3] For the regressions, these variables were multiplied by 100, in order to get percentage values in the results.

[4] We considered regressions with no lags and a lag length equal to 2.

regressions with the ageing index – quotient between number of people aged over 65 and number of people between 0 and 14 – and population density of the municipality. Moreover, the estimations use two-way fixed fixed effects in order control the results by the effect of municipality and year, which capture effects of time-invariant variables – variables that do not vary over time for the municipality/year – on the respective variable. These effects are captured by α and η, which denote municipality and year fixed-effects, respectively. The term h is the forecast horizon, which will be a maximum of five years. Finally, the coefficient δ^h measures what we want to analyse -– the response of y to the shock variable D when the horizon is h. The regressions' sample has a maximal time span of 26 years (1994-2019) and a total of 247 municipalities. This sample does not include the municipalities which are predominantly urban, as it is further explained in chapter 4.

The time period for which the sample data on the yearly consumption of electric energy is available is from 1994 to 2019, which allows us to analyse a generous amount of observations. The availability of observations also allows us to separate the regressions into different time periods: 1994-2019 and 1994-2016, in order to evaluate if the absence of the 2017 wildfire events has any impact on the results. This allows us to analyse if there is any significant disparity between the number of events considered in the regressions of 1994-2016 and the ones for the period up to 2019. This disparity can also be observed in the differences between the number of events of 1994-2019 for the horizons after h=3 and the remaining, since the sample ends in 2019 and therefore 2017 events can only be captured up to h=3.

In sum, the regressions were estimated for the time periods of 1994-2019 and 1994-2016, for different shocks, with and without the presence of lags. These conditions help us to take a broader perspective of the impacts, as they allow us to see the comparisons between different time periods and different levels of burnt area.

4

Data

To build our database, we resorted to national public databases for obtaining data on wildfire statistics and socioeconomic data, both available at a municipal scale and yearly frequency. For information on wildfires, we collected data from Instituto da Conservação da Natureza e das Florestas (ICNF) – for the years previous to 2016 – and PORDATA – for the period after 2015. The combination of this data allows us to build a database with information on wildfires – more specifically, yearly levels of burnt area – that covers the period from 1980 to 2019. For socioeconomic data, we resorted to the databases of PORDATA and INE. After collecting and structuring the data, our database is a panel dataset that contains information on year and municipality, which covers the availability period for the electric energy consumption – 1994-2019 (26 years) – and a total of 260 municipalities.

The final dataset will allow us to estimate not only immediate impacts but also its evolution over the years. Table 4.1 presents the descriptive statistics for the dependent, control and explanatory variables. The listing of all the shocks considered in the regressions is present in the Appendix A, in table A.1.

To conduct the regressions, we excluded the municipalities that are predominantly urban, as we have seen in chapter 2 that wildfire impacts are more severe in rural areas. To achieve this, we excluded from our sample the municipalities for which the population density (number of residents per square kilometer) surpasses 500 [1], based on the urban areas classification in INE (2014). Moreover, we excluded the municipalities which were created in 1998, as well as the ones which preceded them, in order to accurately compare results throughout the time. Subsequently, the final dataset used to conduct the regressions has a total of 247 different municipalities.

[1] For reference, we used data on population density for 2020.

Table 4.1: Descriptive statistics for the dependent, control and explanatory variables

Variables	Obs.	Average	Min	Max	Std. Deviation	Median
Consumption of electric energy (kWh)	6422	97.66M	1.71M	1428.85M	167.46M	37.98M
Ageing index	6422	180.21	30.20	820.50	94.90	158.60
Population density	6421	93.89	3.75	531.85	101.67	57.09
25% burnt area	6422	0.01	0	1	0.11	0
33.3% burnt area	6422	0.01	0	1	0.09	0
50% burnt area	6422	0	0	1	0.06	0

