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The Regional Economic Impact of Wildfires

Following a Synthetic Control Approach

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Master Thesis

presented as partial requirement for obtaining the master's degree in Statistics and Information Management

NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação
Universidade Nova de Lisboa

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by

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

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STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledged the Rules of Conduct and Code of Honor from the NOVA Information Management School.

Lisbon, 12th of July 2024

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ABSTRACT

In June 2017, one of the most impactful wildfires in Portugal`s history hit the Region of Leiria. Much of the region depends on land for its economic activities. Although some studies have been developed for its short-term impact, the question that remains is to what extent this wildfire has impacted the economic activity of this region in the long run. To answer this question, we will examine the impact of this natural hazard on a frequently used proxy of GDP, energy consumption, and on employment by applying the synthetic control approach and using regional NUT III data. This method is a robust approach for causal inference since it enables the estimation of a counterfactual outcome of a treatment group (in this case, the region of Leiria affected by the wildfire) through the construction of a synthetic control group that replicates the pre-treatment trend of the treatment group. The analysis was supported by a dataset with a bundle of economic variables from the period from 2013 to 2022, which were collected from government websites. Our findings indicate the existence of an effect for both variables analyzed but not in the same magnitude.

KEYWORDS

Economic growth; Natural Disaster; Synthetic Control Method; Portugal; Wildfire

Sustainable Development Goals (SDG):

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LIST OF ABBREVIATIONS AND ACRONYMS

ACEA	European Automobile Manufacturers' Association
ATM	Automated Teller Machine
AVIPG	Associação de Vítimas do Incêndio de Pedrógão Grande
DP	Donor Pool
EFFIS	European Forest Fire Information System
EU	European Union
GDP	Gross Domestic Product
IC	Industry Consumption
INCF	Instituto da Conservação da Natureza e das Florestas
INE	Instituto Nacional de Estatística
LOO	Leave-one-Out
MV	Missing Values
NUT	Nomenclatura de Unidade Territorial
PC	Passenger Car
RMPSE	Root Mean Squared Prediction Error
SCM	Synthetic Control Method

1. INTRODUCTION

1.1 RESEARCH PROBLEM

Wildfires are a natural phenomenon in many forest ecosystems globally, which heavily impact the socio-economic state of the regions affected. As stated by the Word Bank (Word Bank, 2024), Europe is warming faster than any other continent, having experienced, in recent decades overwhelming losses and destruction due to climate-related disasters. Portugal is no exception to this phenomenon, and in 2023 Portugal`s fires had a total cost of 377.2 million euros (World Bank, 2024).

The impact on the growth and development of the regions impacted by these disasters is felt across various sectors and economic markets. The consequences depend not only on the magnitude of the fire but also on the measures put in place in the region and on the level of agility of police implementation in response to these events.

There are several direct challenges in the aftermath of a wildfire, which include revenue losses and increased spending demand. The indirect costs are more uncertain since they depend on the factors referred previously and may include macroeconomic impacts such as an increase of unemployment and production inefficiency (Koetsier, 2017).

1.2 RESEARCH GOALS

This study aims to investigate the extension of the impact of the 2017s Wildfire shock in the economy of a Portuguese region on established outcomes in the years that followed the event (2018-2022). With this objective in mind, a synthetic control will be created to mimic the region of Leiria if the situation where the fire did not happen and then compare it with the actual scenario.

1.3 STUDY`S RELEVANCE

There is a lack of theoretical exploration regarding the effect of wildfires on important economic indicators in the medium to long term. Additionally implementing effective investment strategies that prepare countries for climate hazards can be challenging since the changes needed are vast and difficult to estimate. This study contributes to this since it will analyze the longer-term impact of a catastrophic fire to understand where the problem is before trying to implement measures to tackle it.

1.4 STRUCTURE

The structure of this dissertation comprises six chapters: Introduction, Literature Review, Methodology, Empirical Approach, Results, and Conclusion.

The second chapter is about the literature review that sustains this thesis, namely key concepts of natural hazards and how they can affect the economy of a country and a review of the synthetic control method and its potential to study this phenomenon. The third chapter delves into the methodology with more detail, including the assumptions and data requirements that should be followed, and the tests used to determine the validity of the model presented. Subsequently, it also presents the data description and management. Chapter four presents the finding and a discussion. Finally, chapter five presents the contributions and limitations of the study and potential future research.

2. LITERATURE REVIEW

2.1 NATURAL DISASTERS AND THE ECONOMY

Natural hazards such as floods, hurricanes, earthquakes, and tsunamis are extreme natural phenomena that create destruction and pose a threat to human life, property, and the environment. They represent a specific type of macroeconomic risk since they impact economic growth in a nonlinear manner, having significant implications on various sectors of the global economy (Krebs, 2003).

A substantial body of literature studied the immediate and direct socioeconomic impact of natural hazards, with the traditional hypothesis that these events are destructive shocks that comprise multiple factors, including hazard suppression expenses, property damage, and physical infrastructure destruction, which result in an immediate reduction of production and consumption. However, the economic impacts of natural disasters extend beyond the immediate aftermath having long-term effects on economic growth and development, exposing the population to increased social vulnerability. (Felbermayr et al., 2014). While the immediate economic impacts of hazards are well-documented, there is a need for more theoretical exploration of their long-term effects on important economic indicators such as GDP.

Following a disaster, substantial aid flows often materialize. This financial support is generally short-term and funded by external sources rather than local tax revenues. As a result, in the short term, there is an artificially favorable effect on economic output, which may offset its negative consequences, but in the long run the effects are more uncertain. The resource distribution from the consequent response and recovery can reduce investments in other sectors, hindering overall economic progress. The loss of productive assets and the displacement of populations can have lasting effects on communities, leading to social and economic inequalities (Hilhorst, 2014). As the frequency of such incidents escalates, natural disasters will raise the global reported direct losses from today`s $195 billion annually to $234 billion annually by 2040 (Barattieri et al., 2023).

It is crucial to understand that the magnitude of a disaster's economic repercussions on a community is heavily influenced by its pre-disaster economic situation. Areas with stronger socio-economic foundations will incur lesser economic damages when disasters strike (Songwathana, 2018). Diego et al. (2021) agree that efforts should be made to prevent and anticipate forest fires rather than focusing primarily on suppression actions, as is often the case. This observation highlights the role of socio-economic robustness in tackling the detrimental impacts of disasters, pointing to the importance of improving the region`s resilience as a critical component of disaster risk management and recovery planning.

Besides having an impact on the overall economic and social health of regions, disasters still manage to leave a mark on a smaller scope. Deryugina (2022) suggests that natural disasters can influence the equilibrium of the labor market via various pathways, with tourism being one of these channels. When a disaster occurs, that region might lose attractiveness due to its association with that event. In 2022, the GDP contribution of the Travel & Tourism sector expanded by 61.6%, amounting to almost €38 billion, which accounted for 15.8% of Portugal's economy (World Travel & Tourism Council, 2023), which increases Portugal's region`s propensity to be hurt.

