THE IMPACT OF WILDFIRES ON ASSETS AND EMPLOYMENT*

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Draft version, please do not quote.

February 14, 2022

Abstract

This paper analyzes the impact of wildfires on firms' assets and employment levels. We match the firms' balance sheet information with detailed geographic distribution of the burnt areas in Portugal in 2017, using the 7-digit postal code of the firms. This allows us to distinguish treated firms, located in burnt areas, and a control group of firms in non-affected regions. Using a difference-in-differences approach, we find that treated firms have, on average, decreased their assets and employment levels and increased other expenses, that include losses in inventories, comparing to firms in non-burnt areas. Considering the heterogeneity in firms' asset structure, we also find evidence that the negative effect on assets is amplified in firms with higher shares of land and buildings. Firms in the agricultural sector, most recent firms and smaller firms seem to be more vulnerable to this type of event. This analysis allows us to quantify the impacts of wildfires and its heterogeneous effects, which are relevant to inform public policy that design *ex-post* supporting measures for firms affected by wildfires.

JEL classification: D24, L25, Q54, R11
Keywords: wildfires, Portugal, employment, assets, difference-in-differences

*We thank Susana Peralta, Maria A. Cunha-e-Sá, and Ana Fontoura Gouveia for a number of helpful comments and discussions. We also thank the BPLim team and Miguel Portela for the support with the IES admin data. Comments and suggestions provided at the internal seminar at Nova School of Business and Economics are also acknowledged. This work was funded by Fundação para a Ciência e a Tecnologia (UID/ECO/00124/2019, UIDB/00124/2020 and Social Sciences DataLab, PINFRA/22209/2016), POR Lisboa and POR Norte (Social Sciences DataLab, PINFRA/22209/2016). The usual disclaimer applies. Lopes: marta.cardoso@uc3m.es; Póvoa: maria.povoa@novasbe.pt

1 Introduction

Southern Europe has been impacted by significant wildfires in recent years. The increasing frequency and severity of this type of events linked to climate change is predicted by climate models **(IPCC, 2014)** and justify the need to evaluate economic costs, in particular, for affected firms.

While adverse health impacts of wildfires are a growing concern, as recognized by the United Nations **(Rossi, 2020)**, wildfires might also consist in a sudden, severe and exogenous shock for firms that impose negative consequences on their activities. Firms can be impacted by the immediate damage or destruction of physical capital (land, buildings, warehouses, offices and factories) and inventories. Wildfires might also imply the destruction of the ecosystems that support some businesses, such as tourism related to nature or other activities which core business depends on the products/services produced by the affected ecosystems. On the other hand, wildfires can cause deprivation of soil of its protective vegetation layer, increase soil erosion, and reduce long-term ecosystem productivity **(Bastos et al., 2011; Delitti et al., 2005)**, which can affect in particular some sectors of activity that depend on soil quality. There could also be other spillover effects, such as the indirect effects on labour. Illnesses and morbidity caused by fire and smoke may affect workers and the labor market, which in turn may lead to a reduction in labor supply and labor productivity **(Zivin and Neidell, 2012)**. Further impacts are related to business disruptions and the destruction of value chains, that may lead firms to adjust their activity and reduce inputs factors of production (capital and labor).

These negative consequences of wildfires, along with the increasing magnitude and frequency of this type of events, justify the quantification of their effects on firms, which can contribute to the design of a proper and targeted *ex-post* public policy to compensate firms for their losses, or of measures to mitigate the risk of fires.

As being a country at risk due to the effects of climate change with detailed information on this topic, Portugal was used as a case study to analyse the effects of wildfires on a selection of firm variables. We use a unique database containing the geo-localisation of the burnt area that allows us to exploit the regional differences in a very large burnt area in 2017 in Portugal.

We rely on this very precise geo-localised data with the Cartesian coordinates of the polygons of burnt areas matched to the firms' 7-digit postal code to identify the firms located *in* the burnt areas. This allows us to distinguish between firms affected by the wildfires in 2017 (treatment group), and otherwise (control group). We implement a DD strategy to analyse the cumulative effects on the outcome variables, by considering not only the physical and immediate damages, but also other indirect effects, such as business and value chains disruptions and substitution of input factors caused by the wildfires and the potential reconstruction activities, verified within a relatively short time frame. For this purpose, we selected firms' total assets, number of workers and other expenses, which includes the losses in inventories, as outcome variables. We also explore the existence of heterogeneous impacts on firms, according to their sector of activity, the intensity in land and buildings, size, age and export status. We find evidence that in the 2-year period after the wildfire, firms in burnt areas have, on average, lower assets (-10.3%) and employment levels (-6.7%), when compared to companies in non-affected areas. In terms of assets, these results are reinforced for firms that heavily rely their asset structure on tangible assets, in particular, land and buildings, which are more prone to be damaged or destroyed by wildfires. Firms in the agricultural sector, most recent firms and smaller firms seems to be more vulnerable to this type of event, which gives ground to the design of tailored public policy for compensatory schemes for firms affected by wildfires.

This paper follows closely the methodology of **Leiter, Oberhofer and Raschky (2009)**, that examine the impact of floods on the firms' capital accumulation, employment and productivity, using cross-sectional data of European companies. Despite analysing another type of event, these authors also use DD to evaluate the causal effect of floods, considering the firms' asset structure, based on the assumption that the short-run consequences of floods on capital accumulation and employment changes may differ depending on the *vulnerability* of the input factors.

Similarly to our paper, **Issler et al. (2019)** study the impacts of wildfires using a DD approach, but on different outcomes variables. **Issler et al. (2019)** compares mortgage outcomes in fire zones with that in 1-mile ring around the fire zone, which can be subject to some criticism due to potential spillovers effects of wildfires in the outcomes of mortgages located *close enough* to the event. Using a relatively shorter time frame (6 months before and after wildfires), they find a significant increase in the delinquency and foreclosure after a fire in the treatment group, but, surprisingly, these effects decrease once they control for the fire size, which can be related to the coordination externalities afforded in case of larger fires.[1] This paper also studies the *neighborhood effects* of climate-change-driven events, by comparing outcomes in 1-mile ring with in 2-miles ring around the fire zone.

Another strand in the literature examines the effects of exposure to wildfire smoke on health outcomes, such as the health costs among the elderly **(Miller, Molitor and Zou, 2017)**, mortality outcomes **(Kochi et al., 2012)**, and on labor market **(Borgschulte, Molitor and Zou, 2019)**. These studies use satellite images of wildfire smoke plumes to pollution monitor data. **Kochi et al. (2012)** present evidence on the association between wildfire-smoke exposure and the increased risk of mortality, especially for elderly and **Borgschulte, Molitor and Zou (2019)** conclude that reduced air quality impacts worker productivity, which, ultimately, affect firms. Using another type of natural hazard, such as hurricanes, **Belasen and Polachek (2008)** identifies impacts that potentially affect firms. Using a generalized-difference-in-differences (GDD) technique, that incorporates many experimental as well as many control groups, they examine the effects on wages and employment in local labor markets. They also explore the existence of different effects depending on the magnitude of the hurricane and the effects by industry.

In Portugal, the literature related to wildfires predicts the likelihood of ignition occurrence using a set of potentially explanatory variables **(Catry et al., 2009)**, characterizes wildfire occurrence **(Marques et al., 2011; Costa et al., 2010; Verde and Zêzere, 2010)**, and evaluates the existence of a size-dependent pattern, in terms of resulting burned area of wildfire ignitions **(Moreira et al., 2010)**. To our knowledge, it is the first time that the causal impact of wildfires on firms' outcomes is quantified for Portugal.

This paper adds to the existing literature that analyzes the impact of natural events or catastrophes on economic indicators. To our knowledge, this is the first time that the causal impact of wildfires on firms' variables is measured, considering also different effects according to firms' asset structure. The results of this paper have significant implications for environmental and wildfire policy makers, that should account for capital and labor market impacts of wildfires when implementing measures to help firms to recover from a wildfire incident or designing pollution abatement and wildfire mitigation policies. Moreover, our analysis admits the existence of heterogeneous effects, i.e. different responses of firms, according to their sector

[1] County requirements and insurance efforts work together to push the rebuilt and modernization of destroyed homes.

of activity, which may imply that policy makers should take into account the characteristics of the firms when designing the policies.

Whereas other natural disasters are more concentrated in certain regions of the globe, the annual grassland net productivity production loss risk of wildfire affects countries across different continents, such as Australia, Brazil, China and United States **(Shi et al., 2015)**. Despite the fact that we are using Portugal as a case study, the obtained results are also relevant and applicable to other countries affected by wildfires, with similar characteristics.

The remainder of the paper is organised as follows. Section 2 describes the data on firms' balance sheet and burnt areas location. Section 3 details the methodology employed. Section 4 presents the results. Finally, section 5 concludes.

2 Data

In this paper, we exploit two rich databases of enterprises and wildfires in Portugal. The first database is administrative data on the universe of private firms in Portugal, that fulfill their reporting obligations. This database contains information on the balance sheet and profit and loss data. The second database is a unique mapping of the wildfires in the country, which includes both the Cartesian coordinates of the burnt area and type of burnt land. The following subsections provide a brief overview of the data sources, sample selection, and descriptive statistics.

2.1 Firm data

Firm-level panel data is sourced from Informação Empresarial Simplificada (IES) and covers the universe of Portuguese companies that annually fulfill their reporting obligations to the Ministry of Finance, Ministry of Justice, Banco de Portugal and the Statistics Portugal (INE).[2] The database gathers detailed annual information for the non-financial companies in Portugal, and it is available in BPLim, the Microdata Lab from Banco de Portugal.[3] We focus on the period from 2015 to 2018.

The dataset includes variables that characterize the firm and yearly balance sheet and profit and loss data. It is also possible to characterize the firms in terms of economic activity code (CAE)[4] and size. It has also information concerning the location of firms, using the postal code, and the number of establishments.[5] Firm information, such as assets, number of workers and other expenses, are available on a yearly basis.

This study is focused on the impacts of wildfires on subset of sectors of activity: i) agriculture, animal production and forestry, ii) manufacture of wood and iii) pulp paper manufacture. This choice is justified by the literature, that presents evidence of a high vulnerability of these sectors to wildfires, where the losses are more directly and immediately observed, as briefly explained below.

Wildfires have impacts on soil, affecting physical, chemical, mineralogical, and biological soil properties for agriculture and forest, favouring infiltration and soil erosion **(Neary, 2009)**

[2] Instituto Nacional de Estatística

[3] Banco de Portugal Microdata Research Laboratory (BPLIM) (2021): Central Balance Sheet Harmonized Panel. Extraction: June 2021. Version: V1. BANCO DE PORTUGAL. Dataset. https://doi.org/10.17900/CB.CBHP.Jun2021.V1

[4] Código da Atividade Comercial

[5] A given firm might have more than one establishments in Portugal, for instance, one establishment located in Lisbon and another establishment in Viana do Castelo, a district in the North of Portugal.

and of nutrient losses **(Certini, 2005)**. While some argue that the persistence of the effects depend on the severity and characteristics of the fire, **Bowd et al. (2019)** show that they may last up to 80 years. Those effects are most pronounced in case of high intensity and multiple fires **(Pellegrini et al., 2017)**. The sector of animal production can be affected, via the effects on animals, which can be direct and immediate (e.g. due to injuries and death cause by high temperatures and oxygen depletion **(Park et al., 2004)**) or indirect (e.g. due to starvation and lack of water). Forests, used to support wood based industries, such as sawn, pulp and paper, might be also affected by wildfires. Wood availability is threaten by wildfires **Rego et al. (2013)**. However, low-value wood can be used by the pulp and paper industry, if processed within one year and the contamination minimized. As time goes by, the effects of fires become significant **(Lowell and Cahill, 1996)**.

2.2 Wildfires data

We use the burnt area dataset, sourced from Instituto da Conservação da Natureza e da Floresta (ICNF).[6] For each wildfire occurred from 2011 to 2019, we have data about the starting and end time of the event and the number of hectares burnt. More importantly, it includes the Cartesian's coordinates of the polygon of the burnt area. This database only contains information for mainland Portugal. For this reason, we exclude wildfires and firms in Azores and Madeira.

ICNF also provides another dataset that has information on every ignition event in Portugal that was used to characterize the evolution of the burnt area and some descriptive statistics. This database has information on every ignition about the time of the alert, intervention and extinction, duration, total area burnt[7] and location. Furthermore, ignitions are classified by their cause by ICNF (Table 1).[8]

Unfortunately, not all the ignition observations have their counterpart in the mapped burnt area. This is due to two different reasons. First, only the biggest wildfires (above 1 hectare) must be mapped, according to the current law.[9] According to ICNF, only very recent organizational procedures and technological satellite developments[10] ensured that there is a unique key to relate the two databases.

In this paper, we analyze the impact of wildfires on firms located in mainland Portugal. We carefully choose this time frame in order to exploit a significant wildfire wave in 2017, when approximately 540 thousand of hectares burnt. This represents an increase of more than 400regarding the average of burnt area in the five previous years (Figure 1). This year was preceded by 2 years with a much smaller burnt area. We include also 2018 in the analysis, despite the lower area burnt, assuming that the effects of being affected by a wildfire in 2017 persist over time.

[6]This organization contributes to the enhancement and conservation of aspects related to forest resources and nature and biodiversity in Portugal. By the Decree-Law number 124/2006, ICNF prepares the technical specifications to the cartographic survey of areas burnt by wildfires. ICNF is also responsible for the dissemination of mapped burnt areas.

[7]In this database, the area burnt can be disintegrated according to its nature, into populated, brushwood and/or agricultural area burnt.

[8]Wildfires can have a negligent cause, being related to the use of fire (burning practices or smoking, for instance) or starting accidentally, while structural causes are related to hunting and land use. Arson fires can be imputable or non-imputable and natural causes are mostly due to lighting discharges. Ignitions can also be caused by rekindling, or have an unknown cause.

[9]Decree-Law number 124/2006, added by the Decree-Law number 76/2017.

[10]Provision of better satellite images, provided by Sentinel-II, that have a good spatial resolution (10 m) and frequency of passage (images every 5 days for the same location).

In Figure 2 the burnt area weighted by the area in each municipality in 2016 and 2017 is contrasted. Comparing to 2016, we can observe a large number of municipalities that registered high weighted burnt areas in 2017. In 2016, the municipalities that registered larger weighted burnt area are located in Aveiro (Arouca and Águeda), Viana do Castelo (in particular, Vila Nova de Cerveira, Paredes de Coura and Arcos de Valdevez), and Bragança (Freixo de Espada à Cinta). The main affected municipalities in 2017 are in Coimbra (Lousã and Arganil), Leiria (Pedrogão Grande and Alvaiázere) and Castelo Branco (Sertã). The coefficient of correlation is low and negative (-0.02%).

2.3 Descriptive statistics

The evolution of the number of wildfires and burnt area is depicted in Figure 1. From 2011 to 2019, there were 167 509 wildfires in Portugal, according to the ICNF. The years with the highest number of wildfires are 2011 and 2012, that represent, respectively, 17.8% and 15.1% of the wildfires in this period. In terms of the number of wildfires, those years are followed by 2013 (13.8%) and 2017 (12.5%). It is also observed that 2014 is the year with the lowest number of wildfires, corresponding to 5.6% of total wildfires within this time frame.

Due to the wildfires, 1 239 886 hectares burnt from 2011 to 2019 in Portugal. Despite the relatively high number of wildfires in 2011 and 2012, that account for 32.9% of total wildfires, these years only correspond to 15.7% of the burnt area. On the other hand, 2017 is the year with the highest record of burnt area (539 921 hectares), representing 43.5% of the total burnt area in this period.