4.1 Wildfire statistics

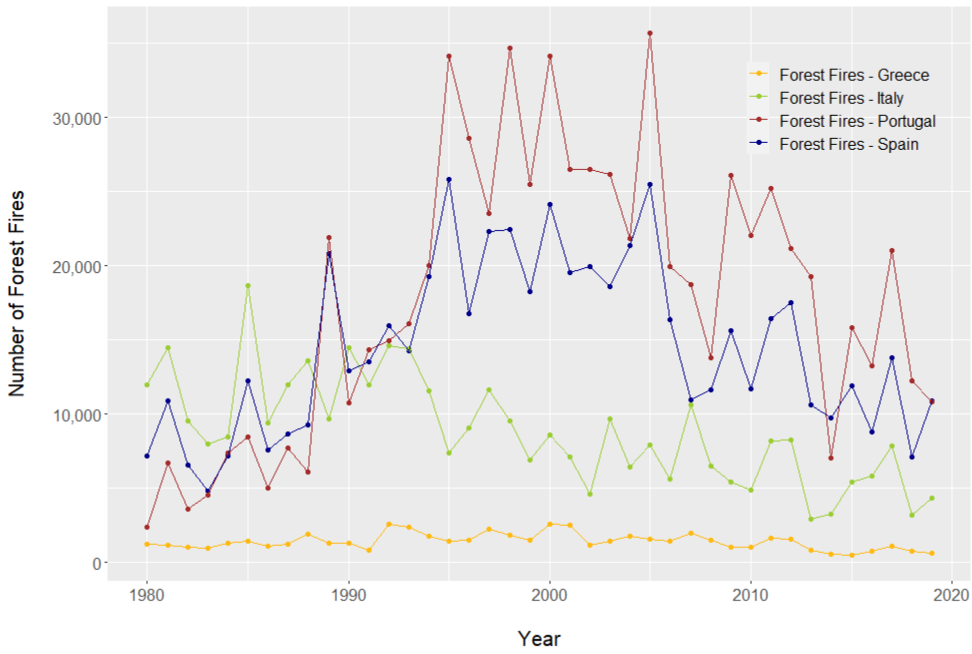
The wildfire data we gathered to conduct our research supports the literature review on wildfire severity in Portugal, as it is reflected in figures 4.1, 4.2 and 4.3, which present the yearly number of forest fires, level of burnt area (ha/Km^2) and burnt area (ha), respectively, for the European countries that are most affected by wildfires. This data was gathered from the PORDATA database.

In figure 4.1, we can observe that, since 1993, the Portuguese fire frequency has been continuously higher than the rest of the countries, with the only exception being 2014. The years that register the worst numbers are 2005, 2000, 1998 and 1995, with the highest number of forest fires – 35,697 – being registered for 2005.

Figure 4.2 also reflects the predominance of wildfires in Portugal, as we can see that, in most years, the country registers the highest levels of burnt area amongst remaining countries. The highest values are registered in 2003, 2005 and 2017, with the year 2017 having almost 6% of the country's land being burnt. This figure reflects the magnitude of the catastrophic wildfire seasons occurred in 2003, 2005 and 2017 and, in fact, the total burnt area of Portugal is also generally superior than in the remaining countries, as we can see in figure 4.3.

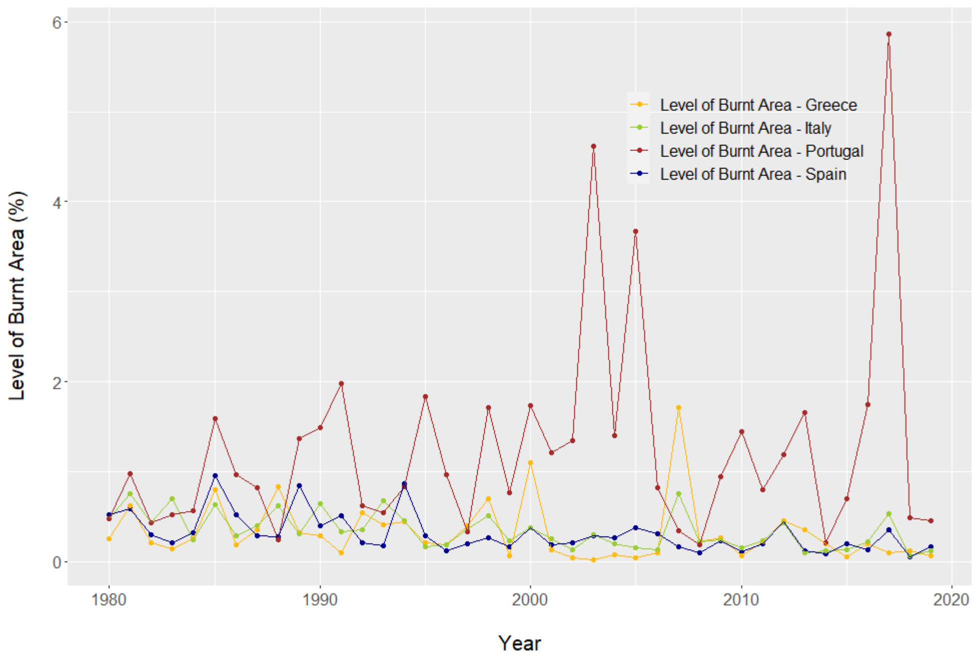
The gathered data supports the findings of Nunes (2012) at the district level, as we can observe in figure 4.4, which shows the mean yearly levels of burnt area for the top 10 most affected districts of Portugal, from 1980 to 2019. In general, the northern and central districts are the most affected, as Porto registers the highest level of burnt area – 1.8% –, followed by Viana do Castelo, Viseu and Coimbra. Moreover, figure 4.5 presents the top 10 municipalities with the highest level of burnt area, for the same