While the immediate consequences of disasters on the economy are perceived as detrimental, some studies based on Schumpeter`s creative destruction defend that the process of reconstruction triggers innovation, since these shocks create investment opportunities to update the capital stock and adopt new technologies (Sehgal et al., 2021), which results in long-run economic growth. This investment in infrastructure and equipment development will also contribute to economic resilience (Bringas et al., 2022), reducing the chance of future wildfire occurrence. External events can disrupt the process of knowledge accumulation and are crucial for the creation of "transformative movements" (Mendonça et al., 2022). This duality in natural disaster effects is presented by Barone et al. (2014) who conducted a study on the impact of two earthquakes in Italy, presenting a short-term negative effect on GDP growth. Yet, for one of the earthquakes, they observed a beneficial effect in the long term.

All in all, although the available studies regarding the economic impact of natural disasters find predominantly negative effects, the literature is still scant and inconclusive. The effects vary across multiple factors, including the severity, nature of the disaster, and the country where it occurs (Fomby et al., 2013).

2.2 WILDFIRES AS GOOD AND EVIL

Wildfires are unplanned fires burning in natural or agricultural areas and vegetation, such as those started by lightning, intrusive human activity, and errant controlled fire activities (Hoover et al., 2021). The European Forest Fire Information System (EFFIS) estimated that in 2022, wildfires in the EU burned 900 000 ha of land. This makes that year the second worst in the wildfire domain since EFFIS started motorizing in 2000.

Meier et al., 2023 assessed the effects of wildfires on employment, income, and economic growth and concluded that wildfires take a toll on regional economies with job losses, reduced income, and slower economic growth. The findings indicate a persistent negative immediate impact of wildfires on the annual regional GDP growth rate in Southern Europe. The study also emphasized the importance of implementing preventive measures and investing in fire management to minimize these impacts. This viewpoint is pointed out by Baylis et al. (2019), who argue that wildfires represent a unique hazard that can see reduced property damage through preemptive investments in workforce and equipment. By studying the impacts that previous fires had in the past, we can better understand how these phenomena work and the threats that they pose.

Furthermore, McCaffrey (2004) emphasizes that wildfires possess characteristics that distinguish them from other natural disasters regarding their economic impacts. For instance, wildfires can have positive effects on ecosystems in specific contexts which contributes to the uncertainty related to the impact of this hazard in the economy of regions.

2.3 WILDFIRES IN PORTUGAL

From the mid-1960s onward, the nations of Southern Europe had socio-economic shifts with the relocating of the population from rural villages to urban cities, which resulted in the successive neglect of territories and cultivated lands. These factors, combined with extended spans of drought and escalating temperatures (Beighley et al., 2018), coupled with ineffective planning and administration, have given rise to an escalation in rural fires, and Portugal is no exception to these phenomena. In fact, the shifts in climate patterns and community restructuring are the key factors in explaining the rising socioeconomic losses in Portugal (Oliveira et al., 2017).

Moreover, Portugal was the European country with the highest density of rural fires, both in terms of ignitions and burnt area, until 2019 (San-Miguel-Ayanz et al., 2019). Figure 2.3 illustrates the evolution of the number of forest fires in Portugal and the respective type of fire occurrence between 2001 and 2022, and we can verify that 2017 was the year with the highest area burned in the 21st Century.

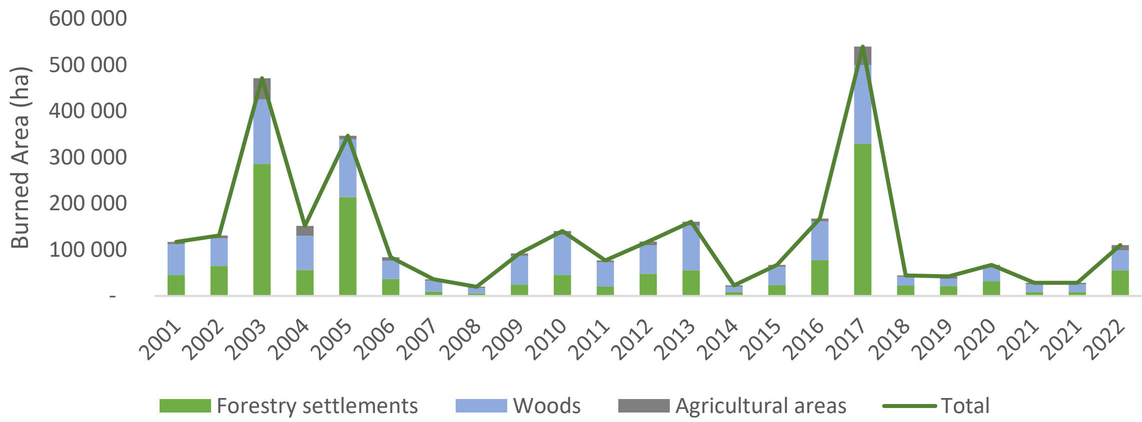

Figure 1 - Evolution of burned area in Portugal from 2001 to 2022 (INCF, 2022)

In Figure 2 presented below, we can observe that some regions in the interior of Portugal, including the region of Leiria, are the ones with the most burned area in 2022, and consequently, the districts most affected by fires.

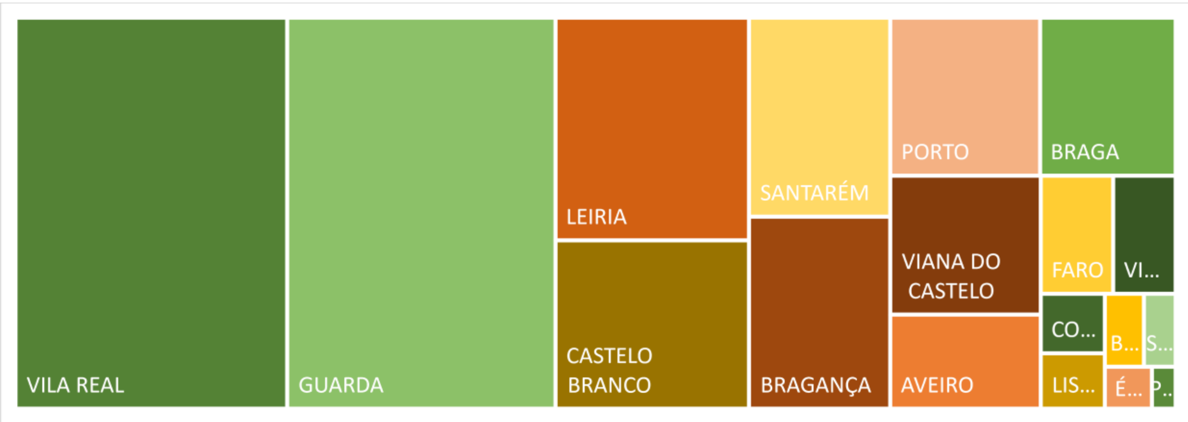

Figure 2 – Total Area burned by district in 2022 (INCF, 2022)

When talking about Portugal´s propensity to wildfires, it is also important to note that each fire results in the loss of raw materials essential to the national wood and derived products industry or paper pulp sector and a direct income loss for the affected property owners. The Portuguese Statistics Institute (INE) stated that the combined value of Forestry Production and Exploitation is estimated at around 1.3 billion euros, supporting about 100 thousand direct jobs. This shows the vast indirect impact that a fire might have on the Portuguese economy.