Figure 3 and Table 2 present the distribution and the number of wildfires by cause from 2011 to 2019 by cause, respectively. In this period, 28.3% of the ignitions are naturally or accidentally caused or due to the use of fire in several activities, such as burning trash or smoking. Arson fires, whether imputable or non-imputable, represent 14.8% of the total ignitions and 8.8% are due to rekindling. In this period, 26.6% of the ignitions are caused by unknown factors, while 21.5% have "other causes", that consider the fires classified as structural (less than 1%) and the ones that do not have a specified cause.

Figure 4 depicts the distribution of ignitions that are accidentally or naturally caused, or due to the fire use. Ignitions cause by fire use are the majority (83.4%), followed by accidents (14.7%), while natural caused wildfires correspond to only 2%.

The geographical distribution of the number of ignitions and burnt area is presented in Table 3. Porto and Braga are the two districts with the highest number of ignitions of wildfires, corresponding to 22% and 10%, respectively. The most affected districts in terms of the number of wildfires do not correspondent to the ones with the highest area burnt. The districts of Coimbra, Guarda, Castelo Branco and Viseu are the ones with the larger burnt area. Approximately 45% the area burnt from 2011 to 2019 is located in these districts.

The geographical distribution of firms under analysis is summarized in Table 4. Our analysis considers 9 938 firms located in mainland Portugal, whose primary sector of activity is one of the following: agriculture, animal production and forestry, manufacture of wood or pulp and paper manufacture. The districts with the highest proportion of firms under analysis are Santarém (10.2%), Aveiro (9.7%) and Lisboa (9%).

Table 5 presents the distribution of firms under analysis by sector of activity. In our study, 37.5% of the firms are in the animal production sector and 31.2% are agricultural firms, followed by the manufacture of wood (17.3%), forestry and logging (11.4%) and manufacture of pulp and paper (2.6%).

Table 6 presents the distribution of firms by size. In mainland Portugal, 86% of the firms are micro enterprises and 12.3% are small enterprises. Only a small proportion of firms are medium-sized (1.6%) or large (0.1%).

The distribution of firms by age is presented in Table 7. In 2016, 34.6% of the firms are relatively newer, having a year of constitution after 2010. For 24.5% of firms the year of constitution was previous to 1996, for 21.3% was between 1996 and 2004 and for 19.6% was between 2005 and 2010.

Table 8 reports the proportion of firms by export status. Firms are classified as exporters in a given year if the value of exports to the total sales is greater than 10%, in that year and in the previous year. According to this criteria, the majority of firms is non-exporting (92.2%).

3 Methodology

Our identification strategy relies on the regional differences on the burnt area due to wildfires. Using a natural experiment, this paper builds on a difference-in-differences design technique (see, for instance, **(Angrist and Pischke, 2009)**).

Having the geographic coordinates of the burnt area and the location of the centroid of the 7-digit firms' postal code, we use a *spatial join* to check which centroids are spatially overlaid by the polygons of the burnt area. This allows the identification of the firms located *in* the burnt areas and the distinction between firms in the treatment and in the control group. In the treatment group we include firms *affected* by the 2017 wildfires, the ones that were *in* a burnt area in 2017, but *outside* in 2015, 2016 and 2018. On the other hand, firms not affected by any wildfire in this period, *outside* a burnt area from 2015 to 2018, are in the control group. Note that this reasoning does not imply that necessarily all the firms located in a region affected by wildfires are directly and physically hit by these events. This approach allows the investigation of the cumulative effects on the outcome variables in the short run, by considering not only the physical and immediate damages, but also other indirect effects, such as business and value chains disruptions and substitution of input factors caused by the wildfires and the potential reconstruction activities, verified within a relatively short time frame.

Using a DD approach, we compute estimates for the effect of wildfires on firms' factors of production - capital and labor - and other expenses. Note that the counterfactual quantity of interest in the standard specification is the difference in the outcome indicators between treatment group and control group that would have been registered if wildfires had not occurred. That is why we rely on the DD estimator, where the causal effect of wildfires on outcomes is the difference between: (i) the difference in firms' outcomes on treated firms before and after the wildfire episode, and (ii) the difference in outcomes on control group before and after the wildfire episode.

In our **standard DD specification**, we have:

$$\log(Y_{ispt}) = \beta_0 + \beta_1 POST_t + \beta_2 T_p + \beta_3 (POST_t.T_p) + \varepsilon_{ispt} \tag{1}$$

Our analysis focuses on three different outcome variables Y: (i) the capital stock measured by total assets, taken from firms' balance sheet data, (ii) the employment level expressed as the number of worked hours and (iii) other expenses, which includes losses on inventories, that is provided by the profit and loss statement of the firms.[11] Therefore, on the left hand side of the

[11]The distribution of each of the outcome variable is despicted in Figures 5 to 7.

equation, we have the logarithm of Y_{ispt}. The indices represent a firm i in a sector of activity s in a 7-digit postal code p at time t.[12]

We observe the firms in two time periods (before and after the wildfire). Therefore, $POST_t$ is a dummy variable, where 0 indicates a time period before the event (2015 and 2016) and 1 indicates a time period after the wildfire (2017 and 2018).[13] The dummy $POST_t$ captures aggregate factors that would cause changes in the firm's variables, even though the wildfire episode might not have occurred.

The dummy variable T_p is equal to 0 or 1, depending on whether the firm is in the control or treatment group, respectively. Note that T_p captures possible differences between the treatment and control groups before the event. Therefore, β_2 accounts for the average permanent differences between the treatment and control groups.

$POST_t.T_p$ is 1 if the firm is in the treatment group, in the period after the wildfires of 2017. Our coefficient of interest would then be β_3, associated with the interaction term of the these two dummy variables. Its estimate is interpreted as the causal effect of wildfire on the dependent variable. Under this specification, β_0 is a constant term.

We ran two alternatives for this baseline specification. In the first, we use firm fixed effects to account for time-invariant variables at firm-level. Note that the effects of previous wildfires to the 2017 ones are captured by these fixed effects.[14]

In the second alternative, we anchored on the firm size and firm growth literature **(Evans, 1987; Sutton, 1997; Fotopoulos and Louri, 2004)**, that argued that the initial size of the firm and its age determine its current size. Therefore, we add to our regression the logarithm of the initial stock of the outcome variable ($lassetsi_{isp}$, $lempli_{isp}$ and $otexpi_{isp}$, respectively) and the logarithm of the year of constitution of the firm ($lstart_{isp}$), as explanatory variables. We also include regional and sectorial effects. The standard errors of coefficients are clustered at the postal code, given that we use wildfire events at the postal code level.

For the DD approach, we impose that all the firms in our sample would have a constitution year before the shock, so we exclude from the analysis all the firms that started operating in 2017 or afterwards. We consider firms with a valid postal code, reporting information and having a consistent activity before the wildfires, which lead us to exclude approximately 28% of observations. Moreover, firms can have more than one establishment and different establishments may be located in different postal costs. Therefore, only firms with only one establishment in mainland Portugal were considered in order to guarantee a one-to-one relationship between firms and geographical location at national level, given that the assessment of the wildfires effects on firms relies critically on their location. Most of the firms have only one establishment, so less than 5% of the firms were excluded due to this criteria.

The trends for the three outcome variables are shown in Figures 8 to 10. The dashed lines separate the pre-treatment and the post-treatment period. In the DD framework, it is assumed that the unobserved variables that affect firms' economic indicators are either time-invariant between the treatment group and the control group or time-varying, although affecting similarly the two groups. This validates our choice of the control group. Graphical analysis suggests that the *common trend assumption* between control and treatment groups is appropriate for our study, so that use can apply the DD strategy.

[12] We assume heteroskedasticity, such that we ran our regressions allowing for the variance of the error terms to differ across the values of the explanatory variables and controlling for it, thus obtaining unbiased estimators.

[13] Outcome variables are with reference to the end of each year.

[14] Note also that firms' past experience of wildfires might condition the consequences of future wildfires events. However, this does not invalidate the use of our treatment variable, as being affected by wildfire is characterized by being an exogenous shock, in terms of its frequency and intensity.

Figures 11 to 13 depict, for each year, the coefficient estimates for the interaction between the treatment group and the corresponding year, when regressing the outcome variables in the interaction between the treatment group and year, and year dummies, under firm fixed effects and clustering at the 4-digital postal code. The coefficients for the years prior to the shock are not statistically different from zero.

Table 9 presents the number of firms by sector of activity, in the treatment and control group. In the control group we consider 9816 firms, while in the treatment group there are 122 firms. In the treatment group, 70.5% of the firms are in the agriculture sector, animal production or forestry and logging sector, and 27.9% in the manufacture of wood. A very small percentage is in the pulp and paper manufacture.

Table 10 compares some key variables that characterize firms in the control and treatment groups, for 2015 and 2016. We compare the mean between the two groups for the following variables: assets, tangible assets, equity, sales, other expenses, return on assets, number of workers and worked hours, size and the constitution year of the firm. Our identification strategy hinges on the two groups being similar before 2017 wildfires. Tests of means reveal no statistical differences for the firms in the control and treatment groups in the selected variables.

3.1 Heterogeneous effects

To explore the existence of heterogeneous effects we compare *more-* and *less-vulnerable* firms in terms of tangible assets, in particular the land and buildings owned by the firms, which are more susceptible to be destroyed or damaged by wildfires. This specification exploits firms' asset structure, given the hypothesis that a higher share of land and buildings on tangible and intangible fixed assets of the firm determines the impacts of wildfires.

Following the approach outlined above, the impacts of the wildfires on the outcomes of interest are estimated as follows:

$$\begin{aligned}\log(Y_{ispt}) = \beta_0 + \beta_1 POST_t + \beta_2 T_p + \beta_3 (POST_t.T_p) + \beta_4 lYi_{isp} + \beta_5 lstart_{isp} + \\ + \beta_6 sland\_s_{ispt} + \beta_7 (POST_t.T_p.sland\_s_{ispt}) + \gamma_s + \delta_p + \varepsilon_{ispt}\end{aligned} \tag{2}$$

In this setting, $POST_t$, T_p and $lstart_{isp}$ are as above.

We also include $sland\_s_{ispt}$, the standardized value for the share of land and buildings on tangible and intangible fixed assets of the firm derived from the balance sheet, as an explanatory variable, as it is considered a suitable proxy for the *vulnerability* of asset structure to physical damages imposed by the wildfires.

The interaction term of the $POST_t.T_p$ dummy with $sland\_s_{ispt}$ is also an explanatory variable, and it will be our coefficient of interest when checking for different impacts on firms, depending on $sland\_s_{ispt}$. Firms can be hit differently by wildfires whether they rely substantially on intangible assets or if it has an operation largely based on tangible assets, such as land, factories, storage, offices and other types of buildings.

To explore the effect of wildfires on the outcome variables, we run both OLS and IV (2SLS) regressions, based on equation (2). In the IV regression, we use as an instrument for the initial amount of capital/labour or other expenses the following variables: (i) the average amount of assets/number of workers/other expenses in each sector of activity and (ii) the industry specific minimum efficient scale, following the methodology proposed by **Leiter, Oberhofer and Raschky (2009)**. The Hausman specification test is used to detect endogenous regressors in our model and to help us to identify the appropriate model.

Given the richness of IES dataset, we check for other heterogeneous impacts, depending on the sector of activity of the firm. It is possible that wildfires do not affect all firms equally and that the response depends on the specificities of the sector of activity.

Other heterogeneous effects are also investigated, depending on the size, age and export status.

4 Results

First, we present the results for our standard DD specification, presented in Equation (1).

As a second step, we focus on the estimates of different effects of wildfires by introducing in our model firms' assets structure. Here, we explore the hypothesis that higher shares of land and buildings on tangible and intangible fixed assets of the firm determine the impacts of wildfires, as modelled in Equation (2).

Following this, we report the estimates for other heterogeneous impacts, depending on the sector of activity, size, age and export status.

4.1 Standard DD specification

The first column of Tables 11, 12 and 13 depict the results of estimating the regression in Equation (1).

Results in Table 11 and 12 show that assets and the number of workers decrease by 8.9% and 6.7% if firms are affected by wildfires, respectively, comparing to non-affected firms. For other expenses, the coefficient of interest is not statistically significant, although presenting the expected sign, as we can observe in Table 13. These results are consistent when adding firms fixed effects (Column 2) and other controls and regional and sectorial effects (Column 3).

The coefficients both on initial assets and on initial employment are smaller than one, which suggest that firms with lower initial levels of assets/employment face higher growth, when comparing to firms with higher initial levels (see Column 3 of Tables 11 and 12, respectively). These findings contradicts **Sutton (1997)**, that proposes that firms' growth is independent of their initial size. However, they are in line with the evidence presented by **Leiter, Oberhofer and Raschky (2009)** and **Fotopoulos and Louri (2004)**, for the case of initial employment.

4.2 Heterogeneous effects on firms' asset structure

Columns 4 and 5 of Tables 11, 12 and 13 depict the results of estimating the regression in Equation (2), using OLS and IV, respectively. In order to choose the appropriate model, we run Hausman specification test to detect endogenous regressors. The results are presented at the bottom of the Tables. The *p-values* for the Wu-Hausman test show that for assets and employment, we should favour the IV over the OLS. For other expenses, the opposite holds. The following interpretation refers to the favoured specification models.

The dummy $POST_t$ captures aggregate factors that would cause changes in the firm's variables, even though the wildfire episode might not have occurred. The estimated coefficient for this dummy is positive and statistically significant for all the outcome variables under analysis, suggesting a positive impact of time on assets/employment/other assets. On the other hand, the estimated coefficient for the treatment dummy T_p indicates that, on average, there are no permanent differences between the treatment and control groups, for the regressions of all the outcome variables.

The estimated DD coefficients indicates that firms affected by wildfires have, on average, decreased levels of assets and employment, comparing to firms in non-affected areas, as observed in Tables 11 and 12. These findings are consistent with the standard DD specification. The DD coefficient for other expenses is also in line with the standard DD specification, but turns now to be statistically significant at a 5% level (Table 13).

As shown in Tables 11 and 12, the coefficient on initial total assets and on initial employment is not statistically different from one, contrarily to the previous results of the DD specification, suggesting that input growth is independent of the initial stock. The year of the constitution of the firm do not reveal an impact on assets nor on employment, as observed in Tables 11 and 12. However, it turns to have an effect for total expenses, that suggests that there is a negative relation between the year that the firms started operating and the level of other expenses.

The coefficients for the standardized value of the share of land and buildings ($sland\_s_{ispt}$) for assets, employment and other expenses is negative, which present some evidence that the correspondent outcome variable decreases for higher shares of land and buildings. The DD effect on assets is greater the higher the share of land and buildings of the firm (Table 11), as expected. While firm's land and buildings, can potentially be affected by wildfires, intangible assets are not. This confirms the existence of heterogeneous effects of wildfires on total assets based on firms' assets structure. In Tables 12 and Table 13, this interaction coefficient is not statistically significant, suggesting that deviations of firms from the mean of the share of land and buildings play no role in determining the effects of wildfires on employment and other expenses.

Tables 14, 15 and 16 present the regressions for the standard DD specification, by the *intensity* in land and buildings. For each sector of activity, we distinguish firms with low intensity, the ones that do not possess any land or buildings, and high intensity (above the percentile 75% of land and buildings, for each sector of activity).[15] As Table 14 shows only high intensity firms present, on average, a decrease in their assets when affected by wildfires, comparing to non-affected ones, in both sectors under analysis. We do not observe heterogeneous impacts for employment and other expenses. These findings are entirely in line to the previous ones, using the model presented in Equation (1).