Figure 4.1: Yearly number of forest fires in South European countries



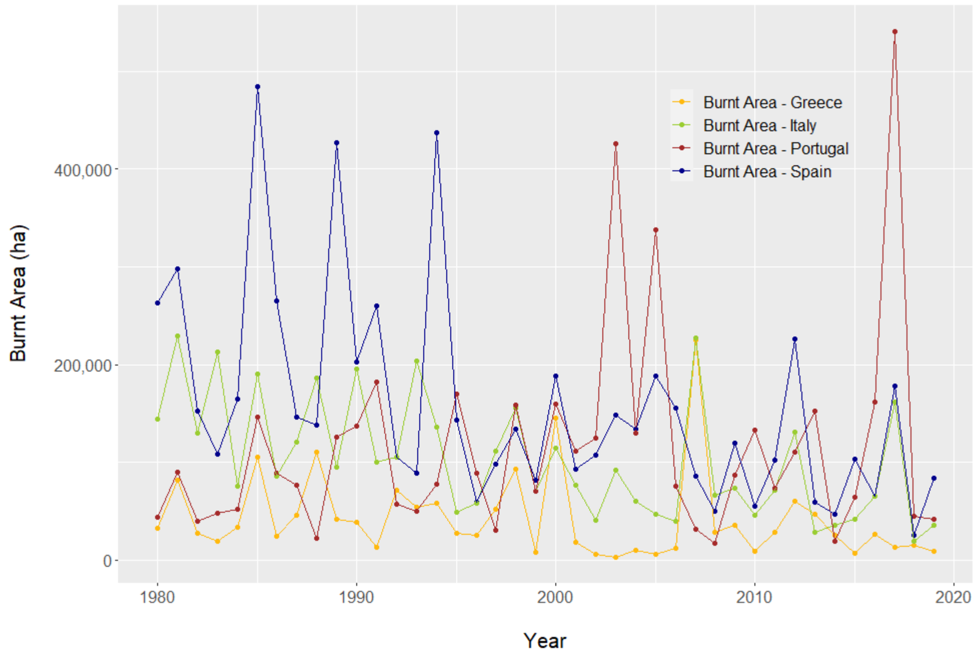
Data source is PORDATA.

Figure 4.2: Yearly level of burnt area in South European countries



Data source is PORDATA.

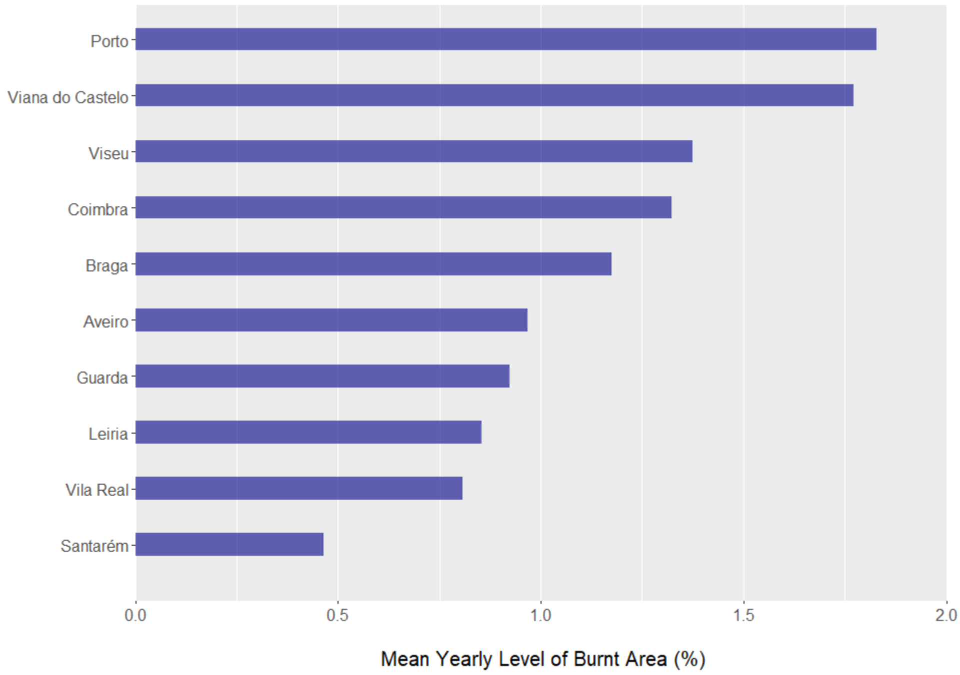
Figure 4.3: Yearly burnt area in South European countries



Data source is PORDATA.