2.4 Initial Effects

Most fires occur in forests, away from where the population lives and works. The recent large wildfires have escalated into populated areas: for example, on 16 June 2017, Pedrogão Grande was hit by the most dramatic and destructive wildfire in Portugal`s history. According to ICNF, more than 45,000 ha (81% of the region) were burdened, which resulted in 64 deaths and a total direct cost of 951 559 €. These extreme impacts happen for various reasons, including poor preparation and initial response, inadequate risk perception and robust and variable winds (Tedim et al., 2018). In Figure 3, we can see how extensive this fire was, affecting the regions of Pedrogão Grande, Castanheira de Pera, Figueiró dos Vinhos, Góis, Pampilhosa da Serra, Penela e Sertã.

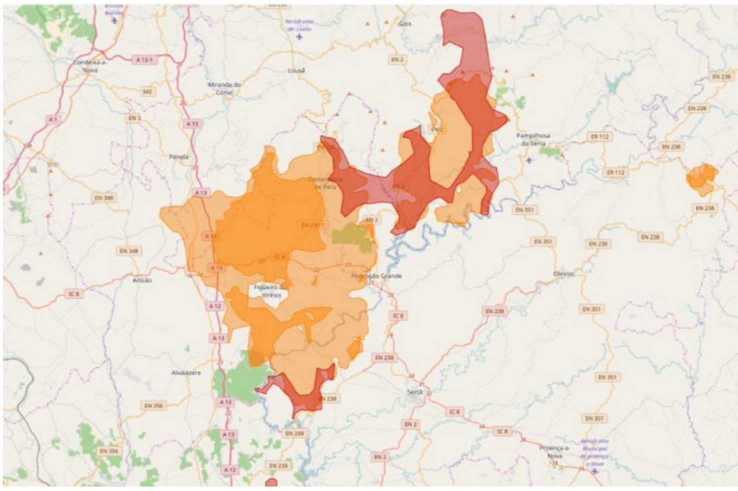

Figure 3 - Área ardida (Sistema Europeu de Informação de Fogos Florestais, 2017)

As seen in Figure 4, wildfires were nothing new to Pedrogão, but it was evident that the severity of damages associated with the 2017 fire as unprecedented. Yet, these immediate impacts do not fully encapsulate the future indirect economic consequences caused by the fire. This study seeks to outline those extended indirect economic effects.

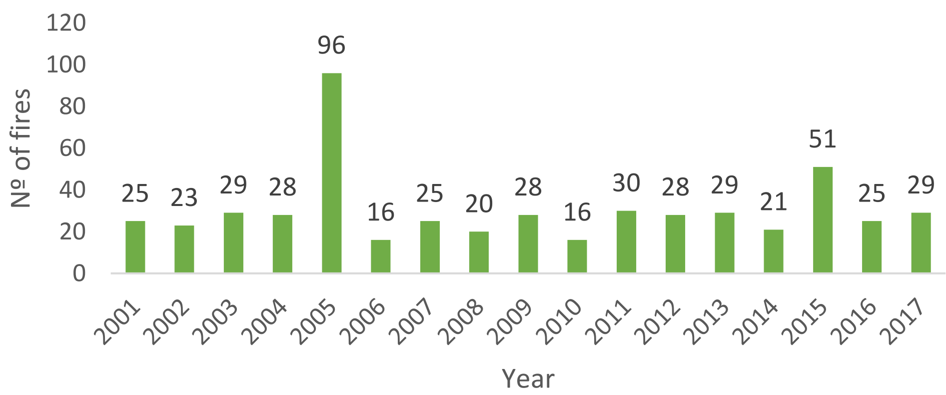

Figure 4 - Nº of fires in Pedrogão grande by year (2001-1017)

2.5 Applying the Synthetic Control Model to study the impact of a shock

Pointing the causal impact of natural disasters on economic growth poses a challenge since most analyses were written shortly after the event and so were only reporting its short-term impact. In those cases, the estimation of long run impacts is unable to separate the real impact of the disaster from other trends and shocks that would have taken place anyway. For example, Vigdor (2008) studied Katrina's impact on New Orleans and highlighted the substantial population decline. However, it is difficult to distinguish these declines from a broader, pre-existing downward trend in the area`s population. To tackle this issue, we propose the Synthetic Control Method (SCM) proposed by Abadie and Gardeazabal (2003), one of the most widely used quasi-experimental statistical tools to measure the impact of a shock on particular outcomes of interest (Ben-Michael et al., 2021).

Comparative case studies of this type rely on the principle that the impact of an intervention can be deduced by contrasting the development of the outcome variables of interest between the unit subjected to the intervention and a collection of units akin to the treated unit but not impacted by the intervention. The distinction from traditional designs lies in the Synthetic Control Method (SCM) since it is a data-driven approach that offers a systematic method for creating a comparison group that closely resembles the group experiencing the shock. More specifically, the goal is to find a "match" for a time series of an outcome of interest before that event from a combination of multiple untreated units that possess the most resemblance to the treated unit.

Cavallo et al (2013) paid attention to the short and long-term effects of natural disasters on the trajectory of per capita income and used this method to investigate the impact. The authors create a measure of exposure to natural disasters based on information regarding the damages caused by the impact and proceed with estimations for different countries based on the intensity of this measure.

Besides the previous study, this methodology has been applied to various problems, such as assessing the impact of carbon taxes in reducing CO_2 (Carattini et al., 2019) analyzing the influence of tobacco control policies on smoking prevalence (Bernal et al., 2017) and examining the economic impact of major sports events, such as the Olympics and the FIFA World Cup, on host cities and countries (Larkin, Pierce, and Gennaro,2016).

We can conclude that this method is a powerful statistical tool for causal inference in comparative case studies, especially when dealing with observational data. Despite its advantages, SCM has some limitations, acknowledged by Abadie (2021) himself, that should be considered. The effectiveness of the Synthetic Control Method (SCM) is significantly influenced by the choice of suitable predictor variables for constructing the synthetic control. Should these variables fail to encompass all elements affecting the outcome of the treated unit, the synthetic control might not accurately reflect the counterfactual situation.

Furthermore, the synthetic control method may face challenges when the treatment effect varies significantly among different subgroups within the population. This heterogeneity in treatment effects can complicate the method's ability to accurately capture and represent the overall impact of the intervention.

3. MATERIALS AND METHODS

In this study the main objective will be to answer the question: what would have happened to the path of the industry electricity consumption of the affected region in the absence of the Wildfire and assess the disaster's impact by contrasting the counterfactual to the observed real path.