4.3 Other heterogeneous effects

Sector of activity

Tables 17, 18 and 19 report the estimates for the DD standard specification and its alternatives for the different sectors of activity under analysis: i) agricultural, animal production and forestry sectors, ii) wood manufacture and iii) pulp and paper manufacture. Tables 20, 21 and 22 go a step further and desegregate the first sector block, running separately the DD standard specification for firms in the i) agriculture sector, ii) animal production and iii) forestry.

As shown in Tables 17 and 20, firms in the agricultural sector and in the pulp and paper manufacture affected by wildfires present, on average, a decrease on assets, comparing to the firms in non-affected areas. Tables 18 and 21 show that firms in the forestry sector and in the pulp and paper manufacture present, on average, a decrease on the employment, *vis-à-vis* the ones that are not in a region affected by wildfires. The increase on other expenses is only shown by the affected firms in the agriculture sector and in the pulp and paper manufacture, as reported in Tables 19 and 22. Firms in the manufacture of wood affected by wildfires do

[15] Due to the low number of observations of firms in pulp and paper manufacture, we exclude this sector from these regressions.

not present any significant change in the variables under analysis, comparing to the ones in the control group.

Size

Tables 23, 24 and 25 report the estimates for the DD standard specification by size of the firms.[16]

As shown in Table 23, micro firms in the treatment group experience, on average, a reduction in their assets, when compared to the control group. Note also that heterogeneous effects by size are not verified for employment or other expenses (Tables 24 and 25).

Age

Tables 26, 27 and 28 report the estimates for the DD standard specification for the different sectors of activity under analysis, by date of establishment of the firm interval.

In terms of assets and employment, the most recent firms (with an establishment date after 2010) affected by the wildfires register a decrease, comparing to firms in non-affected areas (see Tables 26 and 27). No heterogeneous effects by firm age are observable in terms of other expenses (Table 28).

Export status

Tables 29, 30 and 31 report the estimates for the DD standard specification by the export status of the firm.

A decrease in assets and employment is verified in non-exporting firms in areas affected by wildfires, compared to firms in the control group (Tables 29 and 30). No heterogeneous effects by export status are observed in terms of other expenses (Tables 31).

5 Conclusions

Southern Europe has been impacted by significant wildfires in recent years. The increasing frequency and severity of this type of events justify the need to evaluate economic costs, in particular, for affected firms.

Wildfires can consist in a sudden, severe and exogenous shock for firms. The consequences can be various: firms can be impacted by the immediate damage or destruction of physical capital (land, buildings, warehouses, offices, and factories) and raw material or products, but there could be other spillover effects, such as the indirect effects on labour. These effects can be related to the adjustment of firms to potential business disruptions or, in extreme cases, the unfortunate mortality and illnesses of workers caused by fire and smoke.

This paper investigates the short-run effects, within a two-year time frame, of wildfires on firms' input factors and other expenses, which include inventory losses. We also investigate whether these effects are different according to firms' asset structure, allowing for heterogeneous effects according to the ratio of land and buildings owned by the firms on tangible and intangible fixed assets.

A detailed and unique dataset combines the geographic information of the burnt area and firm-level data. This matching allows us to distinguish between firms in burnt areas and firms outside affected zones, before and after the wildfire. In order to estimate the causal effect

[16] Due to the low number of medium and large firms for the sectors of activity under analysis, we focus on the heterogeneous effects between micro and small firms.

of wildfires on input factors and other expenses of firms in the agricultural sector, animal production and forestry, and also on wood and pulp/paper manufacture, we use a DD approach.

We find evidence that firms in burnt areas have, on average, decreased their assets (-8.9%) and employment levels (-6.7%) after the wildfires, compared to the ones in non-affected areas. Other expenses rose in firms in burnt areas relative to non-affected after the wildfires. The negative impact on assets is further aggravated with higher shares of land and buildings, which are more prone to be damaged or destroyed by wildfires.

Given the richness of the data set, we also explore the existence of heterogeneous impacts, according to the sector of activity, age, size and export status of the company. Firms in the agricultural sector, most recent firms and smaller firms seems to be more vulnerable to wildfires.

Further research about this topic can include the causal analysis with varying treatment time and multiple time periods, which is suitable for treatments (wildfires) with varying start dates and varying treatment durations (for instance, firms in burnt areas in two consecutive years) **(Dettmann, Giebler and Weyh, 2020)**.

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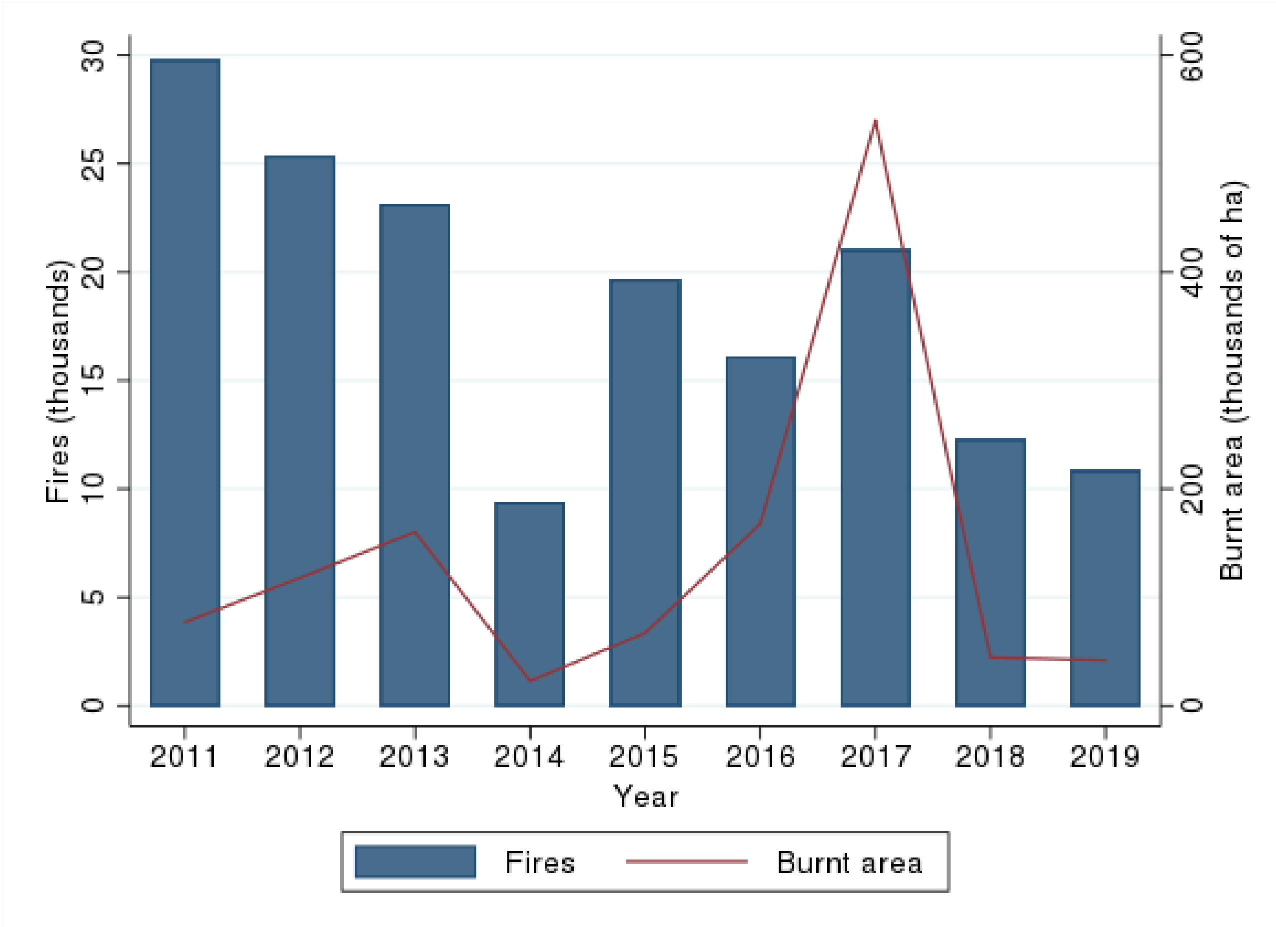
Table 1: Causes of Wildfires

Cause	**Description**
Related to the use of fire	Burning trash, burning practices, rocket firing, campfires, smoking, bee-keeping and chimneys
Accidental	Transportation and communication, machine tools and equipment and other accidental causes
Natural	Lightning discharges
Fireplace	Not imputable, imputable
Rekindle	Fire started again
Structural	Hunting and wildlife, land use, fire mitigation activities, other structural causes
Unknown	Not enough elements to determine the cause

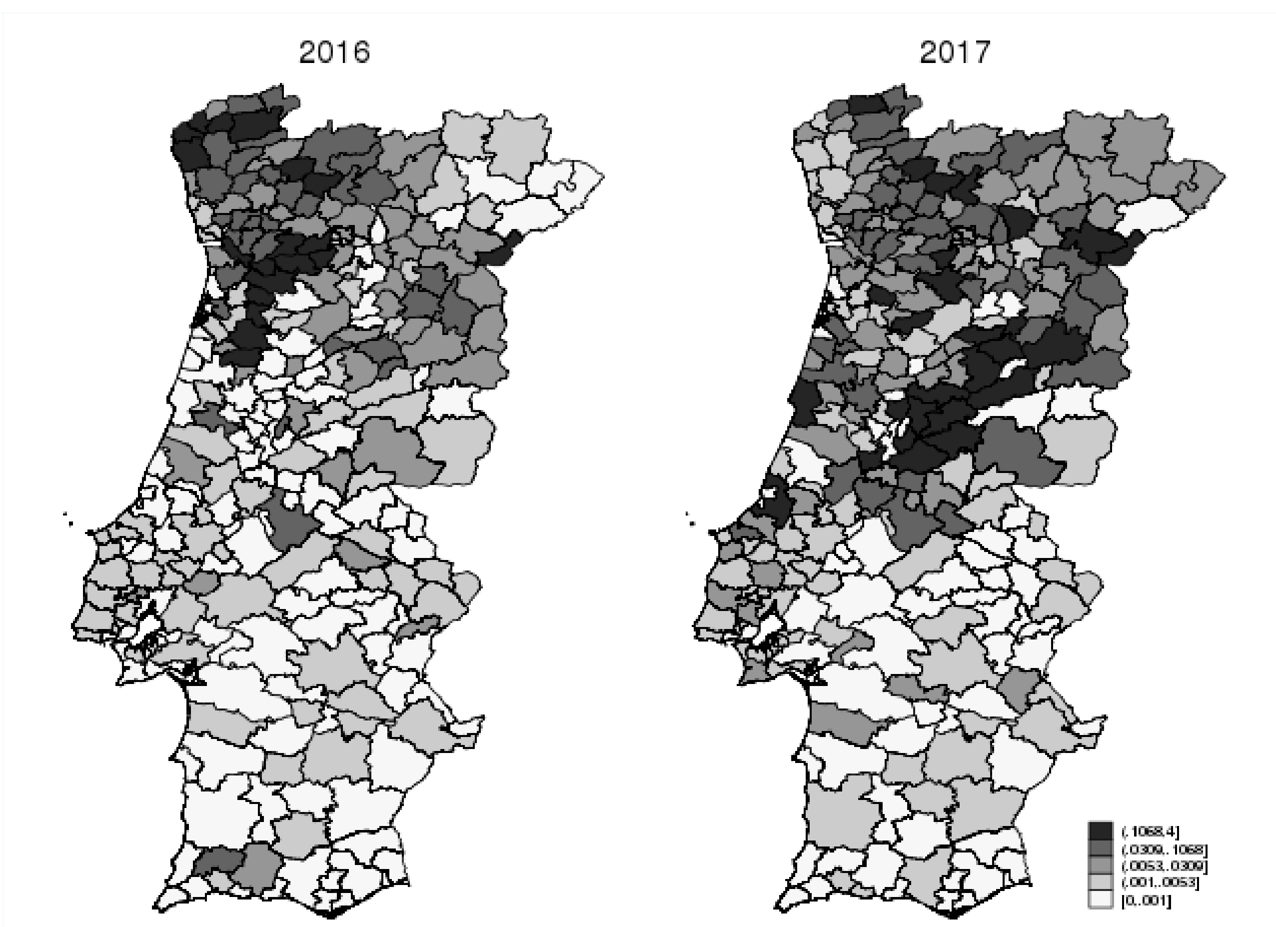
This Table presents and describes the causes of wildfires, according to ICNF.

Figure 1: Wildfires and Burnt Area



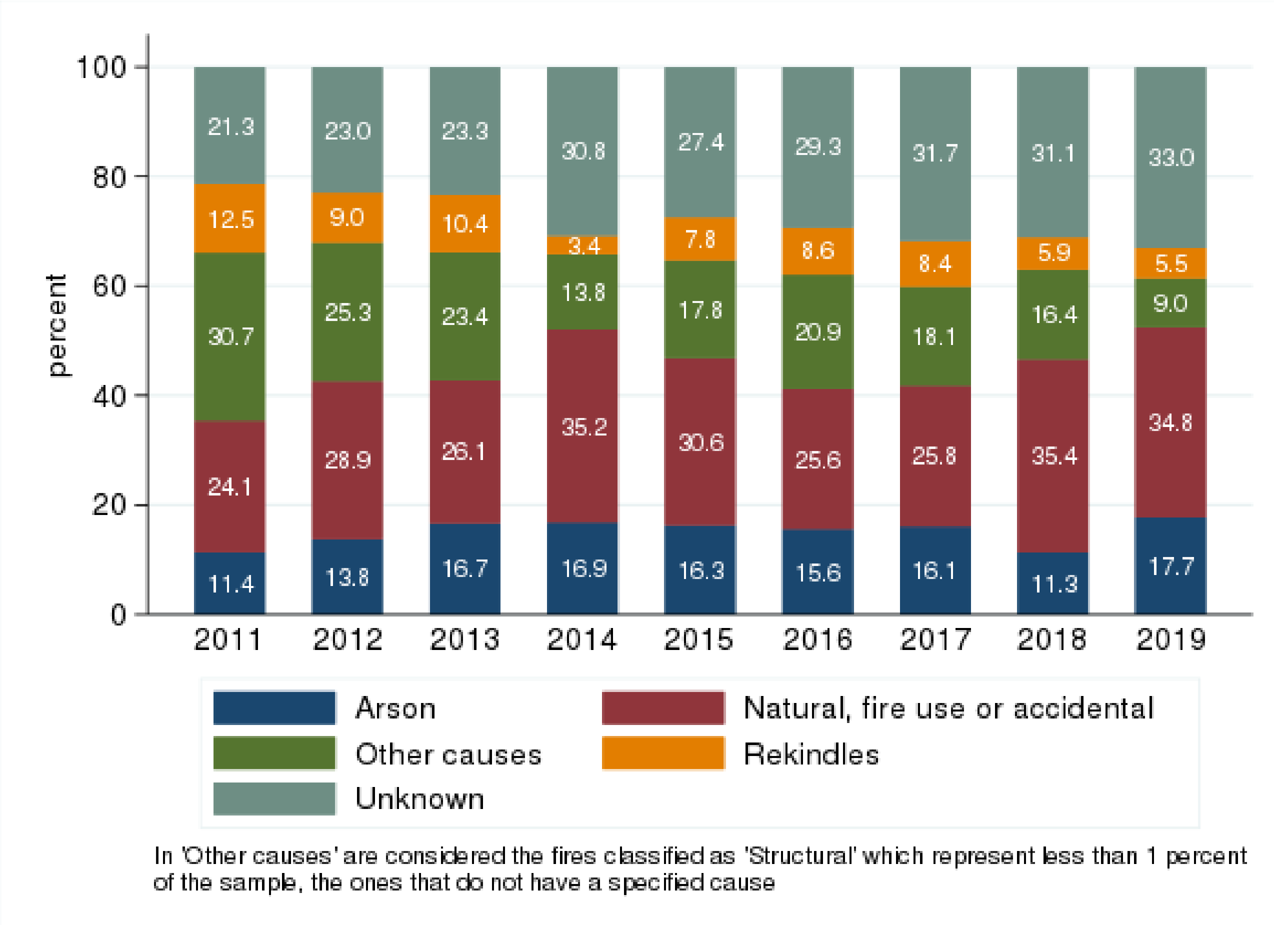
This Figure plots the number of wildfires (thousands) by year. The red line represents the evolution of the burnt area (thousands of hectares). The sample consists of all wildfires in ICNF database in Portugal, between 2011 and 2019.