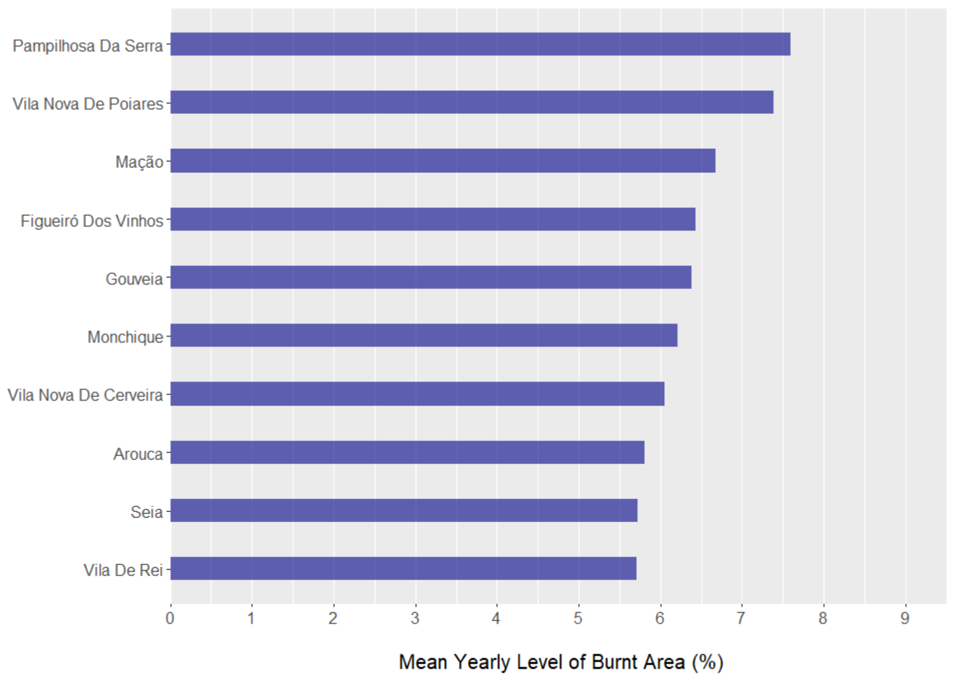
period. The most affected municipality is Pampilhosa da Serra, which belongs to the district of Coimbra, with a level of burt area reaching 7.6%.

Figure 4.4: Top 10 districts with the highest mean yearly level of burnt area in Portugal



Period under consideration is 1980-2019. Data source is PORDATA and ICNF.

Figure 4.5: Top 10 municipalities with the highest mean yearly level of burnt area in Portugal



Period under consideration is 1980-2019. Data source is PORDATA and ICNF.

5

Results

This section presents results obtained from the local projections based on equation (3.1), where the dependent variable under analysis is the electric energy consumption. The regressions are presented for the time periods of 1994-2019 and 1994-2016, several forecast horizons and different shock variables – with and without the presence of lags. The results obtained are shown in figures, where we can see the immediate effect on the dependent variable, in h=1, and its evolution in each horizon. Furthermore, estimations are presented in tables that contain the summaries of the regressions, with some of them being kept only in the Appendix A.

The results obtained for the periods 1994-2019 and 1994-2016 can be observed in figures 5.1 and 5.2, respectively. As seen through figure 5.1, results present statistically significant negative effects in h=1 and h=2 (for the 50% shock), which indicates the presence of an immediate negative effect on electricity consumption, that persists in the following year for the 50% shock. For the 33.3% of burnt area shock, the contemporaneous negative effect reaches more than 1% – more specifically, 1.4%, as seen in table A.2 – and stops being significant in the year after the event. For the 50% shock, the negative impact reaches about 2.5% in h=1 and persists in the following year, where it rises to about 3%. The 25% shock does not present any statistically significant estimates. Although weakened and not significant, the remaining estimates suggest that the effect is mainly negative for all horizons.

These results imply that there is a clear negative impact on the electric energy consumption when catastrophic wildfire events occur. This effect is present in the year that the event occurs, increasing in the following year for larger levels of burnt area. More specifically, a bigger than 50% shock leads to a 3% decrease of electricity consumption, in comparison to its value in the year prior to the shock. Thus, considering electricity consumption as a proxy for economic activity, we can infer that the level of economic activity also decreases about 3%. For the 33.3% shock, the immediate effect is less severe – about 1.4% – and is not present in the second year. The results for the 25% shock suggest that these shocks do not have such significant impacts on the electricity consumption. These results suggests that, the larger the level of burnt area, the more severe and long-lasting are the effects on electricity consumption and, therefore, on economic activity. In the third year, the impact is reduced and stops being statistically significant, which suggests the beginning of recovery.