3.1 THE SYNTHETIC CONTROL METHOD

We will now give a more formal description of the synthetic control method, developed by Abadie et al. (2010), used to study the impact of this wildfire on the regional economy. Take a sample comprising $J + 1$ regions over T time periods, where J = 1 is a treated unit that experiences a shock at time T_0, while the remaining sample is the donor pool. The SCM tries to estimate the impact of the shock on outcome variable Y for this unit at time t:

Let,

$$\tau_{1t} = Y_{1t}^{I} - Y_{1t}^{N}, \tag{1}$$

where Y_{1t}^{I} is the outcome observed at time t and Y_{1t}^{N} the outcome should the shock have not occurred.

Since Y_{1t}^{N}, i.e., what would have happened to the outcome of unit j=1 if it had not been treated, is not directly available in the data for $t \geq T_0$, the SCA method estimates Y_{1t}^{N} using a weighted average of the outcomes of alternative unaffected units in the donor pool as follows:

$$\hat{Y}_{1t}^{N} = \sum_{j=2}^{J+1} w_j Y_{jt}, \tag{2}$$

Given a set of weights, W, the synthetic control estimates $\hat{\tau}_{1t}$ (instead of τ_{1t}):

$$\hat{\tau}_{1t} = Y_{1t}^{I} - \sum_{j=2}^{J+1} w_j Y_{jt}, \tag{3}$$

To avoid extrapolation SCM establish the weights, $W = (w_2, \ldots, w_{J+1})$ to be non-negative and add up to one with $w_j \in [0,1]$. Each element of W represents the weight assigned to unit i in the calculation of the synthetic unit, serving as our potential controls.

With this, there is a need of explaining how the weights are estimated, i.e, the synthetic control estimation, that is done using the following steps:

Given that $w_2, \ldots, w_j$ is chosen so that the resulting control best resembles the characteristics of the affected unit prior to the interventions. With this we know that $w^* = \{w_2^*, \ldots, w_j^*\}$ will minimize:

$$\sum_{i=1}^{k} v_i \left(X_{i1} - \sum_{j=2}^{J} w_j X_{1j}\right)^2, \tag{4}$$

where $v_1, \ldots, v_k$ represents the relative importance of the SC reproducing the values of the unit characteristics that are introduced in the model to calibrate weights. Looking at the expression above we can verify that the only challenge remaining is choosing the values for $v_1, \ldots, v_k$ that in this case are going to be the ones that produce the best fit in terms of how close the synthetic control describes the outcome variable. With this, the mean squared prediction error (MSPE) of the synthetic control regarding Y_{1t}^I is minimized over the pre-intervention period. This process is going to be possible using the Synth R package.

The parameters for this study are summarized in Table 1 below:

Table 1 – Synthetic Control parameters

SCM Parameters	**This study**
Target Variable	Industry energy Consumption Unemployment
Treatment Unit	Região de Leiria
Donor Pool	NUT III
Treatment Period	2017
Pre-intervention Period	2011-2016
Post-intervention Period	2018-2022

3.2 ASSUMPTIONS & SELECTION OF THE DONOR POOL

The synthetic control method offers the advantage of a data-driven selection of a comparison group, as highlighted by Abadie et al. (2021). However, it is crucial to note that the selection on regions in the donor pool is not arbitrary. A careful selection ensures that the synthetic control model is built on a foundation that appropriately represents the counterfactual scenario, enhancing the reliability and validity of the treatment effect estimation.

To achieve this, certain assumptions proposed by Abadie et al. (2021) must be met for the reliable application of the synthetic control method. Firstly, it is crucial to ensure that the treated state is the only one impacted by wildfires of significant magnitude during the observed period in the donor pool. To ensure this condition, we have excluded regions from the donor pool that underwent large wildfires (> or = % of magnitude per NUT III land area as 2017s fire) within a 5-year window, which could introduce bias into the estimated effect.

As highlighted by Abadie et al. (2014), the potential comparison units should not have experienced any exogenous shocks. This concern is related to the no-interference assumption (Angrist and Pischke, 2009), which states that there is potential violation if the fire affects the target variable of regions other than the treated one. Notably, bordering regions might be positively impacted (e.g., benefiting from reconstruction efforts) or negatively affected (e.g., geographically close firms that were either suppliers or clients of the firms damaged by the fire). To address this issue, we have excluded the Region of Coimbra since it was also affected, on a much smaller scale, by the fire. Omitting neighboring regions from the analysis minimizes spillover effects that might skew the accuracy of the results. This precaution ensures that the observed treatment effect remains valid and unbiased, avoiding potential overestimation or underestimation that could arise from unaccounted spillover influences.

Additionally, we eliminated AML and AMP from our analysis due to their distinct access to preventive measures, capital availability, and labor market conditions, which makes them unlikely to be suitable comparison units.

The regions that did not have values for a variable for all pretreatment years under analysis were removed. This way, it is ensured that the model is implemented correctly, and the research is focused only on relevant data points and avoids unnecessary noise.

3.3 Data Requirements

To achieve a successful implementation, the SCM requires specific data characteristics. Firstly, it is essential to gather adequate data on the characteristics of both treated and untreated units before the intervention. These characteristics can include economic indicators, demographic profiles, policy environments, and any other variables relevant to the study. The accuracy of the synthetic control heavily depends on the selection and availability of these pre-intervention variables.

In what concerns the temporal information of the model there are no strict requirements for the number of data points needed for the pre and pos intervention period. The method can be applied with only one pre-intervention time point, but some periods before the intervention are necessary to accurately capture the trends and variability in the data. This means that the consistency of the synthetic control estimator will be greater the larger the number of pre-treatment periods present in the dataset (Abadie, Diamond, Hainmueller, 2010). Finally, the data used for both treated and untreated units should be reliable, consistent, and free from major errors or biases. Inconsistencies or inaccuracies in data collection can significantly affect the validity of the SCM results.

3.3.1 Goodness of fit and Casual Inference

Additionally, the quality of the SC is determined by how closely the weighted synthetic outcomes match the outcomes for the treated units à priori of the treatment. Abadie et el. (2010) propose a cross-validation approach. Specifically, using the Ratio Mean Squared Prediction Error defined as:

$$RMSPE = \sqrt{\frac{1}{T_P}\sum_{t=1}^{Tp}\left(Y_{1t} - \sum_{j=2}^{J+1} w_j * Y_{jt}\right)^2} \tag{5}$$

If the synthetic control is a credible counterfactual, we expect that after the MSPE minimization end year, and before the treatment, the treated and control regions would exhibit similar evolution patterns. Also, the minimization of the post-treatment RMSPE for placebos is essential to ensure that the disparity in outcomes during treated episodes is predominantly attributed to the treatment itself.

This approach minimizes the variability in estimation and allows us to deduce that the observed treatment effect is better that what could be attributed to random chance. Nevertheless, there is no established convention for determining a "sufficiently good" RMSPE cut-off for a synthetic control since it depends on the magnitude of the variable being studies. But we know that the RMSPE can be viewed as a percentage difference (due to the logarithmic nature of the dependent variable). Therefore, if the pre-RMSPE is 0.10 or less, the average absolute difference between actual and synthetic unit costs is less than 10% during the pre-program period.

3.3.2 Placebo test: In space placebo

This test is employed to study the credibility of estimates by accessing if there would be no treatment effect (null hypothesis) and how frequently would we randomly generate an ATE (Average Treatment Effect) estimate of a substantial size. We cannot conclude the presence of a large effect in the post-intervention period if that difference is also present in the pre-intervention period.