Figure 2: Burnt Area by Municipality



This Figure maps the total burnt area weighed by the area by municipality in mainland Portugal, in 2016 and 2017. The sample consists of all wildfires in ICNF database in Portugal, between in 2016 and 2017.

Figure 3: Relative Frequency of Wildfires by Cause



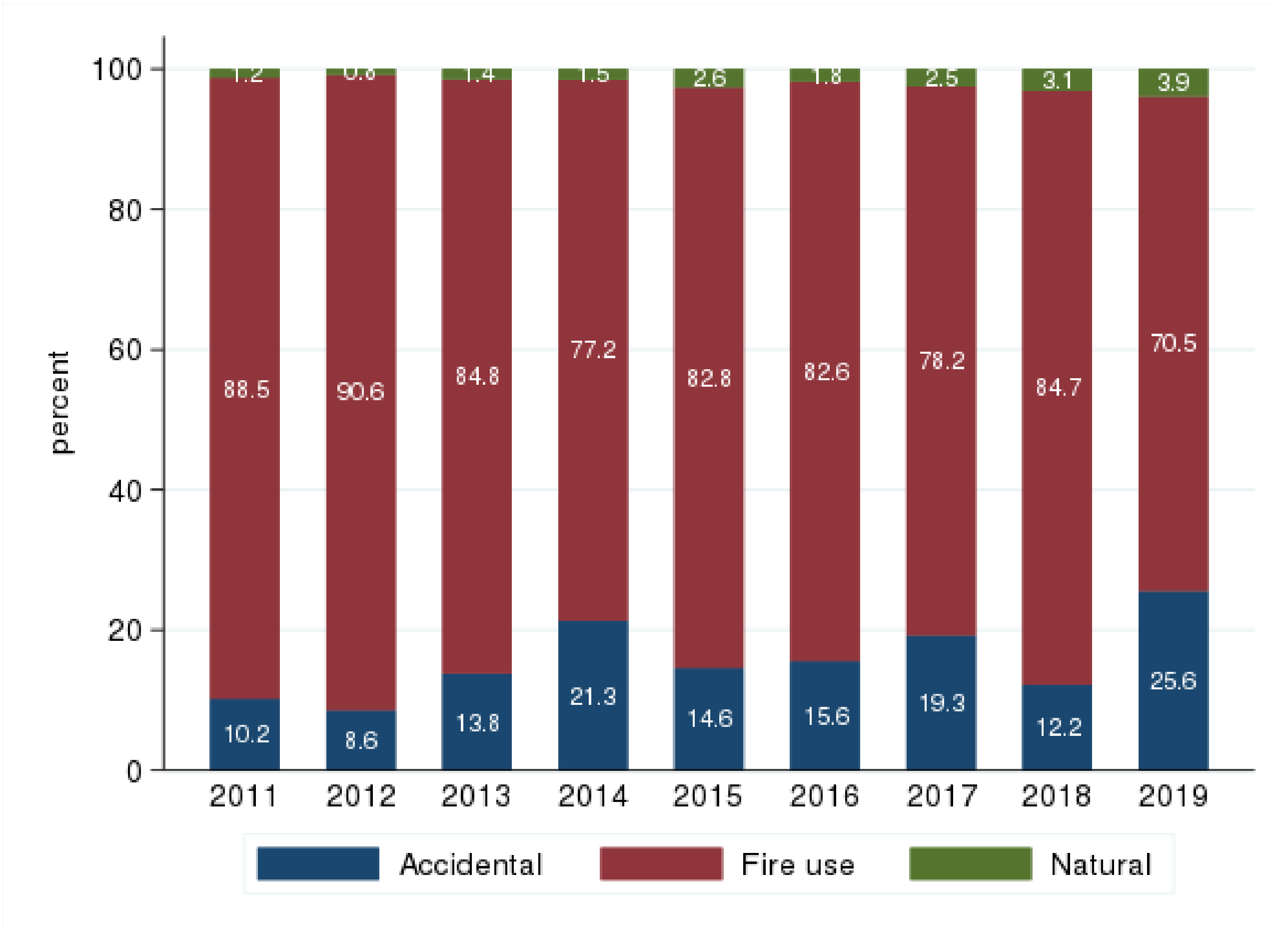
This Figure plots the relative frequency of wildfires by cause and by year. The sample consists of all wildfires in ICNF database in Portugal, between 2011 and 2019.

Table 2: Number of Wildfires by Cause

Causes	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**Total from 2011 to 2019**
Related to the use of fire	6342	6629	5114	2549	4974	3400	4235	3678	2655	39 576
Accidental	734	630	833	704	879	642	1044	529	964	6959
Natural	89	58	86	49	156	75	134	135	146	928
Related to the use of fire, accidental or natural causes	**7165**	**7317**	**6033**	**3302**	**6009**	**4117**	**5413**	**4342**	**3765**	**47 463**
Arson	3381	3493	3862	1582	3205	2514	3378	1385	1920	24 720
Rekindle	3736	2292	2416	319	1535	1384	1758	723	595	14 758
Unknown	6351	5826	5396	2890	5392	4722	6661	3813	3578	44 629
Other causes	9149	6424	5422	1295	3502	3367	3796	2010	974	35 939
Total	**29 782**	**25 352**	**23 129**	**9388**	**19 643**	**16 104**	**21 006**	**12 273**	**10 832**	**167 509**

This Table presents the number of wildfires by cause between 2011 and 2019 for the sample of wildfires in ICNF database.

Figure 4: Relative Frequency of Wildfires by Cause - Accidental, due to Fire Use or Natural Causes



This Figure plots the relative frequency of wildfires by cause and by year. The sample consists of all wildfires caused accidentally, due to fire use and naturally in ICNF database in Portugal, between 2011 and 2019.

Table 3: Wildfires by District

	Number of wildfires		Burnt area	
	Total	**%**	**Total (ha)**	**%**
Aveiro	13349	8,0%	71649,2	5,8%
Beja	2955	1,8%	15005,4	1,2%
Braga	16803	10,0%	68804,2	5,5%
Bragança	5978	3,6%	95084,9	7,7%
Castelo Branco	4263	2,5%	130229,5	10,5%
Coimbra	5722	3,4%	159675,1	12,9%
Évora	2170	1,3%	8102,7	0,7%
Faro	3657	2,2%	61437,0	5,0%
Guarda	4801	2,9%	145753,9	11,8%
Leiria	6278	3,7%	86195,3	7,0%
Lisboa	12800	7,6%	9535,1	0,8%
Portalegre	2498	1,5%	13255,9	1,1%
Porto	36824	22%	51444,4	4,1%
Santarém	7662	4,6%	31609,1	2,5%
Setúbal	6678	4,0%	6318,9	0,5%
Viana do Castelo	11065	6,6%	73591,1	5,9%
Vila Real	10793	6,4%	87109,8	7,0%
Viseu	13213	7,9%	125084,3	10,1%
Total	167509	100,0%	1239885,9	100,0%

This Table presents the number and the relative frequency of wildfires by district of ignition and the total number of hectares and the relative frequency of burnt area by district of ignition. The sample consists of all wildfires in ICNF database in Portugal, between in 2011 and 2019.

Table 4: Firms by District

	Total	**Distribution**
Aveiro	963	9.7%
Beja	688	6.9%
Braga	710	7.1%
Bragança	241	2.4%
Castelo Branco	369	3.7%
Coimbra	329	3.3%
Évora	665	6.7%
Faro	325	3.3%
Guarda	209	2.1%
Leiria	659	6.7%
Lisboa	894	9%
Portalegre	505	5.1%
Porto	790	8.0%
Santarém	1016	10.2%
Setúbal	494	5.0%
Viana do Castelo	222	2.2%
Vila Real	252	2.5%
Viseu	607	6.1%
Total	**9938**	**100.0%**

This Table presents the number and the relative frequency of firms by district. The sample consists of all firms in IES database in Portugal, in 2016, whose primary sector of activity is one of the following: agriculture, animal production and forestry, manufacture of wood or pulp and paper manufacture.

Table 5: Firms by Sector of Activity

	Total	**Distribution**
Agriculture	3100	31.2%
Animal production	3726	37.5%
Forestry and logging	1134	11.4%
Manufacture of wood	1717	17.3%
Manufacture of pulp/paper	261	2.6%
Total	**9938**	**100.0%**

This Table presents the number and the relative frequency of firms by sector of activity. The sample consists of all firms in IES database in Portugal, in 2016, whose primary sector of activity is one of the following: agriculture, animal production and forestry, manufacture of wood or pulp and paper manufacture.

Table 6: Firms by Size

	Total	**Distribution**
Micro enterprises	8538	86.0%
Small enterprises	1225	12.3%
Medium-sized enterprises	159	1.6%
Large enterprises	16	0.1%
Total	**9938**	**100.0%**

This Table presents the number and the relative frequency of firms by size. The sample consists of all firms in IES database in Portugal, in 2016, whose primary sector of activity is one of the following: agriculture, animal production and forestry, manufacture of wood or pulp and paper manufacture.

Table 7: Firms by Age

	Total	**Distribution**
<1996	2437	24.5%
1996-2004	2115	21.3%
2005-2010	1947	19.6%
>2010	3439	34.6%
Total	**9938**	**100.0%**

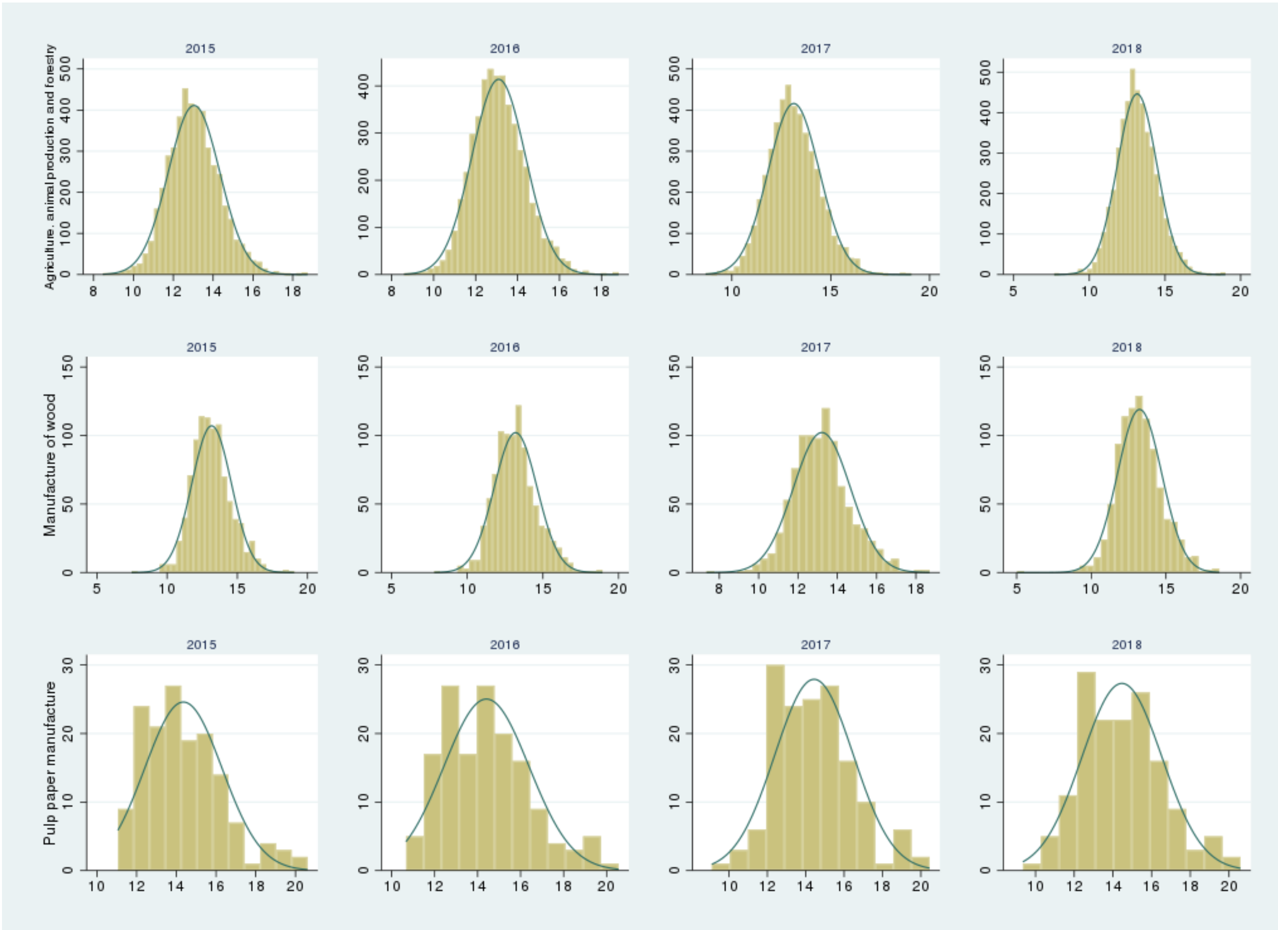
This Table presents the number and the relative frequency of firms by age. The sample consists of all firms in IES database in Portugal, in 2016, whose primary sector of activity is one of the following: agriculture, animal production and forestry, manufacture of wood or pulp and paper manufacture.