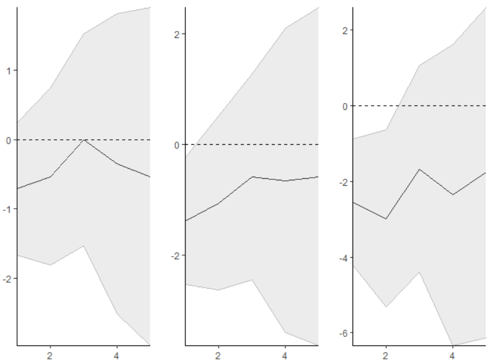
In general, the results for the regressions with and without the presence of lags do not differ significantly, which means that the effect upon the dependent variable is not strongly determined by previous shocks – meaning, the occurrence of catastrophic events in the two years prior to the event – neither by the past values of the control variables – ageing index and population density.

The number of events used in the regressions for 1994-2019 decreases significantly after h=3 and the confidence bands for these horizons are also wider, which indicates that these estimates have more uncertainty. This can be explained by the fact that, from h=4 onwards, it is no longer possible to consider the shocks occurred in the year of 2017 – since the sample ends in 2019 – and they stop being considered in the regressions. Since the number of shocks in these horizons is more scarce, results are not so significant and, therefore, we can not strictly compare estimations between h=4 and h=5. Similarly, the sample data for the regressions of 1994-2016 do not cover the 2017 events and thus the number of events that is used is lower. Consequently, we can observe in figure 5.2 that these results are less conclusive, not statistically significant and show larger uncertainty. These results indicate that, when we include the 2017 occurrences, estimates are more significant but also more negative, which reinforces the idea that the level of burnt area and number of catastrophic occurrences for this year was substantially larger, and that these events had a considerable impact on the Portuguese economic activity.

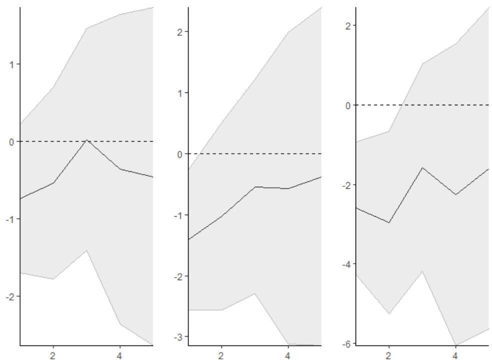
The tables from 5.1 to A.4 display the summaries of the results for the consumption of electric energy. The table 5.1 is presented below as an example, which shows statistically significant results for the period 1994-2019, with lagged values. Remaining tables are presented in the Appendix A.

Figure 5.1: Impulse response function of electric energy consumption, for 1994-2019

(a) Impulse responses of electric energy consumption for 1994-2019, with lags



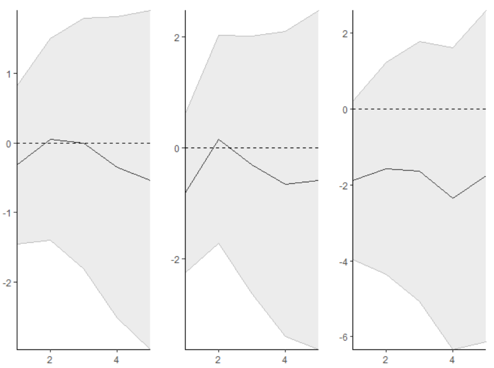
(b) Impulse responses of electric energy consumption for 1994-2019, with no lags



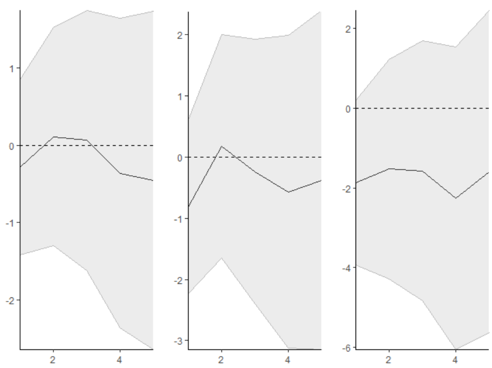
The estimations are based on equation (3.1). The dependent variable is the logarithm of electric energy consumption. Control variables are included. Confidence bands of 90%. The sample includes 247 municipalities. The figures present the estimations for the shocks of 25%, 33.3% and 50% of burnt area, respectively, from left to right. Results presented with and without lags. Lagged values included are of the explanatory and control variables, with lag length equal to 2.

Figure 5.2: Impulse response function of electric energy consumption, for 1994-2016

(a) Impulse responses of electric energy consumption for 1994-2016, with lags



(b) Impulse responses of electric energy consumption for 1994-2016, with no lags



The estimations are based on equation (3.1). The dependent variable is the logarithm of electric energy consumption. Control variables are included. Confidence bands of 90%. The sample includes 247 municipalities. The figures present the estimations for the shocks of 25%, 33.3% and 50% of burnt area, respectively, from left to right. Results presented with and without lags. Lagged values included are of the explanatory and control variables, with lag length equal to 2.