For us to trust a determined model, the control units mustn`t have a much larger pretreatment MSPE compared to the treated unit. So, the significance of the treatment effect of the model is validated by comparing the ratio between the MSPE. If the post/pre MSPE ratio for the treated unit is large, then the treatment effects are significant.

Doing this involves assigning a placebo treatment to each donor country and calculating the difference between the post-intervention trend of each donor country and its synthetic control. In this case, the smaller the difference, the stronger the robustness. To evaluate this in an easier way the p-value of obtaining a post/pre-MSPE ratio is defined as follows:

$$p - value \ = \frac{1}{N+1} \sum_{i=1}^{N+1} \left(\frac{MSPE_{i,\text{ post}}}{MSPE_{i,\text{ pre}}} \geq \frac{MSPE_{1,\text{ post}}}{MSPE_{1,\text{ pre}}} \right) \tag{6}$$

Abadie et al. (2010) and Abadie et al. (2015) defend that the p-value for the placebo test presented is "the probability of obtaining an estimate at least as large as the one obtained for the unit representing the case of interest when the intervention is reassigned at random in the data set". For this method, the treatment effect is computed using the treatment unit and then the same process is done to several of the control units (which remained untreated). The expected outcome for this test is that the "treatment effect" would hover around zero.

3.3.3 ROBUSTNESS TEST: LEAVE-ONE-OUT

Abadie (2020) illustrates this robustness test by systematically removing each country from the donor pool, one at a time, and performing the analysis of each scenario. What we need to ensure is that all "leave-one-out" estimates closely track the variable of interest chosen before the intervention. This process will enforce sparsity within the underlying control groups. Following this procedure, if we obtain the same behavior for the estimates of this study, we can be more confident in our model.

3.4 DATA

The panel data used for the following analysis was taken from the INE website, and it covers all NUT III across Portugal`s mainland from 2013 to 2022. Our outcome of interest is the energy consumption of the industry sector in Kilowatts and the number of people Unemployment.

Since we want to construct a synthetic control with units that did not experience the shock, we have selected for analysis only the regions that did not suffer from significant fire events in the years of analysis. To do this selection, we used a dataset from INE with the respective burned area of each NUT III by land area percentage from 2013 to 2022.

The period considered in the analysis spans from 2017 (the year of the fire) to 2022 (the last year with information available). The period from 2013-2016 is used as a pre-treatment phase, serving the analysis by helping to find counterfactuals capable of representing the trajectory of the region of Pedrogão Grande without the fire happening. Recall that the synthetic Region of Leiria is constructed as a weighted average of potential control NUT III in the donor pool. The final dataset used to conduct the regressions has a total of 18 different NUT III.

Table 2 – Descriptive statistics for the dependent and predictor variables

Variables	Obs.	Average	Min	Max	Std. Deviation
Industry Energy Consumption (Kwh)	180	500 M	39 M	2020 M	446 M
Unemployment (Thousands)	162	102.74	33.55	203.34	54.58
Domestic Energy Consumption (Kwh)	180	290 M	98 M	532 M	138 M
Land Area (Km^2)	180	3964.94	1245.79	8542.72	2126.37
ATM Payments (Nº)	180	11.68	7.1	16.7	2.05
Regional Expenses (€)	157	194907.3	84 086	339 281	56814.22
PIB Per Capita (€)	180	83.84	14.98	143.1	14.98
Vehicles sold (Nº)	162	3165.20	450	9400	2096.67
Population Density (Nº/ Km2)	180	100.21	13.5	339.8	99.67

3.4.1 EXPLANATORY VARIABLES

- **Electricity consumption and economic activity**

To evaluate the long-term economic consequences of the wildfire, our analysis centered on the impact this event had on the overall economic activity. Specifically, we will analyze the event's influence on Pedrogão's annual electric energy consumption, which serves as a reliable measure of economic activity levels. This approach follows the one implemented by Miguel St. Aubyn (2020) to study the impact of the Covid-19 pandemic on Portuguese economic activity. Given the higher frequency of actualized regional electricity consumption data compared to other variables, it makes sense to leverage this existing instrument to gain a more comprehensive understanding of the wildfire's impact on the region's economic dynamics.

Energy has a crucial role in economic production, permeating all aspects of social production and consumption (Lu et al., 2024), thereby having a significant impact on economic growth for all economies. The correlation between Energy and economic growth has always been a main subject of research, and numerous findings as the one by Lu et al. (2024) support the idea that the electricity consumption indices from the industrial sector have a positive correlation with GDP and should be used to monitor economic performance. Narayan and Prasad (2008) analyzed 30 OECD countries using bootstrap testing and the result is in light with the theory of a strong effect of electricity consumption on GDP in several countries such as Italy, the Czech Republic, the UK, and Portugal. Hassan et al. (2022) examined the role of electricity consumption in achieving sustainable economic growth in Portugal, France, and Finland by capturing the effects of structural breaks in the series. The findings revealed that both long- and short-run effects of electricity on growth in Portugal and Finland are positive and significant.

Considering the numerous studies that examine the relationship between energy consumption and economic development, we propose to use regional energy consumption as a proxy for economic activity.

- **Employment and economic activity**

Employment is the backbone of a thriving economy, providing opportunities worldwide. They act as the driving force behind economic expansion and progress.

The damage to properties and infrastructures resulting from wildfires disturbs business activities but the process of rebuilding may increase local economic activity (Walls et al., 2023). With this notion, this variable may show us that if we had a more significant presence of creative destruction or build-back together scenarios, two conceptions previously explained.

3.4.2 PREDICTOR VARIABLES

- **Land size (Km^2):** this dimension directly impacts the production, distribution, and consumption capabilities of any region. Smaller regions may have fewer natural resources and space for physical infrastructures which contributes to economic diversification. Moreover, rural abandonment associated with decreasing population density and an aging population is the primary factor (Diego et al., 2021) of forest fires. Consequently, many authors have used this variable to analyze the economic effects of forest fires across multiple sectors, including Cavallo et al. (2013), Otrachshenko & Nunes (2021), and Sousa (2021).

- **Population density (Nº/ Km^2):** with this variable we can capture the demographic characteristics of the affected area, which are essential factors in understanding the economic repercussions of a wildfire. In a study by Rahman (2020) the importance of considering population density, along with other variables, in analyzing the effects on energy consumption and environmental quality, highlights its relevance of as an important factor in understanding broader economic interactions.

- **Motor vehicle registrations (Nº):** This variable, which includes passenger cars and commercial vehicles is proven to reflect economic growth trends. The graph below shows this phenomenon from 2008 to 2021, with both lines for the yearly growth in vehicle registrations and GDP growth following the same path for this period.