Table 8: Firms by Export Status

	Total	**Distribution**
Exporting firms	772	7.8%
Non-exporting firms	9166	92.2%
Total	**9938**	**100.0%**

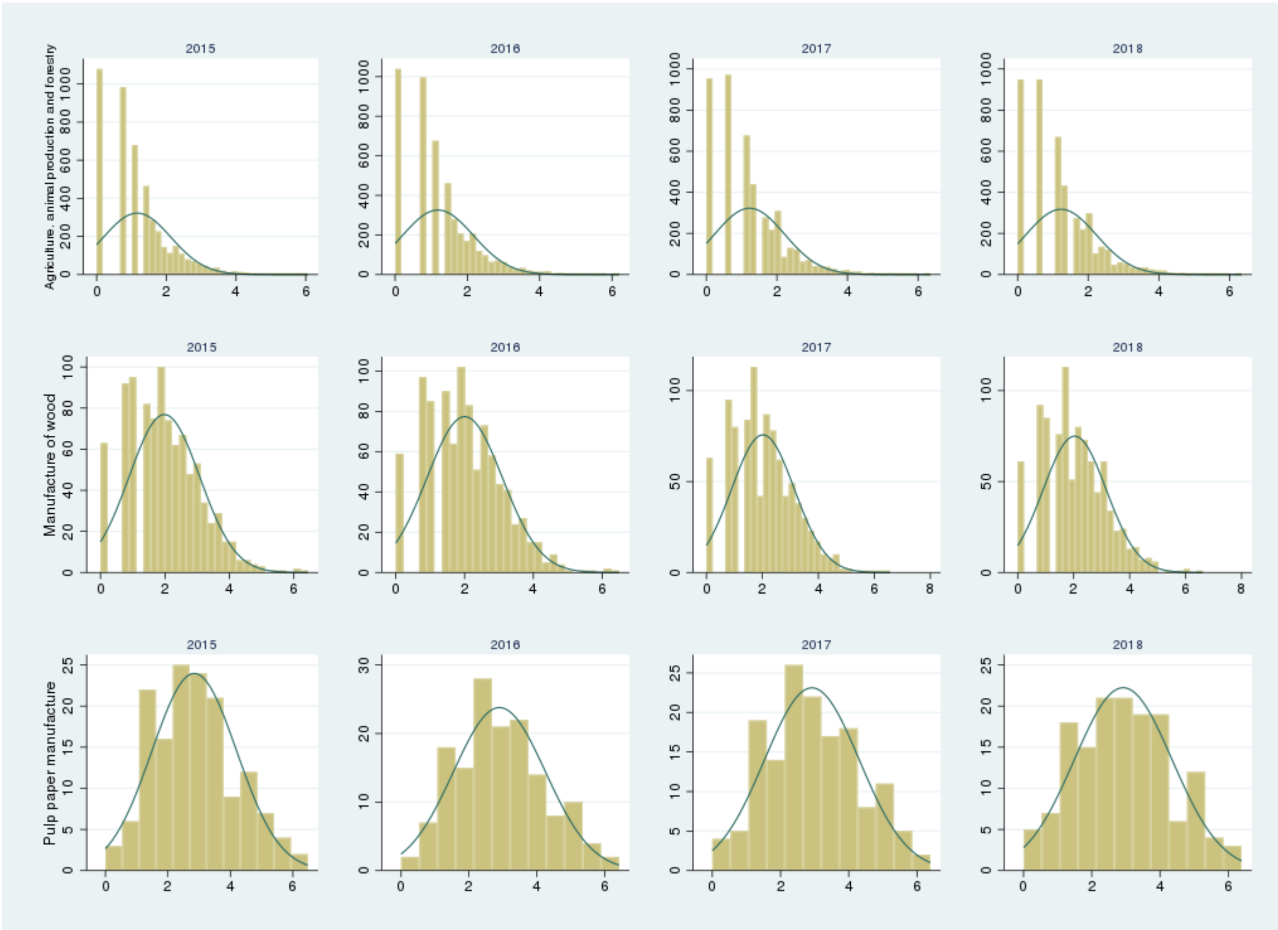
This Table presents the number and the relative frequency of firms by export status. The sample consists of all firms in IES database in Portugal, in 2016, whose primary sector of activity is one of the following: agriculture, animal production and forestry, manufacture of wood or pulp and paper manufacture.

Figure 5: Distribution of lassets by Year and Sector of Activity



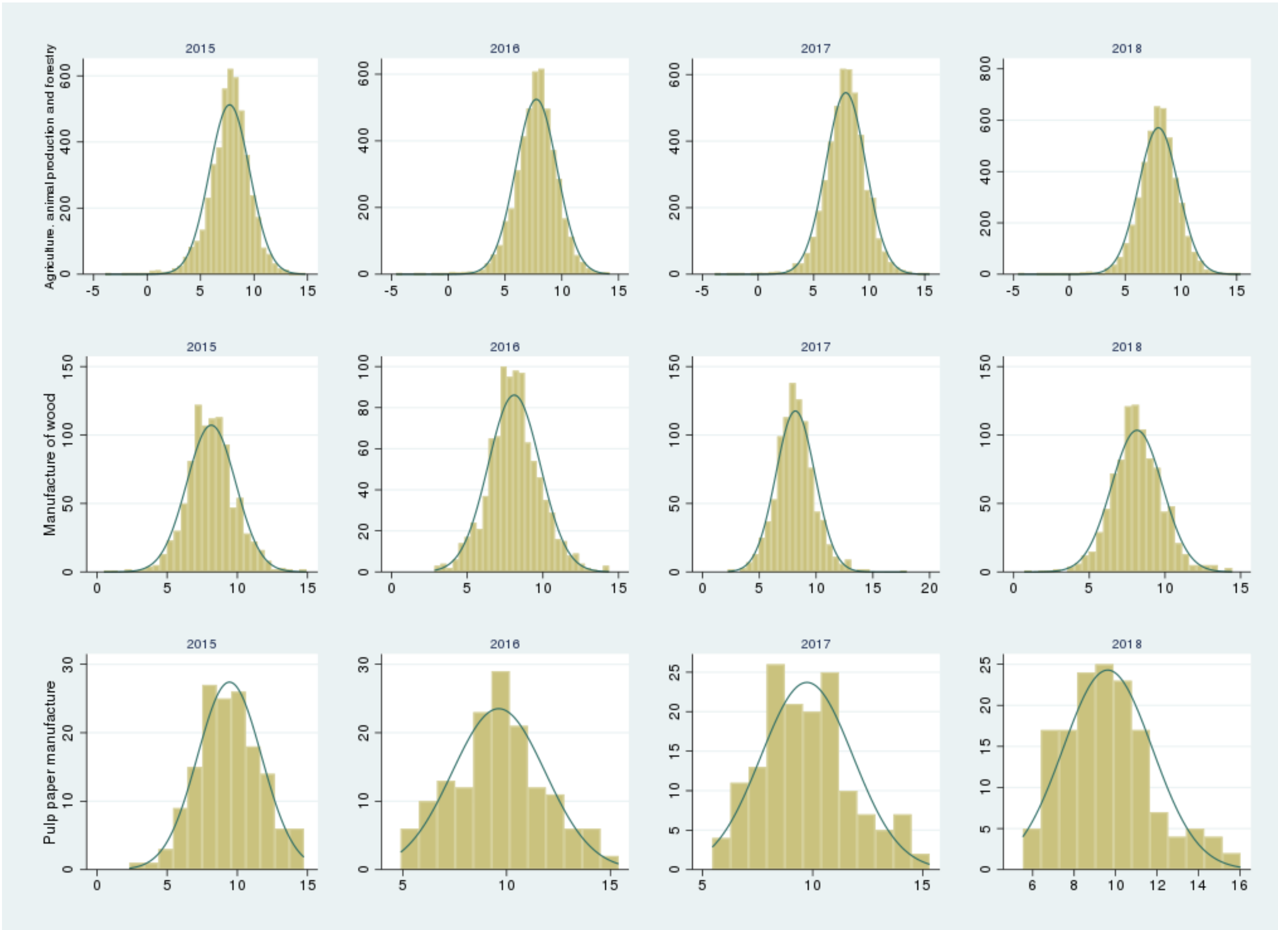
This Figure depicts the distribution of the outcome variable logarithm of assets by year and sector of activity. The sample consists of all firms in IES database in Portugal, in 2016, whose primary sector of activity is one of the following: agriculture, animal production and forestry, manufacture of wood or pulp and paper manufacture.

Figure 6: Distribution of lempl by Year and Sector of Activity



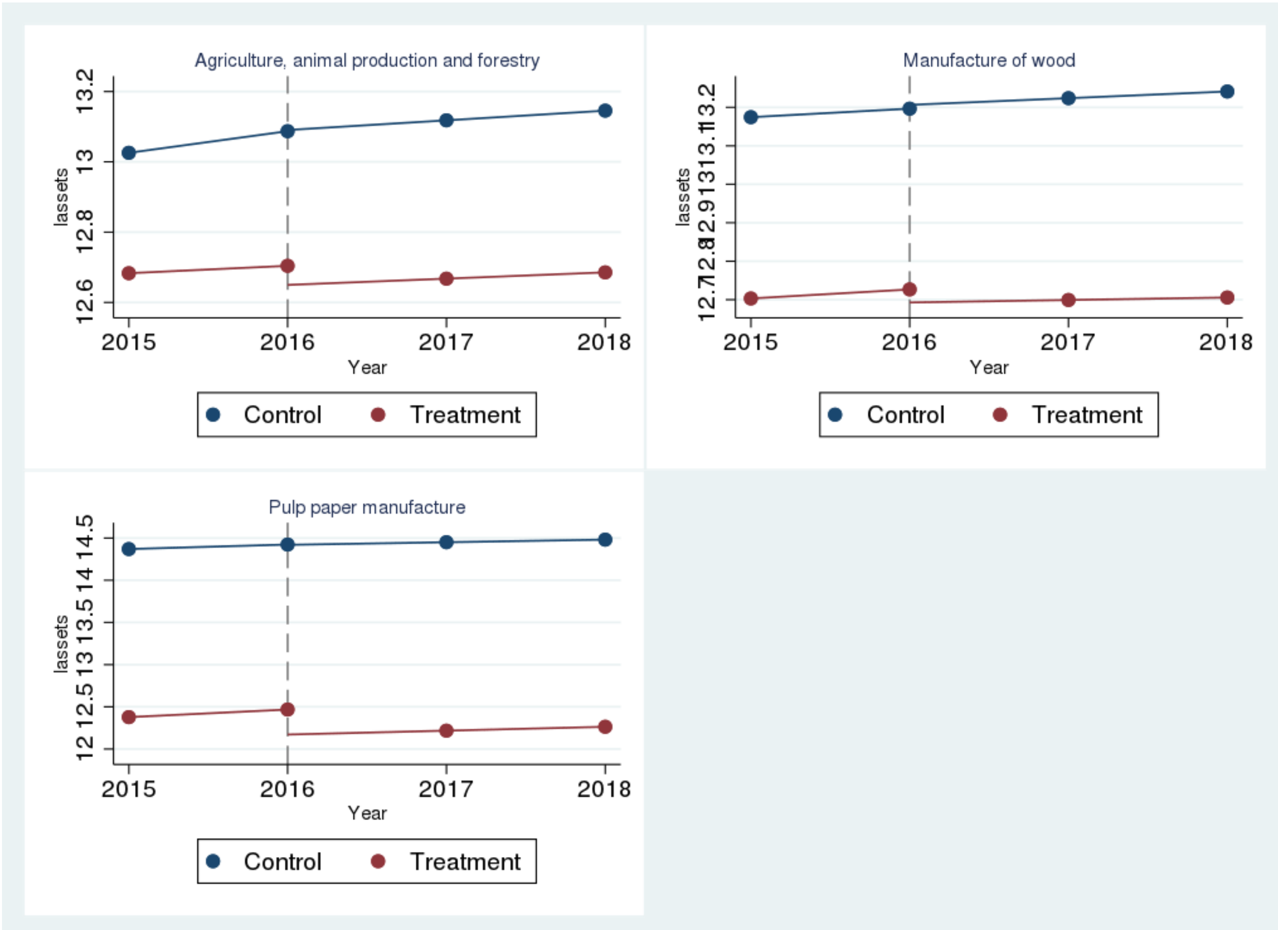
This Figure depicts the distribution of the outcome variable logarithm of the number of workers by year and sector of activity. The sample consists of all firms in IES database in Portugal, in 2016, whose primary sector of activity is one of the following: agriculture, animal production and forestry, manufacture of wood or pulp and paper manufacture.

Figure 7: Distribution of lotexp by Year and Sector of Activity



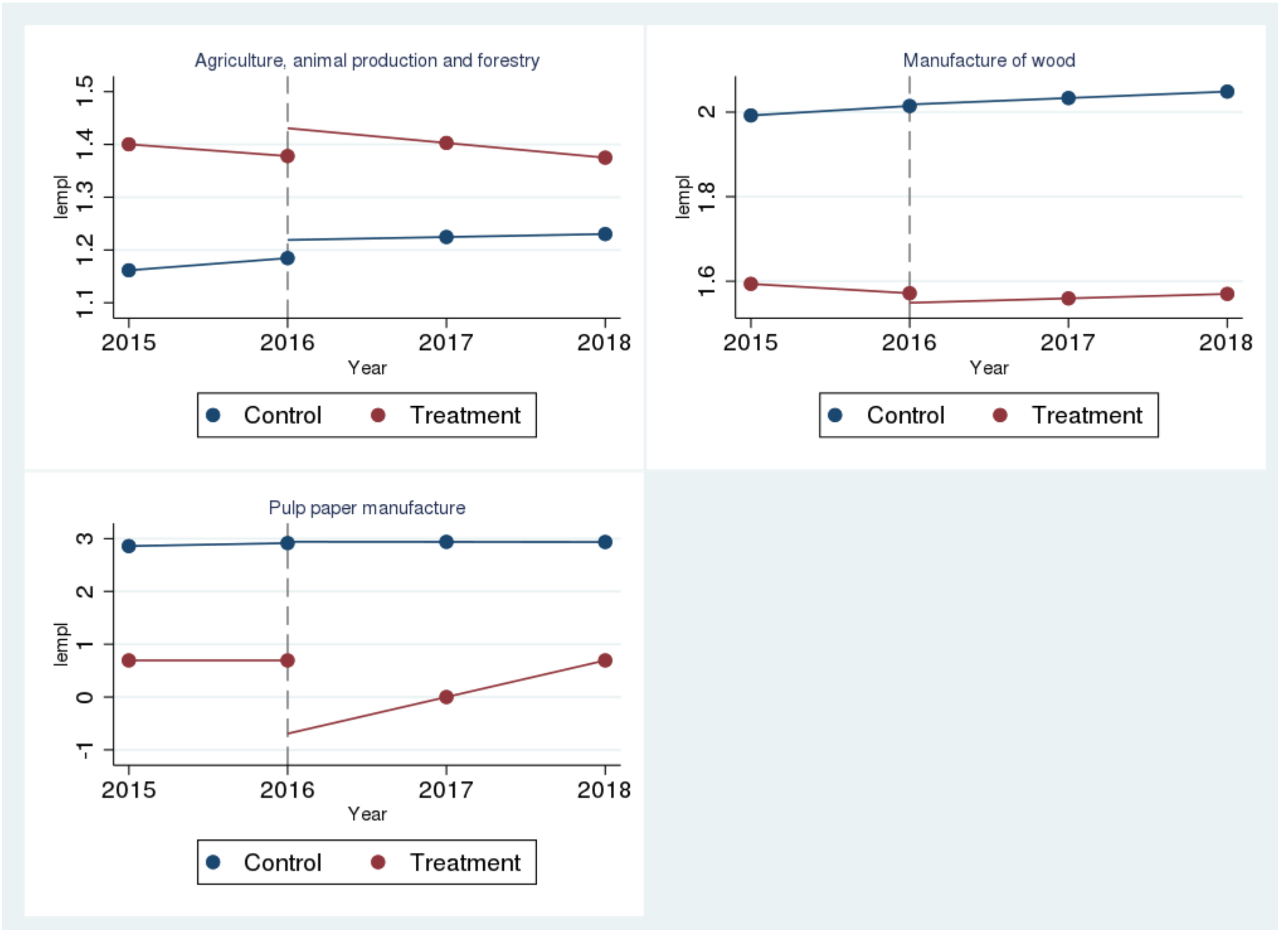
This Figure depicts the distribution of the outcome variable logarithm of other expenditures by year and sector of activity. The sample consists of all firms in IES database in Portugal, in 2016, whose primary sector of activity is one of the following: agriculture, animal production and forestry, manufacture of wood or pulp and paper manufacture.