Table 5.1: Impulse response function of electric energy consumption for 1994-2019, with lags

Shock	h = 1	h = 2	h = 3	h = 4	h = 5
1. 25% of burnt area	-0.7120 (0.5811)	-0.5384 (0.7756)	-0.0030 (0.9296)	-0.3496 (1.3145)	-0.5347 (1.4786)
Observations	6149	5904	5658	5412	5166
Number of Events included	110	110	109	81	77
2. 33.3% of burnt area	-1.3842** (0.6940)	-1.0591 (0.9551)	-0.5903 (1.1283)	-0.6519 (1.6676)	-0.5813 (1.8526)
Observations	6149	5904	5658	5412	5166
Number of Events included	74	74	73	49	47
3. 50% of burnt area	-2.5506** (1.0100)	-2.9769** (1.4156)	-1.6694 (1.6525)	-2.3579 (2.4124)	-1.7668 (2.6419)
Observations	6149	5904	5658	5412	5166
Number of Events included	33	33	33	22	20

[a] The estimations are based on equation (3.1). The dependent variable is the logarithm of electric energy consumption. The period under study is 1994-2019. Control variables are included. Lagged values of the explanatory and control variables included, with lag length equal to 2. Confidence bands of 90%. Robust-clustered standard errors are in parentheses. Significance levels of 10, 5 and 1 percent are represented by *, ** and ***, respectively. The sample includes 247 municipalities.

6

Conclusions

In general, results indicate that catastrophic wildfires, responsible for large levels of burnt area, can have a negative effect on the consumption of electric energy. The impact is immediate, and increases in the following year for larger levels of burnt area. As this index can be used as an approximation for the level of economic activity, we can use these results for obtaining estimates of wildfire effects on the level of economic activity. More specifically, for levels of burnt area over 33.3%, impacts are felt in the year that the event occurs, indicating a decline of more than 1% comparing to the value previous to the shock. When the burnt area is larger – over 50% –, impacts are more severe and longer-lasting, and we can estimate that the level of economic activity of a municipality decreases 2.5% in the year that the event occurs and 3% in the year after.

Consistent with much of the existing literature, the results obtained confirm that large natural events can have significant negative impacts on the economic activity. Moreover, they indicate that economic impacts can be felt, not only immediately, but also in the year that follows the occurrence of a large event.

Several reasons can be responsible for this negative impact on the economic activity. The occurrence of catastrophic wildfires is usually associated with large magnitudes of direct damages on housing, crops and infrastructures, which demands investments in reconstruction measures. Moreover, damages can lead to insurance losses and disturb tourism and businesses activities, affecting households and the overall economic activity. The people affected – directly or indirectly – by wildfires may also need various types of assistance like housing or food supplies. This combination of expenses and business interruption that can arise when large wildfire events occur can be responsible for business interruption and large amounts of losses, impacting negatively the economic activity of a municipality. Additionally, larger events are usually responsible for larger levels of destruction and thus can have more severe impacts on the economy.

This study makes a contribution for understanding wildfire impacts in Portugal and hopefully our results can serve as a motivation for further research on wildfire economic impacts, extending this work by analysing possible wildfire impacts on other economic variables. We hope these results emphasise the need to invest in wildfire mitigation strategies, in order to prevent and mitigate possible negative impacts on the economic activity of municipalities.

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A

Appendix

Table A.1: List of shocks considered in the regressions, for 25%, 33.3% and 50% of burnt area.

25%		33.3%		50%	
Municipality	Year	Municipality	Year	Municipality	Year
Abrantes	2003	Abrantes	2003	Arganil	2017
Águeda	2016	Alfândega Da Fé	2013	Arouca	2005
Alfândega Da Fé	2013	Arganil	2017	Arouca	2016
Aljezur	2003	Arouca	2005	Batalha	2003
Arcos De Valdevez	2006	Arouca	2016	Caminha	2005
Arganil	2005	Batalha	1995	Castanheira De Pêra	2017
Arganil	2017	Batalha	2003	Castelo De Vide	2003
Arouca	2005	Caminha	2005	Chamusca	2003
Arouca	2016	Carregal Do Sal	2005	Figueiró Dos Vinhos	2005
Baião	2005	Carregal Do Sal	2017	Figueiró Dos Vinhos	2017
Batalha	1995	Castanheira De Pêra	2017	Gavião	2003
Batalha	2003	Castelo De Paiva	2017	Mação	2003
Cabeceiras De Basto	2005	Castelo De Vide	2003	Mação	2017
Caminha	2005	Chamusca	2003	Marinha Grande	2017
Carregal Do Sal	2005	Figueiró Dos Vinhos	2005	Marvão	2003
Carregal Do Sal	2017	Figueiró Dos Vinhos	2017	Mira	2017
Castanheira De Pêra	2017	Freixo De Espada À Cinta	2017	Miranda Do Corvo	2005
Castelo De Paiva	2017	Gavião	2003	Monchique	2003
Castelo De Vide	2003	Góis	2017	Nisa	2003
Castro Daire	2005	Gouveia	2017	Oleiros	2003
Castro Marim	2004	Guarda	2003	Oliveira Do Hospital	2017
Celorico Da Beira	1994	Lagos	2003	Pampilhosa Da Serra	2005
Celorico De Basto	2005	Loulé	2004	Pampilhosa Da Serra	2017
Chamusca	2003	Mação	2003	Pedrógão Grande	2017