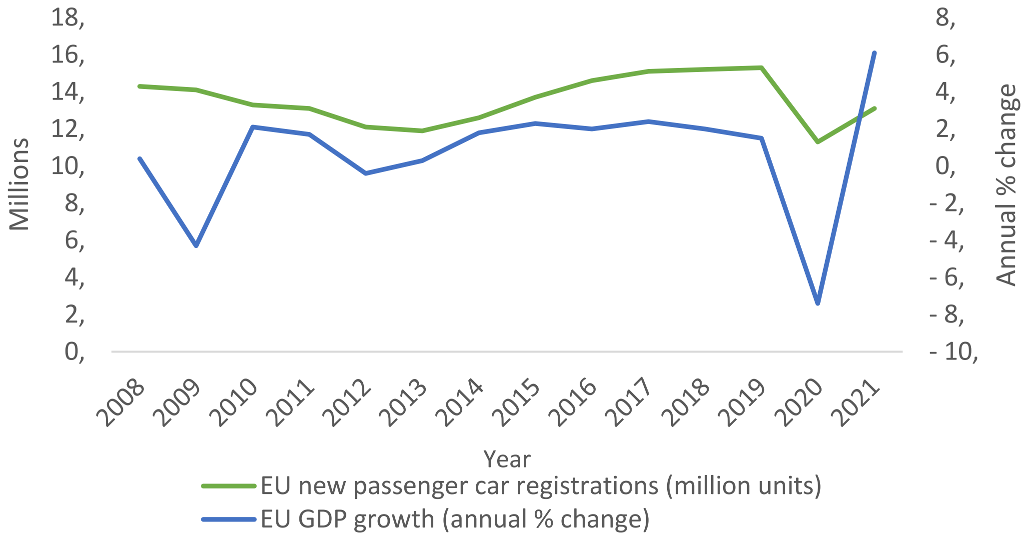

Figure 5 - Evolution of PC Registrations and DGP growth. Source: ACEA

- **Exports (€):** Increasing exports generate foreign exchange, create jobs, encourage specialization, and diversify the economy. Dritsakis et al. (2016) examined the relationship between trade openness and growth for the 30 newest EU Members using annual data from 1995 to 2013. The study found that the export sector encourages economic activity, both in the short and long-run.

- **Public expenditure (€):** Achieving a continuous and fair economic expansion is the primary goal of public spending policy (IMF, 1995). The allocation of funds for essential services such as education, healthcare, infrastructure, and public safety, plays a crucial role in shaping economic activity. Researchers have discovered mixed findings in what are the effects of this variable on economic growth, but all agree that public spending has an association with economic growth.

- **GDP per capita:** represents the total value of all goods and services produced within a region`s borders. It serves as a fundamental indicator for assessing the economic performance of that region and comparing it to other economies. It measures economic activity or income per person and is one of the core indicators of economic performance (OECD, 2015).

- **Electronic payments (Nº ATMs):** this variable represents the use of cash in circulation. It can indicate the economy's liquidity and level of economic activity. An increase in electronic payments boosts consumption and economic activity (Zandi, 2013). The level of utilization and adoption of this payment method reflects the state development of the economy of the region which will contribute to a sustainable economic activity.

4. RESULTS

We now transition to the results chapter, where the empirical insights garnered from the analysis are brought to the forefront. This chapter stands as a cornerstone, detailing the outcomes of applying the SCM to assess the economic influence of this wildfire and evaluating its effects on the industry energy consumption. In this section, additional analysis will be conducted to inspect the impact of this event on employment, which is also proved to be related to economic activity but might be differently affected by the treatment.

4.1 Main Findings

The goal of this procedure is to find the approximate trajectory of the indicator of interest that the treated unit would likely have followed if it had not been subject to the wildfire. This is achieved by calculating a weighted average of the untreated units, with the weights minimizing the distance from the behavior of the treated unit in the pre-treatment period. Then, the trajectory of the synthetic control is projected into the post-treatment period. Figure 6, called the Path plot, illustrates this procedure, and allows us to compare the real Energy Consumption evolution between the region of Leiria ("Treatment") and its synthetic version. The difference between the trajectories may be the effect of the intervention, in this case, the 2017s wildfire.

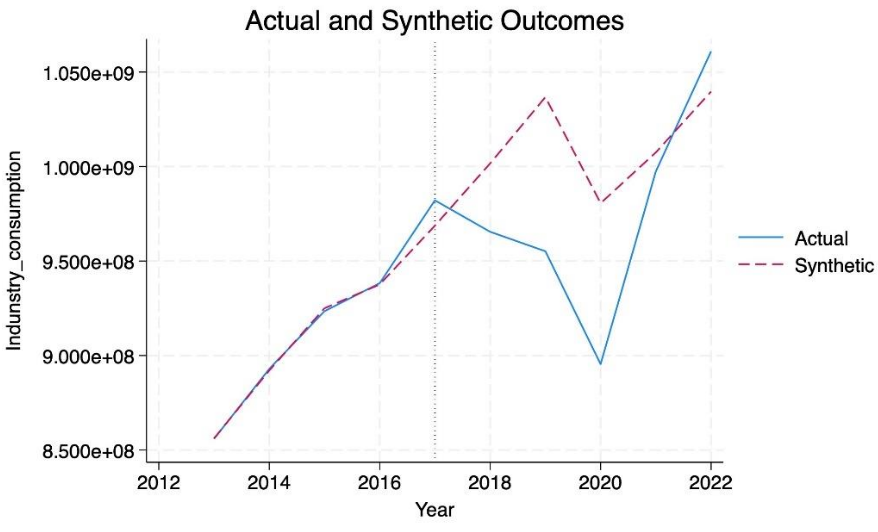

Figure 6 – Time series for real Energy Consumption of the Region of Leiria and its synthetic economy

As can be seen the fit of the model seems good, the synthetic variable follows the same behavior as the real version until 2017. After that period, we can observe a substantial different behavior between the two lines. Although the result seems reasonable, we should consider that this change of path can result from other idiosyncratic events that are not considered in this model.

Table 3 compares the weights computed by the synthetic control method using the nested optimization process in STATA. This combination of optimal weights is the one chosen by our model to minimize the pre-referendum differences between the region of Leiria and its artificial “twin”.

Table 3 – Predictor Weights for SCM (Industry consumption)

Predictor	V.Weight
Population density	0.28
Vehicle Sold	0.25
PIB per Capita	0.24
Region Expenses	0.12
Exports	0.11

With the previous results we can evaluate how well the model is replicating the pretreatment characteristics of the treated unit. Our Synthetic control achieves a great covariate balance such that the largest covariate difference in percentage in absolute value between actual and synthetic Leiria Region is only 1.20% for GDP per capita.

The optimal unit weights such that the resulting synthetic control minimizes the RMSPE over the validation period are represented in table 4 below. The weights chosen, reveal that the synthetic control for Leiria Region consists of a combination of Oeste, Alentejo Litoral, Região de Aveiro and Cávado, while all remaining control units receive a weight of 0.

Table 4 – Units Weights for SCM (Industry consumption)

Unit	U.Weight
Região de Aveiro	0.432
Alentejo Litoral	0.207
Cávado	0.137
Oeste	0.117
Beira Baixa	0.107

The same procedure was performed on Figure 7, this time regarding unemployment with a similar conclusion being attained. From 2017 onwards, even do the effect is smaller, we can conclude that the wildfire seems to have an impact on the number of people unemployed.