Figure 8: Trends for Outcome Variable lassets by Sector of Activity



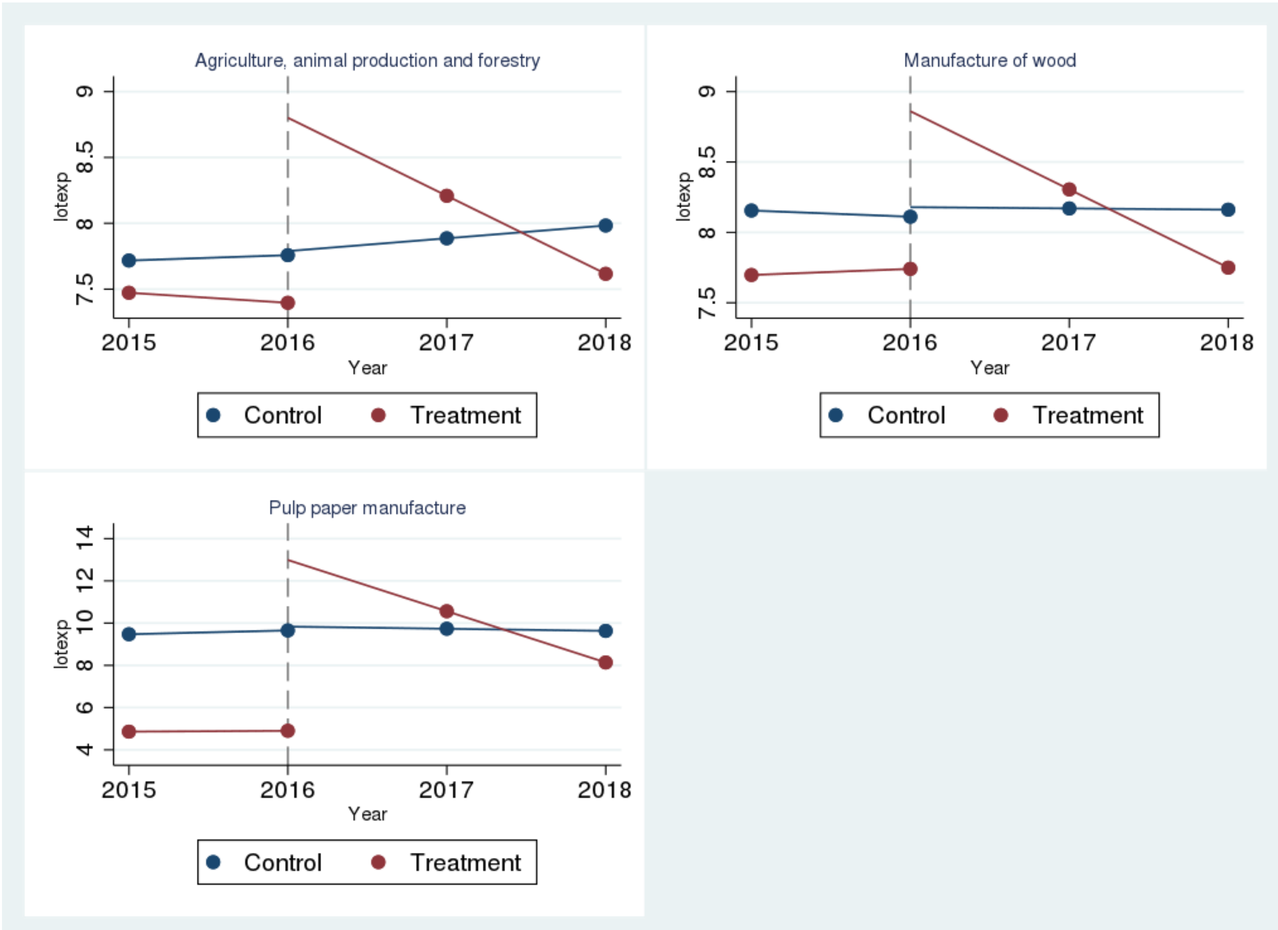
This Figur depicts the evolution of the logarithm of assets from 2015 to 2018, for the treatment and the control group. The dashed lines separate the pre-treatment and the post-treatment period. The first graph depicts the evolution for the agriculture, animal production and forestry firms. The second for the firms in the manufacture of wood sector. The third graph plots the evolution for the firms in the pulp and paper manufacture. The sample consists of firms in IES database in Portugal, whose primary sector of activity is one of the following: agriculture, animal production and forestry, manufacture of wood or pulp and paper manufacture.

Figure 9: Trends for Outcome Variable lempl by Sector of Activity



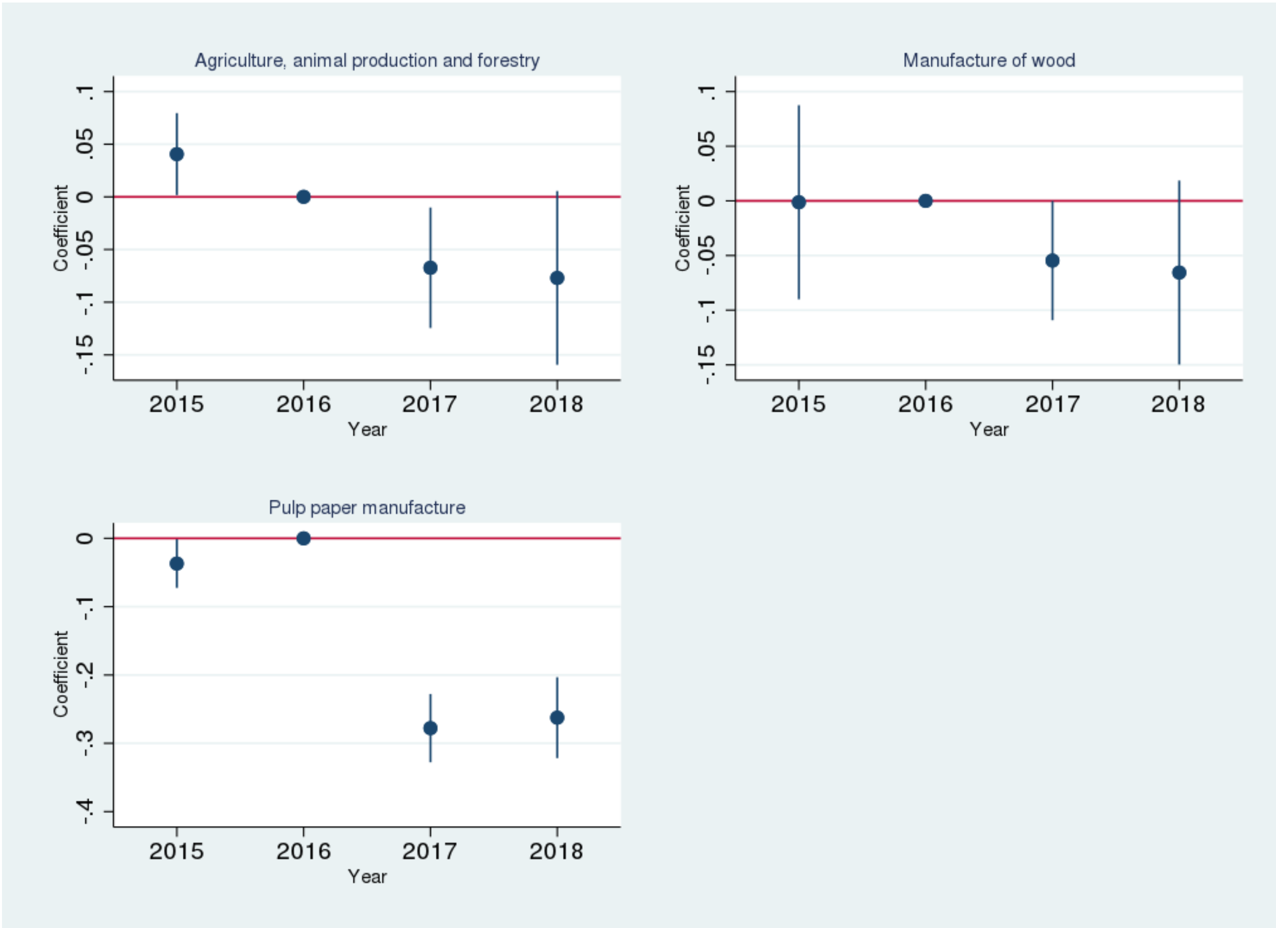
This Figure depicts the evolution of the logarithm of the number of workers from 2015 to 2018, for the treatment and the control group. The dashed lines separate the pre-treatment and the post-treatment period. The first graph depicts the evolution for the agriculture, animal production and forestry firms. The second for the firms in the manufacture of wood sector. The third graph plots the evolution for the firms in the pulp and paper manufacture. The sample consists of firms in IES database in Portugal, whose primary sector of activity is one of the following: agriculture, animal production and forestry, manufacture of wood or pulp and paper manufacture.

Figure 10: Trends for Outcome Variable lotexp by Sector of Activity



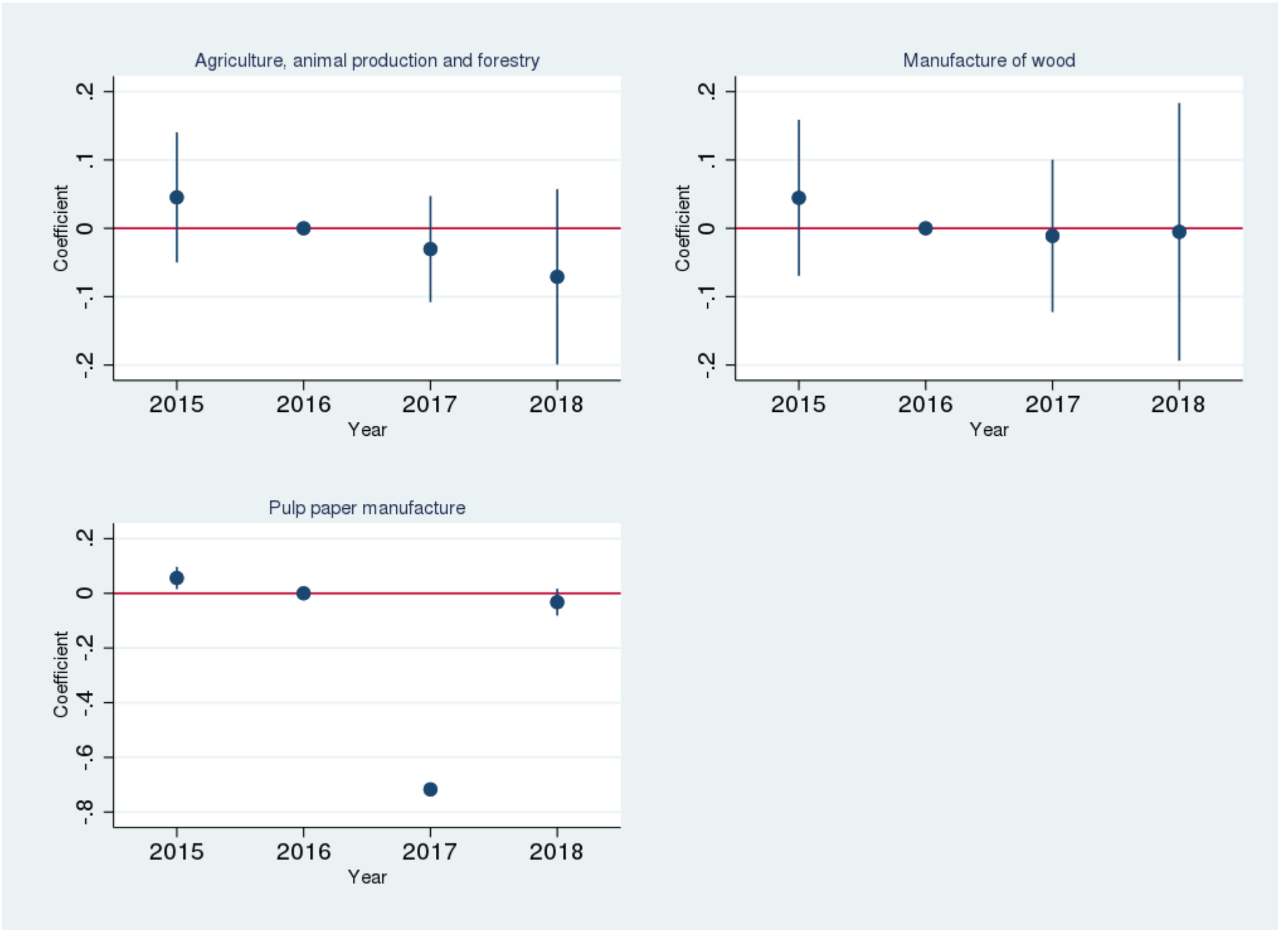
This Figure depicts the evolution of the logarithm of other expenses from 2015 to 2018, for the treatment and the control group. The dashed lines separate the pre-treatment and the post-treatment period. The first graph depicts the evolution for the agriculture, animal production and forestry firms. The second for the firms in the manufacture of wood sector. The third graph plots the evolution for the firms in the pulp and paper manufacture. The sample consists of firms in IES database in Portugal, whose primary sector of activity is one of the following: agriculture, animal production and forestry, manufacture of wood or pulp and paper manufacture.

Figure 11: Event Study for Outcome Variable lassets by Sector of Activity



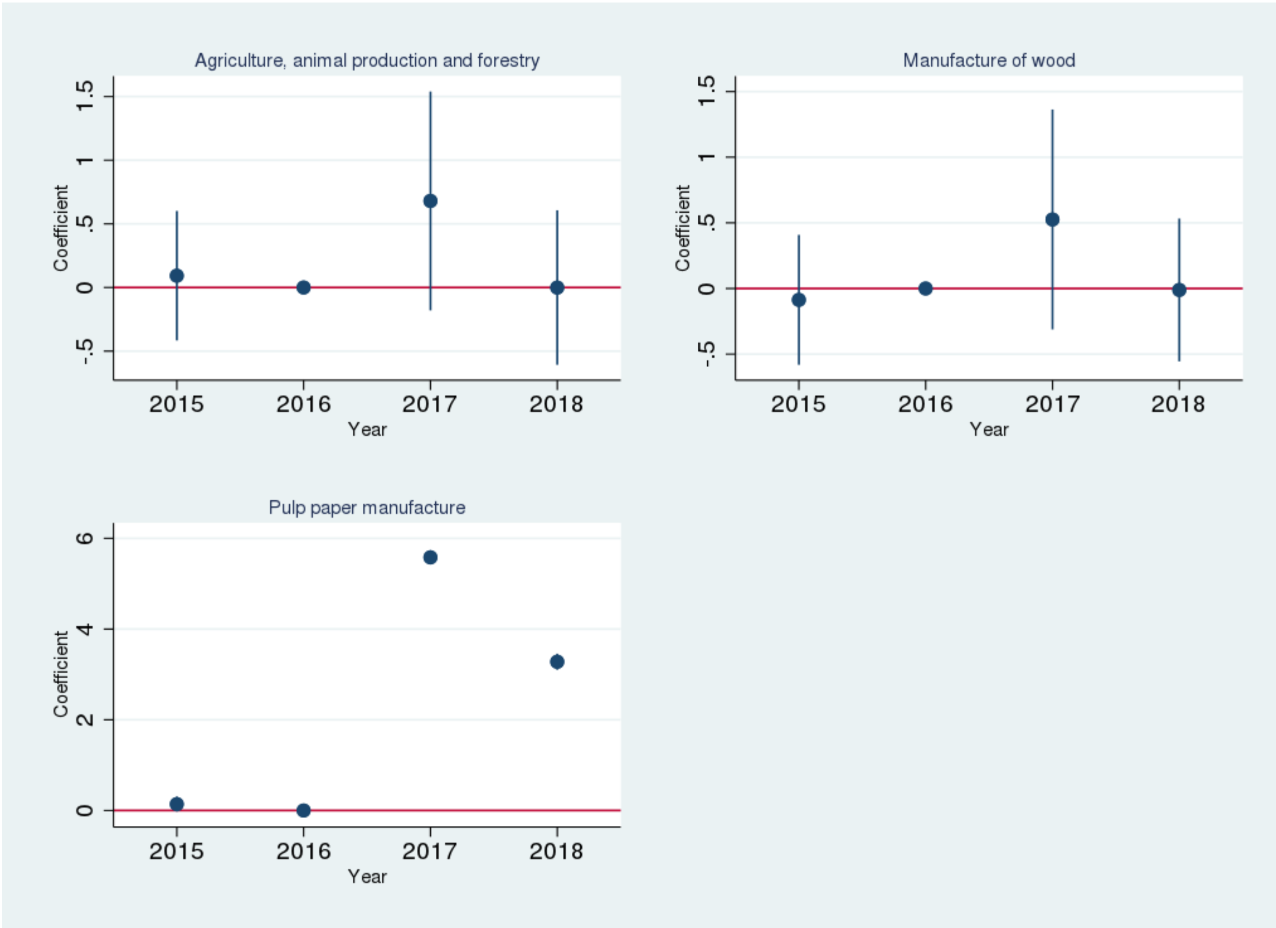
This Figure presents the coefficient estimates for the interaction between the treatment group and year, when regressing the outcome variable logarithm of assets in the interaction between the treatment group and year and year dummies, under firm fixed effects and clustering at the 4-digital postal code. The first graph depicts the evolution for the agriculture, animal production and forestry firms. The second for the firms in the manufacture of wood sector. The third graph plots the evolution for the firms in the pulp and paper manufacture. The sample consists of firms in IES database in Portugal, whose primary sector of activity is one of the following: agriculture, animal production and forestry, manufacture of wood or pulp and paper manufacture.