Table A.1: List of shocks considered in the regressions, for 25%, 33.3% and 50% of burnt area.

25%		33.3%		50%	
Municipality	Year	Municipality	Year	Municipality	Year
Coimbra	2005	Mação	2017	Penafiel	2005
Constância	2003	Mangualde	2017	Proença A Nova	2003
Fafe	2005	Manteigas	2005	Santa Comba Dão	2017
Figueiró Dos Vinhos	2005	Marinha Grande	2017	Sardoal	2007
Figueiró Dos Vinhos	2017	Marvão	2003	Sertã	2003
Freixo De Espada À Cinta	2017	Mira	2017	Vila De Rei	2003
Gavião	2003	Miranda do Corvo	2005	Vila Nova De Cerveira	2005
Góis	2017	Monchique	2003	Vila Nova De Cerveira	2016
Gouveia	2017	Monchique	2018	Vouzela	2017
Guarda	2003	Nelas	2002		
Lagos	2003	Nisa	2003		
Loulé	2004	Oleiros	2003		
Lousã	2017	Oliveira do Hospital	2017		
Mação	2003	Ourém	2005		
Mação	2017	Pampilhosa Da Serra	2005		
Mangualde	2017	Pampilhosa Da Serra	2017		
Manteigas	2005	Pedrógão Grande	2017		
Marco De Canaveses	2005	Penacova	2017		
Marinha Grande	2003	Penafiel	2005		
Marinha Grande	2017	Penalva Do Castelo	2005		
Marvão	2003	Penela	2017		
Mira	2017	Portimão	2003		
Miranda Do Corvo	2005	Proença A Nova	2003		
Monchique	2003	Ribeira De Pena	2010		
Monchique	2018	Santa Comba Dão	2017		
Mortágua	2017	São Brás De Alportel	2004		
Nelas	2002	São Pedro Do Sul	2005		
Nelas	2005	Sardoal	1995		
Nelas	2017	Sardoal	2007		
Nisa	2003	Seia	2005		
Oleiros	2003	Seia	2017		
Oleiros	2017	Sertã	2003		
Oliveira do Hospital	2017	Sertã	2017		
Ourém	2003	Silves	2003		
Pampilhosa Da Serra	2005	Tábua	2017		

Table A.1: List of shocks considered in the regressions, for 25%, 33.3% and 50% of burnt area.

25%		33.3%		50%	
Municipality	Year	Municipality	Year	Municipality	Year
Pampilhosa Da Serra	2017	Tábuaco	2000		
Paredes de Coura	2006	Tavira	2012		
Paredes de Coura	2016	Tondela	2017		
Pedrógão Grande	2005	Vale De Cambra	2005		
Pedrógão Grande	2017	Viana Do Castelo	2005		
Penacova	2017	Vila De Rei	2003		
Penafiel	2005	Vila Nova Da Barquinha	2005		
Penalva do Castelo	2005	Vila Nova De Cerveira	2005		
Penela	2005	Vila Nova De Cerveira	2016		
Penela	2017	Vila Nova De Poiares	1998		
Peso Da Régua	2009	Vila Nova De Poiares	2002		
Pombal	2005	Vila Nova De Poiares	2005		
Ponte Da Barca	2002	Vila Nova De Poiares	2017		
Ponte Da Barca	2010	Vila Pouca De Aguiar	2005		
Portimão	2003	Vouzela	2017		
Porto De Mós	2006				
Proença A Nova	2003				
Resende	2005				
Ribeira De Pena	2010				
Santa Comba Dão	2017				
São Brás De Alportel	2004				
São Pedro Do Sul	2005				
Sardoal	1995				
Sardoal	2005				
Sardoal	2007				
Seia	2005				
Seia	2017				
Sertã	2003				
Sertã	2017				
Silves	2003				
Tábua	2017				
Tábuaco	2000				
Tavira	2012				
Tondela	2017				
Vale De Cambra	2005				

Table A.1: List of shocks considered in the regressions, for 25%, 33.3% and 50% of burnt area.