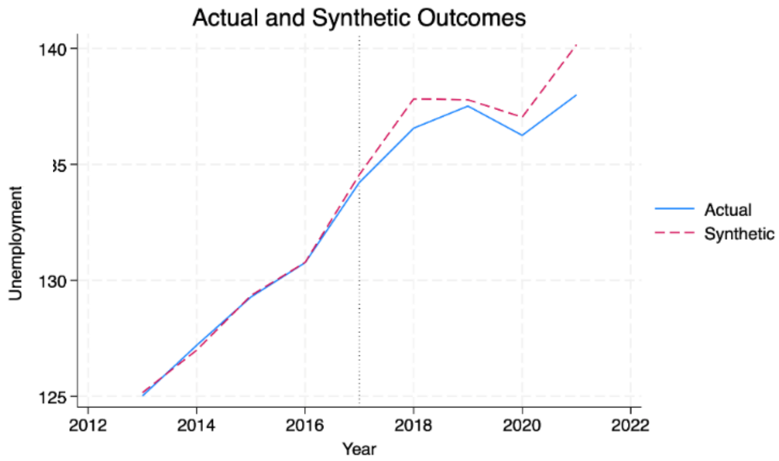

Figure 7 – Nº (thousands) of people unemployed in the Region of Leiria and its synthetic

In this case, the effect presented is relatively weaker when compared to the previous one, but we can still observe an impact. Although this disaster destroyed 48 companies (AVIPG, 2020), the number of people getting unemployment was smaller. This might be caused by the fact that there was the need for a higher workforce in particular segments to recover the damages in the region.

For extension purposes, Table 5 and 6 also show the weight attributed to each variable and NUT III for creating of the synthetic model for the unemployment variable. Again, the weights were chosen to minimize the pre-treatment difference between the actual and synthetic regions of Leiria.

Table 5 – Predictor Weights for SCM (Unemployment)

Predictor	**V.Weight**
Domestic Consumption	0.50
Region Expenses	0.45
ATM Payments/1000 hab	0.04
Population Density	0.005
PIB per capita	0.005

Table 6 – Units Weights for SCM (Unemployment)

Unit	**U.Weight**
Região de Aveiro	0.468
Beira Baixa	0.206
Cávado	0.127
Alentejo Litoral	0.104
Oeste	0.095

4.2. PLACEBO AND ROBUSTNESS CHECKS

This section aims to assess the quality assurance of our analyses and to identify if there were factors that influenced the response of the method under study. With this, we ensure that the data-generating processes were accurately implemented.

Firstly, our models show an excellent pretreatment fit, where both R^2 reach approximately 0.97 which means, in this case, that approximately 97% of the variance in the outcome variable is explained by the predictor variables in the model.

The RMSE of the model is 9.32 for the Energy consumption and 0.13 for the Unemployment Model. Considering the magnitude of the 1st variable that has values between 242-2914 Million Kwh we can conclude that an RMSE of 9.32 also it indicates the presence of accuracy in our model in making predictions of the target variable.

4.2.1 PLACEBO TEST

The next step to evaluate our model is to perform placebo tests. For this study we used both forms of placebo tests, in which the conventional statistical inference for the SCM relies, the in-space placebo test (Abadie, Diamond, and Hainmueller 2010) and the in-time placebo test (Abadie, Diamond, and Hainmueller 2015).

To demonstrate the effectiveness of the treatment, the trajectory of the variable of interest (Energy consumption and Unemployment) should be higher for the treated unit compared to the placebo units. The probability of the previous situation happening, given the available sample of placebo tests, is given by a pseudo p-value. Figure 8, illustrates the ratios between post-2017 RMSPE and the pre-2017 RMSPE for all regions in the donor pool, measuring the magnitude of the difference of the outcome of interest between each region and its respective synthetic.

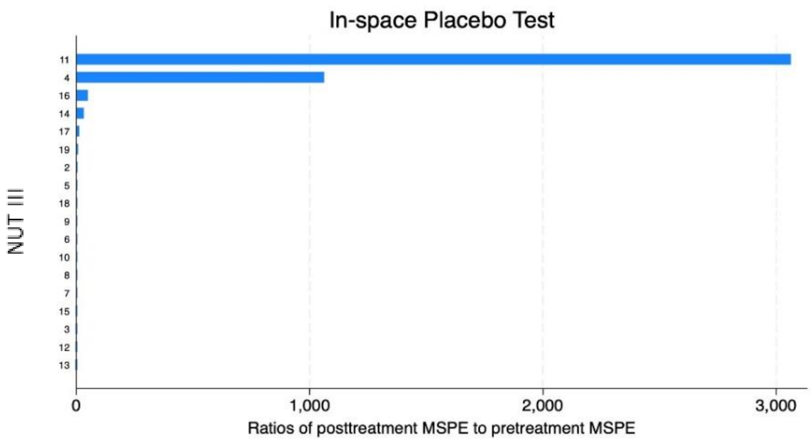

Figure 8 - In Space placebo Test for Energy Consumption

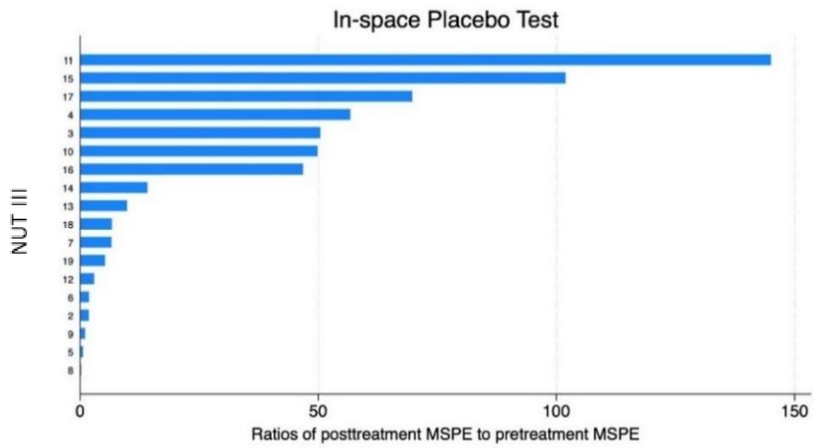

Figure 9 – In Space placebo Test for Employment

Leiria that is referred as NUT number 11 has a post/pre MSPE ratio ranked as the first largest for both Energy Consumption and Unemployment. This yields a MSPE-based p-value of 0.053 (i.e., 1/19), which means that that if we were chose a region at random from the sample, the chances of obtaining a ratio as high as this one would be 0.053.

4.2.2 Leave-One-Out test

To test the model, the LOO robustness test proposed by Abadie, Diamond, and Hainmueller (2015) was implemented. This will assess the sensitivity of our main results to changes in the region`s weights. Recall that as a weighted average of donor units, the optimal synthetic control usually exhibits sparsity, with most control units assigned a zero weight. Hence, it is necessary to evaluate if the estimated treatment effects are disproportionately influenced by a single control unit with a non-zero weight. As referred before, this test will exclude the regions with a positive weight share from the control group for each treated region.