Figure 12: Event Study for Outcome Variable lempl by Sector of Activity



This Figure presents the coefficient estimates for the interaction between the treatment group and year, when regressing the outcome variable logarithm of the number of workers in the interaction between the treatment group and year and year dummies, under firm fixed effects and clustering at the 4-digital postal code. The first graph depicts the evolution for the agriculture, animal production and forestry firms. The second for the firms in the manufacture of wood sector. The third graph plots the evolution for the firms in the pulp and paper manufacture. The sample consists of firms in IES database in Portugal, whose primary sector of activity is one of the following: agriculture, animal production and forestry, manufacture of wood or pulp and paper manufacture.

Figure 13: Event Study for Outcome Variable lotexp by Sector of Activity



This Figure presents the coefficient estimates for the interaction between the treatment group and year, when regressing the outcome variable logarithm of other expenses in the interaction between the treatment group and year and year dummies, under firm fixed effects and clustering at the 4-digital postal code. The first graph depicts the evolution for the agriculture, animal production and forestry firms. The second for the firms in the manufacture of wood sector. The third graph plots the evolution for the firms in the pulp and paper manufacture. The sample consists of firms in IES database in Portugal, whose primary sector of activity is one of the following: agriculture, animal production and forestry, manufacture of wood or pulp and paper manufacture.

Table 9: Firms in the Treatment and Control Group, by Sector of Activity

	Treatment Group	**Control Group**
Agriculture	13	3087
Animal production	22	3704
Forestry and logging	51	1083
Manufacture of wood	34	1683
Manufacture of pulp/paper	2	259
Total	**122**	**9816**

This Table presents the number of firms by sector of activity, in the treatment and control group. The sample consists of all firms in IES database in Portugal, in 2016, whose primary sector of activity is one of the following: agriculture, animal production and forestry, manufacture of wood or pulp and paper manufacture.

Table 10: Key variables of control and treatment groups for 2015 and 2016 (averages and *t-tests*)

	Treatment group	**Control group**	**Difference**	**T-test**	**Unit**
Assets	486,7	1219,1	732,4	0.3183	10^3 euros
Tangible assets	227,3	572,6	345,3	0.3094	10^3 euros
Equity	158,6	494,3	335,7	0.2368	10^3 euros
Sales	321,1	779,6	458,5	0,4338	10^3 euros
Other expenses	4,7	11,4	6,7	0.2312	10^3 euros
ROA	-1,4	-5,3	-3,8	0.8522	%
Workers	5,3	6,7	1,4	0.2958	Number
Worked hours	9066,6	11491,0	2424,6	0.3044	Number
Size	1,13	1,16	0,03	0.2413	Categorical
Constitution year	2002,8	2002,4	-0,4	0.6624	Date (year)

This Table presents the average and *t-tests* results for the some key variables of the firms. The first column presents the average for the treated firms, i.e., those in the burnt area in 2017, while the second column presents the average for the firms in the control group. Column 3 presents the difference between the control and the treatment group. Column 4, indicates the *p-value* of the simple *t-test* applied to the difference displayed in column 3. In column 5 are displayed the units for each of the variable.

The variable *size* classifies the firms according to four dimension categories following the Commission Recommendation 2003/361/CE: micro enterprises, small enterprises, medium-sized enterprises and large enterprises. This classification is based on the number of employees and either total turnover or assets. Micro enterprises have a staff headcount lower than 10 and turnover or balance sheet total less than €2m and are classified as 1. Small enterprises have a staff headcount lower than 50 and turnover or balance sheet total less than €10m and are classified as 2. Medium-sized enterprises have a staff headcount lower than 250 and turnover less than €50m or balance sheet total less than €43m and are classified as 3. Large enterprises are classified as 4.

Table 11: Estimates of Wildfire on Assets - Standard DD Specification

VARIABLES	OLS (1)	OLS (2)	OLS (3)	OLS (4)	IV (5)
1.POST	0.071***	0.071***	0.071***	0.071***	0.071***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
1.T	-0.415***		-0.005	-0.011	-0.016
	(0.123)		(0.013)	(0.013)	(0.015)
1.POST#1.T	-0.089***	-0.089***	-0.089***	-0.103***	-0.103***
	(0.026)	(0.026)	(0.026)	(0.027)	(0.027)
lassetsi			0.978***	0.978***	
			(0.004)	(0.004)	
lassetsi_hat					0.955***
					(0.036)
lstart			3.644***	3.213***	1.983
			(0.649)	(0.622)	(1.945)
sland_s				-0.024***	-0.021***
				(0.007)	(0.004)
DID_sland				-0.046**	-0.044**
				(0.020)	(0.021)
Observations	23,496	23,496	23,496	23,493	23,493
R-squared		0.030			0.945
Number of firms	5,874	5,874	5,874	5,874	
FIRM FE		YES			
SECTOR OF ACTIVITY			YES	YES	YES
DISTRICT			YES	YES	YES
F stat					5.828
Wu-Hausman F stat					0.474
p-values Wu-Hausman F stat					0.492

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This Table reports estimates of a regression of the logarithm of assets. Column (1) reports the results using the standard DD specification. Column (2) reports the results adding firm fixed effects. Column (3) reports the results controlling for the logarithm of the initial value of assets (*lassetsi*) and for the date of constitution of the firm (*lstart*) and adding sector of activity at 2-digit level and district dummies as covariates. Column (4) reports the results controlling for the $sland\_s_{ispt}$, the standardized value for the share of land and buildings on tangible and intangible fixed assets of the firm derived from the balance sheet, and using an interaction term of $sland\_s_{ispt}$ and the DD dummy variable. Column (5) reports the results employing IV, by using the (i) the average amount of total assets for the 3-digit sector of activity and (ii) the industry specific minimum efficient scale to instrument the initial stock of assets. All regressions include a constant term. The sample consists of all firms in IES database in Portugal, between 2015 to 2018, whose primary sector of activity is one of the following: agriculture, animal production and forestry, manufacture of wood or pulp and paper manufacture. Robust standard errors are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Table 12: Estimates of Wildfire on Workers - Standard DD Specification

VARIABLES	OLS (1)	OLS (2)	OLS (3)	OLS (4)	IV (5)
1.POST	0.031***	0.031***	0.032***	0.032***	0.033***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
1.T	0.091		-0.009	-0.013	-0.012
	(0.111)		(0.020)	(0.020)	(0.020)
1.POST#1.T	-0.067*	-0.067*	-0.067*	-0.084**	-0.094**
	(0.037)	(0.037)	(0.037)	(0.037)	(0.038)
lempli			0.953***	0.951***	
			(0.005)	(0.005)	
lempli_hat					0.986***
					(0.047)
lstart			1.852***	1.487**	2.620
			(0.653)	(0.646)	(1.786)
sland_s				-0.016***	-0.016***
				(0.004)	(0.006)
DID_sland				-0.052	-0.080
				(0.043)	(0.051)
Observations	22,775	22,775	22,775	22,772	22,772
R-squared		0.004			0.890
Number of firms	5,758	5,758	5,758	5,758	
FIRM FE		YES			
SECTOR OF ACTIVITY			YES	YES	YES
DISTRICT			YES	YES	YES
F stat					15.92
Wu-Hausman F stat					0.572
p-values Wu-Hausman F stat					0.450

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This Table reports estimates of a regression of the logarithm of the number of workers. Column (1) reports the results using the standard DD specification. Column (2) reports the results adding firm fixed effects. Column (3) reports the results controlling for the logarithm of the initial value of the number of workers (*lempli*) and for the date of constitution of the firm (*lstart*) and adding sector of activity at 2-digit level and district dummies as covariates. Column (4) reports the results controlling for the $sland\_s_{ispt}$, the standardized value for the share of land and buildings on tangible and intangible fixed assets of the firm derived from the balance sheet, and using an interaction term of $sland\_s_{ispt}$ and the DD dummy variable. Column (5) reports the results employing IV, by using the (i) the average amount of total number of workers for the 3-digit sector of activity and (ii) the industry specific minimum efficient scale to instrument the initial stock of the number of workers. All regressions include a constant term. The sample consists of all firms in IES database in Portugal, between 2015 to 2018, whose primary sector of activity is one of the following: agriculture, animal production and forestry, manufacture of wood or pulp and paper manufacture. Robust standard errors are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Table 13: Estimates of Wildfire on Other Expenses - Standard DD Specification

	OLS	OLS	OLS	OLS	IV
VARIABLES	(1)	(2)	(3)	(4)	(5)
1.POST	0.156***	0.153***	0.156***	0.157***	0.157***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
1.T	-0.355**		-0.094	-0.100	-0.020
	(0.178)		(0.091)	(0.092)	(0.102)
1.POST#1.T	0.326	0.329	0.321	0.397**	0.408**
	(0.209)	(0.209)	(0.210)	(0.200)	(0.191)
lOtExpi			0.728***	0.728***	
			(0.009)	(0.009)	
lOtExpi_hat					0.974***
					(0.077)
lstart			-10.300***	-10.758***	5.662
			(1.526)	(1.554)	(5.263)
sland_s				-0.024**	-0.022*
				(0.010)	(0.012)
DID_sland				0.256	0.311
				(0.177)	(0.262)
Observations	22,782	22,782	22,782	22,779	22,779
R-squared		0.008			0.537
Number of firms	5,754	5,754	5,754	5,754	
FIRM FE		YES			
SECTOR OF ACTIVITY			YES	YES	YES
DISTRICT			YES	YES	YES
F stat					6.356
Wu-Hausman F stat					7.323
p-values Wu-Hausman F stat					0.00707

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This Table reports estimates of a regression of the logarithm of other expenses. Column (1) reports the results using the standard DD specification. Column (2) reports the results adding firm fixed effects. Column (3) reports the results controlling for the logarithm of the initial other expenses (*lotexpi*) and for the date of constitution of the firm (*lstart*) and adding sector of activity at 2-digit level and district dummies as covariates. Column (4) reports the results controlling for the $sland\_s_{ispt}$, the standardized value for the share of land and buildings on tangible and intangible fixed assets of the firm derived from the balance sheet, and using an interaction term of $sland\_s_{ispt}$ and the DD dummy variable. Column (5) reports the results employing IV, by using the (i) the average amount of other expenses for the 3-digit sector of activity and (ii) the industry specific minimum efficient scale to instrument the initial value of other expenses. All regressions include a constant term. The sample consists of all firms in IES database in Portugal, between 2015 to 2018, whose primary sector of activity is one of the following: agriculture, animal production and forestry, manufacture of wood or pulp and paper manufacture. Robust standard errors are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Table 14: Estimates of Wildfire on Assets - Heterogeneity by Intensity in Land and Buildings

	Agriculture, animal production and forestry		**Manufacture of wood**	
	Low	**High**	**Low**	**High**
1.POST	0.285***	0.079***	0.131***	0.074***
	(0.016)	(0.009)	(0.020)	(0.012)
1.T	-0.277	-0.227	-0.606*	-0.737*
	(0.231)	(0.306)	(0.318)	(0.441)
1.POST#1.T	-0.198	-0.208***	-0.007	-0.174*
	(0.129)	(0.064)	(0.109)	(0.092)
Observations	10,907	7,952	2,763	1,712
Number of firms	2,733	1,988	693	428

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

This Table reports estimates of a regression of the logarithm of assets, using the standard DD specification, by sector of activity and intensity in land and buildings. For each sector of activity, we distinguish firms with low intensity, the ones that do not possess any land or buildings, and high intensity (above the percentile 25% of land and buildings, for each sector of activity). All regressions include a constant term. The sample consists of all firms in IES database in Portugal, between 2015 to 2018, whose primary sector of activity is one of the following: agriculture or animal production. Robust standard errors are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Table 15: Estimates of Wildfire on Workers - Heterogeneity by Intensity in Land and Buildings

	Agriculture, animal production and forestry		**Manufacture of wood**	
	Low	**High**	**Low**	**High**
1.POST	0.022**	0.052***	0.033***	0.032**
	(0.009)	(0.013)	(0.011)	(0.015)
1.T	0.060	0.440*	-0.504**	-0.920*
	(0.099)	(0.251)	(0.198)	(0.519)
1.POST#1.T	-0.127**	-0.152***	-0.004	-0.239
	(0.057)	(0.050)	(0.091)	(0.238)
Observations	10,035	7,692	2,664	1,694
Number of firms	2,573	1,939	678	427

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

This Table reports estimates of a regression of the logarithm of the number of workers, using the standard DD specification, by sector of activity and intensity in land and buildings. For each sector of activity, we distinguish firms with low intensity, the ones that do not possess any land or buildings, and high intensity (above the percentile 25% of land and buildings, for each sector of activity). All regressions include a constant term. The sample consists of all firms in IES database in Portugal, between 2015 to 2018, whose primary sector of activity is one of the following: agriculture or animal production. Robust standard errors are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Table 16: Estimates of Wildfire on Other Expenses - Heterogeneity by Intensity in Land and Buildings

	Agriculture, animal production and forestry		**Manufacture of wood**	
	Low	**High**	**Low**	**High**
1.POST	0.389***	0.170***	0.286***	0.045
	(0.033)	(0.022)	(0.074)	(0.050)
1.T	0.316	0.022	-1.007**	-0.932**
	(0.324)	(0.388)	(0.437)	(0.439)
1.POST#1.T	-0.302	-0.075	0.136	0.343
	(0.194)	(0.399)	(0.463)	(0.624)
Observations	9,401	7,780	2,564	1,688
Number of firms	2,440	1,956	662	425

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

This Table reports estimates of a regression of the logarithm of other expenses, using the standard DD specification, by sector of activity and intensity in land and buildings. For each sector of activity, we distinguish firms with low intensity, the ones that do not possess any land or buildings, and high intensity (above the percentile 25% of land and buildings, for each sector of activity). All regressions include a constant term. The sample consists of all firms in IES database in Portugal, between 2015 to 2018, whose primary sector of activity is one of the following: agriculture or animal production. Robust standard errors are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Table 17: Estimates of Wildfire on Assets by Sector of Activity - Standard DD Specification