25%		33.3%		50%	
Municipality	Year	Municipality	Year	Municipality	Year
Valenca	2005				
Viana Do Castelo	2005				
Vila De Rei	2003				
Vila Nova Da Barquinha	2005				
Vila Nova De Cerveira	2005				
Vila Nova De Cerveira	2016				
Vila Nova De Paiva	2005				
Vila Nova De Paiva	2013				
Vila Nova De Poiares	1998				
Vila Nova De Poiares	2002				
Vila Nova De Poiares	2005				
Vila Nova De Poiares	2017				
Vila Pouca De Aguiar	2005				
Vila Real	2005				
Vila Real De Santo Antonio	2004				
Vila Velha De Ródão	2003				
Vouzela	2017				

Table A.2: Impulse response function of electric energy consumption for 1994-2019, with no lags

Shock	**h = 1**	**h = 2**	**h = 3**	**h = 4**	**h = 5**
1. 25% of burnt area	-0.7383 (0.5816)	-0.5382 (0.7517)	0.0232 (0.8701)	-0.3607 (1.2121)	-0.4558 (1.3227)
Observations	6149	5904	5658	5412	5166
Number of Events included	110	110	109	81	77
2. 33.3% of burnt area	-1.4119** (0.6943)	-1.0321 (0.9297)	-0.5428 (1.0661)	-0.5694 (1.5475)	-0.3775 (1.6775)
Observations	6150	5904	5658	5412	5166
Number of Events included	74	74	73	49	47
3. 50% of burnt area	-2.5975*** (1.0073)	-2.9593** (1.3898)	-1.5768 (1.5828)	-2.2597 (2.3005)	-1.5939 (2.4467)
Observations	6150	5904	5658	5412	5166
Number of Events included	33	33	33	22	20

[a] The estimations are based on equation (3.1). The dependent variable is the logarithm of electric energy consumption. The period under study is 1994-2019. Control variables are included. No lags included. Confidence bands of 90%. Robust-clustered standard errors are in parentheses. Significance levels of 10, 5 and 1 percent are represented by *, ** and ***, respectively. The sample includes 247 municipalities.

Table A.3: Impulse response function of electric energy consumption for 1994-2016, with lags

Shock	h = 1	h = 2	h = 3	h = 4	h = 5
1. 25% of burnt area	-0.3172 (0.6923)	0.0483 (0.8795)	-0.0085 (1.0953)	-0.3496 (1.3145)	-0.5347 (1.4786)
Observations	5412	5412	5412	5412	5166
Number of Events included	81	81	81	81	77
2. 33.3% of burnt area	-0.8157 (0.8679)	0.1492 (1.1375)	-0.3082 (1.4057)	-0.6518 (1.6676)	-0.5813 (1.8525)
Observations	5412	5412	5412	5412	5166
Number of Events included	49	49	49	49	47
3. 50% of burnt area	-1.8813 (1.2630)	-1.5736 (1.6919)	-1.6416 (2.0761)	-2.3579 (2.4124)	-1.7668 (2.6419)
Observations	5412	5412	5412	5412	5166
Number of Events included	22	22	22	22	20

[a] The estimations are based on equation (3.1). The dependent variable is the logarithm of electric energy consumption. The period under study is 1994-2016. Control variables are included. Lagged values of the explanatory and control variables included, with lag length equal to 2. Confidence bands of 90%. Robust-clustered standard errors are in parentheses. Significance levels of 10, 5 and 1 percent are represented by *, ** and ***, respectively. The sample includes 247 municipalities.

Table A.4: Impulse response function of electric energy consumption for 1994-2016, with no lags

Shock	**h = 1**	**h = 2**	**h = 3**	**h = 4**	**h = 5**
1. 25% of burnt area	-0.2855 (0.6882)	0.1078 (0.8535)	0.0626 (0.1016)	-0.3607 (1.2121)	-0.4559 (0.1323)
Observations	5412	5412	5412	5412	5166
Number of Events included	81	81	81	81	77
2. 33.3% of burnt area	-0.8157 (0.8605)	0.1751 (1.1082)	-0.2386 (1.3095)	-0.5694 (1.5476)	-0.3776 (1.6775)
Observations	5412	5412	5412	5412	5166
Number of Events included	49	49	48	49	47
3. 50% of burnt area	-1.8671 (1.2502)	-1.5318 (1.6715)	-1.5754 (1.9781)	-2.2597 (2.3005)	-1.5939 (2.4467)
Observations	5412	5412	5412	5412	5166
Number of Events included	22	22	22	22	20

[a] The estimations are based on equation (3.1). The dependent variable is the logarithm of electric energy consumption. The period under study is 1994-2016. Control variables are included. No lags included. Confidence bands of 90%. Robust-clustered standard errors are in parentheses. Significance levels of 10, 5 and 1 percent are represented by *, ** and ***, respectively. The sample includes 247 municipalities.