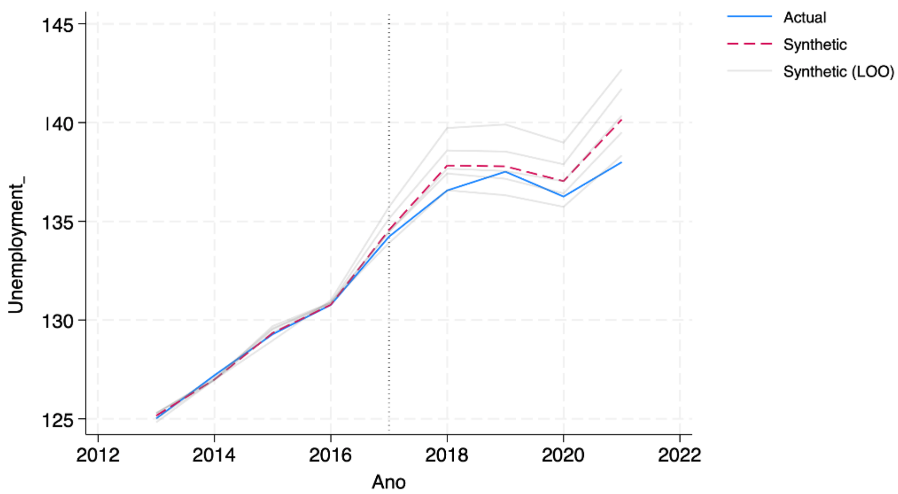

Figure 10 – LOO Test for Unemployment

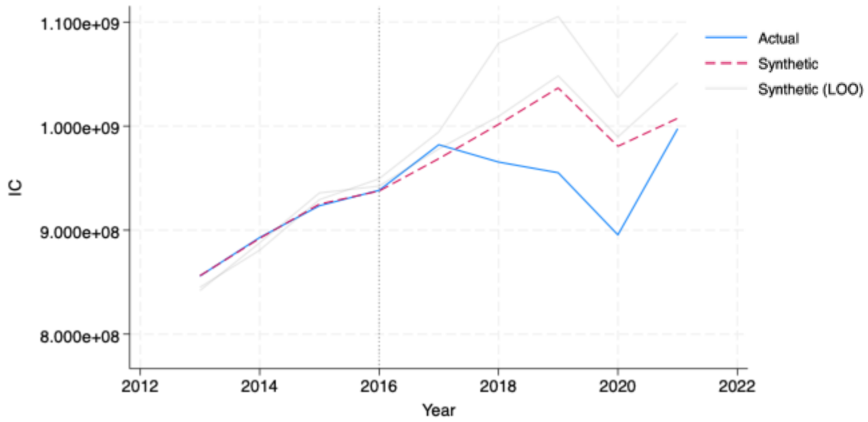

Figure 11 – LOO Test for Industry Consumption

Figures 10 and 11 present the actual, predicted, and LOO predicted outputs of both outcome variables. We can verify that the results are qualitatively similar, no matter which control unit with a nonzero weight is excluded, i.e., the synthetic red line trend matches the ones from the constructed (LOO) lines. These findings suggest robustness, as the estimated treatment effects are not predominantly influenced by any specific control unit.

5.CONCLUSION

This study aims to understand the impact of a Wildfire on economic activity in the long run. This dissertation innovates the empirical analysis of Wildfires through the introduction of an innovative approach for estimating their impacts, being a valuable contribution to the literature. We show that taking advantage of information into the past state interactions between variables may lead to a functional construction of a synthetic which gives us substantial insights about the hypothetical economic conditions of a region if a shock did not occur.

Shocks leave different scares on different components of the economy. Our results indicate that this wildfire triggered a substantial negative impact on economic activity. We also found that the number of people unemployed reduced, showing that not all components of the economy will respond in the same manner. Moreover, the outcomes of this study highlight the necessity for further investigation to comprehensively grasp the consequences of this wildfire on the Region of Leiria`s economy. While the synthetic control method employed is an effective instrument for assessing the effects of a particular intervention, it does not come devoid of constraints.

The methodology developed in this study is particularly useful for assessing the effects of an intervention involving geographic units. In this context, a consolidated database of Portuguese NUT III was constructed. This database includes 9 quantitative variables for the period from 2013 to 2022, allowing the realization of multiple dimension evaluations of different local realities.

It is also important to outline some constraints of this dissertation and make some suggestions for future research to continue the research on this topic. The selection of the variables used was significantly influenced since many potentially relevant data are not available at the NUT III level. Furthermore, other variables should be incorporated, including some previously mentioned, and in a future analysis, a longer time frame should be undertaken, as this dissertation was constrained by data limitations.

For a future study, it would be interesting to evaluate the impact of regional wildfire policy on the development of the local communities after the wildfire, as many authors believe the social construction of the regions is very important to determine how regions are going to be impacted by this event. Additionally, through the investigation of this study, the importance of an in-depth analysis of the social impacts of this event became evident.

The main lesson is clear, in a world where the number of natural hazards is increasing, there is an urgency to allocate resources towards wildfire management practices, aiming to tackle potential adverse effects on economic operations. Investing in the local resources available to engage in wildfire recovery is essential to improve the way local communities deal with this hazard and its economic impacts.

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ANNEXES

TableA1
Description of all variables used in this study.

Unemployment	Fonte: INE. Desemprego – indivíduos totais por Local de residência (NUTS – 2013); Anual
Population density	Fonte: INE. Densidade populacional (Nº/Km^2) por Local de residência (NUTS – 2013); Anual
Exports	Fonte: INE. Exportações (€) de bens por Localização geográfica (NUTS – 2013); Anual
ATM Payments	Fonte: INE. Caixas de multibanco por 10 000 habitantes (Nº) por localização geográfica; Anual
Energy Consumption	Fonte: INE. Consumo de energia elétrica (KWh) por Localização geográfica (NUTS – 2013) e tipo de consumo (Indústria e Doméstico); Anual
GDP per Capita	Fonte: INE. Produto Interno Bruto per capita em relação à média nacional (Portugal = 100)
Municipality Expenses	Fonte: INE. Despesas das câmaras municipais por Localização geográfica (NUTS – 2013); Anual
Vehicles sold	Fonte: INE. Número de veículos ligeiros automóveis vendidos (NUTS – 2013); Anual
Land Area	Fonte: INE. Superfície (Km^2) das unidades territoriais por Localização geográfica (NUTS – 2013); Anual
Burned area	Fonte: INCF, 2022. Burned area in Portugal; Anual

TableA2
List of donor pool NUT III

NUT II	NUT III
Norte	Alto Minho; Cávado; Douro; Ave; Alto Tâmega; Tâmega e Sousa; Terras de Trás-os-Montes; Viseu Dão Lafões
Centro	Região de Aveiro; Beira Baixa; Beiras e Serra da Estrela; Região de Leiria
Oeste e vale do Tejo	Oeste; Lezíria do Tejo
Alentejo	Alentejo Central; Alentejo Litoral; Alto Alentejo; Baixo Alentejo

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