	Agriculture, animal production and forestry			**Manufacture of wood**			**Pulp paper manufacture**		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
1.POST	0.075***	0.075***	0.075***	0.047***	0.047***	0.047***	0.069**	0.069**	0.069**
	(0.006)	(0.006)	(0.006)	(0.011)	(0.011)	(0.011)	(0.031)	(0.031)	(0.031)
1.T	-0.363**		-0.002	-0.471**		-0.005	-1.974***		0.003
	(0.154)		(0.016)	(0.236)		(0.027)	(0.190)		(0.053)
1.POST#1.T	-0.092***	-0.092***	-0.092***	-0.059	-0.059	-0.059	-0.252***	-0.252***	-0.252***
	(0.031)	(0.031)	(0.031)	(0.046)	(0.046)	(0.046)	(0.031)	(0.031)	(0.031)
lassetsi			0.965***			1.008***			1.026***
			(0.004)			(0.005)			(0.015)
lstart			2.924***			5.153***			5.303
			(0.768)			(1.135)			(3.629)
Observations	19,072	19,072	19,072	3,820	3,820	3,820	604	604	604
R-squared		0.033			0.016			0.030	
Number of firms	4,768	4,768	4,768	955	955	955	151	151	151
FIRM FE		YES			YES			YES	
SECTOR OF ACTIVITY			YES			YES			YES
DISTRICT			YES			YES			YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

This Table reports estimates of a regression of the logarithm of assets. Column (1) reports the results using the standard DD specification. Column (2) reports the results adding firm fixed effects. Column (3) reports the results controlling for the logarithm of the initial value of assets (*lassetsi*) and for the date of constitution of the firm (*lstart*) and adding sector of activity at 2-digit level and district dummies as covariates. All regressions include a constant term. The sample consists of all firms in IES database in Portugal, between 2015 to 2018, whose primary sector of activity is one of the following: agriculture, animal production and forestry, manufacture of wood or pulp and paper manufacture. Robust standard errors are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Table 18: Estimates of Wildfire on Workers by Sector of Activity - Standard DD Specification

	Agriculture, animal production and forestry			**Manufacture of wood**			**Pulp paper manufacture**		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
1.POST	0.034***	0.033***	0.035***	0.013*	0.012	0.013*	0.056**	0.056**	0.056**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.024)	(0.024)	(0.025)
1.T	0.216*		0.022	-0.421*		-0.058*	-2.194***		-0.029
	(0.118)		(0.024)	(0.221)		(0.033)	(0.116)		(0.062)
1.POST#1.T	-0.072*	-0.073*	-0.072*	-0.031	-0.030	-0.031	-0.403***	-0.403***	-0.403***
	(0.039)	(0.039)	(0.039)	(0.073)	(0.073)	(0.073)	(0.024)	(0.024)	(0.025)
lempli			0.940***			0.987***			1.001***
			(0.006)			(0.007)			(0.022)
lstart			1.243			4.084***			5.525**
			(0.798)			(1.036)			(2.644)
Observations	18,397	18,397	18,397	3,775	3,775	3,775	603	603	603
R-squared		0.004			0.001			0.027	
Number of firms	4,655	4,655	4,655	952	952	952	151	151	151
FIRM FE		YES			YES			YES	
SECTOR OF ACTIVITY			YES			YES			YES
DISTRICT			YES			YES			YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

This Table reports estimates of a regression of the logarithm of the number of workers. Column (1) reports the results using the standard DD specification. Column (2) reports the results adding firm fixed effects. Column (3) reports the results controlling for the logarithm of the initial value of the number of workers (*lempli*) and for the date of constitution of the firm (*lstart*) and adding sector of activity at 2-digit level and district dummies as covariates. All regressions include a constant term. The sample consists of all firms in IES database in Portugal, between 2015 to 2018, whose primary sector of activity is one of the following: agriculture, animal production and forestry, manufacture of wood or pulp and paper manufacture. Robust standard errors are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Table 19: Estimates of Wildfire on Other Expenses by Sector of Activity - Standard DD Specification

	Agriculture, animal production and forestry			**Manufacture of wood**			**Pulp paper manufacture**		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
1.POST	0.184***	0.181***	0.185***	0.022	0.020	0.023	0.109*	0.108*	0.106
	(0.017)	(0.017)	(0.017)	(0.032)	(0.032)	(0.032)	(0.063)	(0.063)	(0.064)
1.T	-0.294		-0.104	-0.416*		-0.012	-4.682***		-0.835**
	(0.244)		(0.142)	(0.232)		(0.104)	(0.205)		(0.403)
1.POST#1.T	0.286	0.289	0.283	0.298	0.301	0.288	4.359***	4.359***	4.362***
	(0.293)	(0.294)	(0.294)	(0.302)	(0.302)	(0.301)	(0.063)	(0.063)	(0.064)
lOtExpi			0.704***			0.814***			0.859***
			(0.010)			(0.014)			(0.042)
lstart			-13.185***			0.974			-22.556***
			(1.714)			(3.764)			(8.335)
Observations	18,439	18,439	18,439	3,740	3,740	3,740	603	603	603
R-squared		0.010			0.001			0.082	
Number of firms	4,659	4,659	4,659	944	944	944	151	151	151
FIRM FE		YES			YES			YES	
SECTOR OF ACTIVITY			YES			YES			YES
DISTRICT			YES			YES			YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

This Table reports estimates of a regression of the logarithm of other expenses. Column (1) reports the results using the standard DD specification. Column (2) reports the results adding firm fixed effects. Column (3) reports the results controlling for the logarithm of the initial value of other expenses (*lotexpi*) and for the date of constitution of the firm (*lstart*) and adding sector of activity at 2-digit level and district dummies as covariates. All regressions include a constant term. The sample consists of all firms in IES database in Portugal, between 2015 to 2018, whose primary sector of activity is one of the following: agriculture, animal production and forestry, manufacture of wood or pulp and paper manufacture. Robust standard errors are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Table 20: Estimates of Wildfire on Assets by Sector of Activity: Agriculture, Animal Production and Forestry and Logging - Standard DD Specification

VARIABLES	**Agriculture**	**Animal Production**	**Forestry and Logging**
1.POST	0.083***	0.065***	0.101***
	(0.009)	(0.006)	(0.016)
1.T	0.250	-0.541**	-0.756***
	(0.409)	(0.227)	(0.200)
1.POST#1.T	-0.242*	-0.049	-0.041
	(0.130)	(0.073)	(0.035)
Observations	7,856	9,636	1,580
Number of firms	1,964	2,409	395

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

This Table reports estimates of a regression of the logarithm of assets, using the standard DD specification. Column (1) reports the results for the agricultural sector, Column (2) for the firms in animal production a d Column (3) for the firms in forestry and logging. All regressions include a constant term. The sample consists of all firms in IES database in Portugal, between 2015 to 2018, whose primary sector of activity is one of the following: agriculture, animal production and forestry. Robust standard errors are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Table 21: Estimates of Wildfire on Workers by Sector of Activity - Agriculture, Animal Production and Forestry and Logging

VARIABLES	**Agriculture**	**Animal Production**	**Forestry and Logging**
1.POST	0.054***	0.025***	-0.006
	(0.013)	(0.008)	(0.017)
1.T	0.692**	-0.141	-0.033
	(0.280)	(0.156)	(0.182)
1.POST#1.T	-0.012	-0.015	-0.144***
	(0.072)	(0.044)	(0.056)
Observations	7,487	9,364	1,546
Number of firms	1,900	2,363	392

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This Table reports estimates of a regression of the logarithm of the number of workers, using the standard DD specification. Column (1) reports the results for the agricultural sector, Column (2) for the firms in animal production a d Column (3) for the firms in forestry and logging. All regressions include a constant term. The sample consists of all firms in IES database in Portugal, between 2015 to 2018, whose primary sector of activity is one of the following: agriculture, animal production and forestry. Robust standard errors are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Table 22: Estimates of Wildfire on Other Expenses by Sector of Activity - Agriculture, Animal Production and Forestry and Logging

VARIABLES	**Agriculture**	**Animal Production**	**Forestry and Logging**
1.POST	0.200***	0.192***	0.059
	(0.028)	(0.024)	(0.051)
1.T	0.079	-0.740	-0.466
	(0.398)	(0.476)	(0.374)
1.POST#1.T	0.729*	0.290	0.045
	(0.428)	(0.457)	(0.348)
Observations	7,539	9,356	1,544
Number of firms	1,908	2,361	390

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

This Table reports estimates of a regression of the logarithm of other expenses, using the standard DD specification. Column (1) reports the results for the agricultural sector, Column (2) for the firms in animal production a d Column (3) for the firms in forestry and logging. All regressions include a constant term. The sample consists of all firms in IES database in Portugal, between 2015 to 2018, whose primary sector of activity is one of the following: agriculture, animal production and forestry. Robust standard errors are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Table 23: Estimates of Wildfire on Assets - Heterogeneity by Size

VARIABLES	**Micro**	**Small**
1.POST	0.147***	0.122***
	(0.008)	(0.009)
1.T	-0.421***	-0.091
	(0.103)	(0.241)
1.POST#1.T	-0.111**	0.018
	(0.055)	(0.030)
Observations	34,026	4,884
Number of firms	8,818	1,635

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

This Table reports estimates of a regression of the logarithm of assets, using the standard DD specification, by size. All regressions include a constant term. The sample consists of all firms in IES database in Portugal, between 2015 to 2018, that are classified as micro or small companies and whose primary sector of activity is one of the following: agriculture, animal production and forestry, manufacture of wood or pulp and paper manufacture. Robust standard errors are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Table 24: Estimates of Wildfire on Workers - Heterogeneity by Size

VARIABLES	**Micro**	**Small**
1.POST	0.038***	0.060***
	(0.009)	(0.013)
1.T	0.138**	-0.023
	(0.065)	(0.131)
1.POST#1.T	-0.031	-0.023
	(0.050)	(0.066)
Observations	32,146	4,858
Number of firms	8,483	1,616

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

This Table reports estimates of a regression of the logarithm of the number of workers, using the standard DD specification, by size. All regressions include a constant term. The sample consists of all firms in IES database in Portugal, between 2015 to 2018, that are classified as micro or small companies and whose primary sector of activity is one of the following: agriculture, animal production and forestry, manufacture of wood or pulp and paper manufacture. Robust standard errors are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Table 25: Estimates of Wildfire on Other Expenses - Heterogeneity by Size

VARIABLES	**Micro**	**Small**
1.POST	0.273***	0.112***
	(0.017)	(0.036)
1.T	-0.169	0.086
	(0.153)	(0.253)
1.POST#1.T	0.111	0.137
	(0.133)	(0.455)
Observations	31,468	4,795
Number of firms	8,325	1,600

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

This Table reports estimates of a regression of the logarithm of other expenses, using the standard DD specification, by size. All regressions include a constant term. The sample consists of all firms in IES database in Portugal, between 2015 to 2018, that are classified as micro or small companies and whose primary sector of activity is one of the following: agriculture, animal production and forestry, manufacture of wood or pulp and paper manufacture. Robust standard errors are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Table 26: Estimates of Wildfire on Assets - Heterogeneity by Age

VARIABLES	**<1996**	**1996-2004**	**2005-2010**	**>2010**
1.POST	0.026***	0.038***	0.079***	0.339***
	(0.008)	(0.009)	(0.010)	(0.015)
1.T	-0.366	-0.546**	-0.097	-0.443**
	(0.267)	(0.236)	(0.201)	(0.224)
1.POST#1.T	0.000	-0.086*	-0.048	-0.230*
	(0.041)	(0.044)	(0.075)	(0.124)
Observations	9,736	8,448	7,771	13,695
Number of firms	2,435	2,114	1,945	3,429

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

This Table reports estimates of a regression of the logarithm of assets, using the standard DD specification, by age. All regressions include a constant term. The sample consists of all firms in IES database in Portugal, between 2015 to 2018, whose primary sector of activity is one of the following: agriculture, animal production and forestry, manufacture of wood or pulp and paper manufacture. Robust standard errors are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Table 27: Estimates of Wildfire on Workers - Heterogeneity by Age

VARIABLES	**<1996**	**1996-2004**	**2005-2010**	**>2010**
1.POST	-0.021**	0.001	0.027*	0.136***
	(0.010)	(0.013)	(0.016)	(0.014)
1.T	0.072	-0.071	0.349**	0.097
	(0.222)	(0.186)	(0.136)	(0.097)
1.POST#1.T	-0.052	0.143	-0.021	-0.213***
	(0.042)	(0.118)	(0.073)	(0.070)
Observations	9,514	8,253	7,433	12,542
Number of firms	2,405	2,089	1,894	3,204

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

This Table reports estimates of a regression of the logarithm of the number of workers, using the standard DD specification, by age. All regressions include a constant term. The sample consists of all firms in IES database in Portugal, between 2015 to 2018, whose primary sector of activity is one of the following: agriculture, animal production and forestry, manufacture of wood or pulp and paper manufacture. Robust standard errors are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Table 28: Estimates of Wildfire on Other Expenses - Heterogeneity by Age

VARIABLES	**<1996**	**1996-2004**	**2005-2010**	**>2010**
1.POST	0.056**	0.117***	0.127***	0.576***
	(0.023)	(0.025)	(0.029)	(0.030)
1.T	-0.481**	-0.331	0.699***	-0.305
	(0.216)	(0.243)	(0.256)	(0.296)
1.POST#1.T	0.232	0.070	0.072	0.057
	(0.212)	(0.215)	(0.311)	(0.251)
Observations	9,512	8,140	7,390	11,952
Number of firms	2,397	2,066	1,887	3,080

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

This Table reports estimates of a regression of the logarithm of other expenses, using the standard DD specification, by age. All regressions include a constant term. The sample consists of all firms in IES database in Portugal, between 2015 to 2018, whose primary sector of activity is one of the following: agriculture, animal production and forestry, manufacture of wood or pulp and paper manufacture. Robust standard errors are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Table 29: Estimates of Wildfire on Assets - Heterogeneity by Export Status

VARIABLES	**Non-exporting**	**Exporting**
1.POST	0.151***	0.108***
	(0.007)	(0.011)
1.T	-0.447***	-0.402
	(0.116)	(0.351)
1.POST#1.T	-0.109**	-0.046
	(0.048)	(0.102)
Observations	36,290	3,360
Number of firms	9,345	1,237

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

This Table reports estimates of a regression of the logarithm of assets, using the standard DD specification, by export status. All regressions include a constant term. The sample consists of all firms in IES database in Portugal, between 2015 to 2018, whose primary sector of activity is one of the following: agriculture, animal production and forestry, manufacture of wood or pulp and paper manufacture. Robust standard errors are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Table 30: Estimates of Wildfire on Workers - Heterogeneity by Export Status

VARIABLES	**Non-exporting**	**Exporting**
1.POST	0.027***	0.093***
	(0.005)	(0.015)
1.T	0.045	-0.242
	(0.074)	(0.277)
1.POST#1.T	-0.073**	-0.170*
	(0.032)	(0.090)
Observations	34,427	3,315
Number of firms	9,011	1,222

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

This Table reports estimates of a regression of the logarithm of the number of workers, using the standard DD specification, by export status. All regressions include a constant term. The sample consists of all firms in IES database in Portugal, between 2015 to 2018, whose primary sector of activity is one of the following: agriculture, animal production and forestry, manufacture of wood or pulp and paper manufacture. Robust standard errors are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Table 31: Estimates of Wildfire on Other Expenses - Heterogeneity by Export Status

VARIABLES	**Non-exporting**	**Exporting**
1.POST	0.261***	0.137***
	(0.016)	(0.043)
1.T	-0.225	-0.741
	(0.147)	(0.462)
1.POST#1.T	0.083	1.034
	(0.135)	(0.772)
Observations	33,708	3,286
Number of firms	8,849	1,209

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

This Table reports estimates of a regression of the logarithm of other expenses, using the standard DD specification, by export status. All regressions include a constant term. The sample consists of all firms in IES database in Portugal, between 2015 to 2018, whose primary sector of activity is one of the following: agriculture, animal production and forestry, manufacture of wood or pulp and paper manufacture. Robust standard errors are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.