Government Assistance and Firm Investment: Evidence from a Natural Disaster

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May 2023

Abstract

Natural disasters dramatically affect firms, but they also provide an opportunity to start anew. We exploit the 15-16 October 2017 Portuguese wildfires and the ensuing official assistance that subsidized 85% of the losses, applying a differences-in-differences approach. Firms affected by the wildfires increase output, the book value of fixed assets, and employment, but productivity does not increase. Affected firms borrow long-term credit and hoard cash, and there is no evidence of excessive risk-taking. Overall, the evidence does not support the "build back better" effect, and is consistent with the theory that firms invest both in scale and in liquidity insurance.

Keywords: Natural Disasters, Investment, Liquidity, Government Spending

JEL Classification Codes: D22

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†This research has been financed by Portuguese public funds through FCT - Fundação para a Ciência e a Tecnologia, I.P., in the framework of the project with references UIDB/04105/2020.

1 Introduction

Catastrophic events dramatically affect firms, but they also provide an opportunity to start anew. In most developed economies, for example, governments respond to natural disasters by helping firms to restore production capacity and employment. Yet, little is known about how firms fare after natural disasters, and in particular how output, employment, investment, and liquidity jointly evolve in the aftermath of these catastrophes.

This paper does three things. First, we provide firm-level estimates of the causal effect of a natural shock on real variables pertaining to firms, such as fixed assets, output, and employment. The estimates of the causal effect encompass the direct effect of the shock, and the ancillary effect of official aid. Second, we complement the analysis by assessing the impact of the disaster on firm sales, profitability, wage bill, and productivity. Finally, we provide details on the financial response of the firms in the aftermath of a natural shock, by looking into variables such as cash holdings, credit lines, and long-term credit.

The setting for this study is the central region of Portugal before and after being hit by wildfires on 15-16 October 2017. In 2017, there were 39 444 firms that employed 209 543 workers in the central region of Portugal. The wildfires destroyed the facilities of 483 firms (1.22% of the total number of firms) with an immediate impact on 4238 jobs (2.02% of the total number of employees), causing an estimated loss equal to 269 million euros in property damage (0.76% of the GDP of the region). Firms in our sample had access to government subsidies that accounted for 85% of total uninsured losses, and these subsidies financed 57.6% of the increase in fixed assets of the median firm from December 2016 until December 2020.

We measure the impact of the wildfires combining data from the entity that managed the government subsidies, the Portuguese credit registry, and firm balance sheets and income statements. We apply a differences-in-differences approach that compares a treated group of firms with a control group in a window of approximately three years after the wildfires. Treated firms are those firms that received a subsidy, and were thus affected by the wildfires. We compare the treated firms with a group of control firms that have similar characteristics such as location, industry, fixed assets, number of employees, profitability, and overdue credit and that did not receive a subsidy (and were not affected by the wildfires).

We establish three main findings after comparing the behavior of firms before and after the wildfires. First, the natural disaster and the ensuing official assistance *increased* fixed assets and output. There was a large overshooting in the evolution of the values of fixed assets and output. The overshooting in the book value of fixed assets is strikingly large, with treated firms increasing fixed assets more than control firms by 198.02% on average, from December 2016 until December 2020. The average accumulated difference in output in the period 2018-2020 was 41.98%. We find evidence favorable to the hypothesis that employment increased between 4% and 8% (depending on the measure of employment) in the treated group when compared with the control group during the same period. The extraordinary discrepancies between the growth of fixed assets and the growth of output and employment suggests that the increase in the book value of capital was much larger than the increase in the economic value of capital.

Second, treated firms increased sales, profits and the wage bill, but not their productivity. Treated firms increased their sales, profits (measured by earnings before interest, taxes, depreciation, and amortization, EBITDA), and their wage bill more than control firms by 21.9%, 63.1%, and 18.13% on average, respectively. Yet, we do not find evidence in favor of the hypothesis that the new investment increased productivity.

Third, treated firms do not use their cash holdings or their credit lines to address the liquidity shock; instead, they increase their borrowing immediately after the shock. In a larger time window, from December 2016 until December 2020, treated firms increased cash holdings and long-term bank credit more than control firms by 32.18%, and 66.53% on average, respectively. These results suggest that part of the increase in fixed assets and in cash holdings was financed with long-term debt.

Our first finding suggests that official assistance protects employment and the productive capacity after the wildfires. Our results also suggest that the evolution of the book value of fixed assets is not a reliable indicator of the response of firms to natural disasters. Accounting procedures are likely to bias upward the increase in the value of fixed assets, as old assets with low salvage value are replaced with expensive new assets. Given this distortion in the book value of fixed assets, our finding on the evolution of output and employment in the aftermath of the wildfires is especially meaningful. The evolution of wages, profits and indirect measures of productivity do suggest output and employment are reliable indicators of the *economic* response to natural disasters.

Our second finding suggests there is no "build back better" effect in terms of productivity. It seems as if the Portuguese government favoured the speed of the economic recovery, instead of inducing firms to increase their efficiency. The inertia in productivity together with the evolution of fixed assets and output suggest that the official funding creates opportunities for firms to increase their scale, rather than improving their efficiency. This increase in scale is financed with subsidies and bank loans, so that most of the gains in added value in a three-year horizon were appropriated by banks.

Our third finding suggests that treated firms rely on long-term credit, hoard cash, and do not draw down their existing credit lines in the aftermath of the wildfires. Overall, our findings are in line with Holmström and Tirole (1998), whereby firms arrange financing in advance using both the asset and the liability sides of their balance sheets. On the asset side, they hoard cash; on the liability side, they contract credit lines, credit guarantees, or obtain long-term credit that gives them flexibility in their management of liquidity. Consistent with bank screening, we do not find evidence of excessive risk taking in the aftermath of the wildfires.

The remainder of this paper is organized as follows. The next section reviews the literature, and the following section describes the natural shock and the subsidy scheme. Section 4 details the data and the variables, and Section 5 explains the empirical methodology. Section 6 discusses the impact of the natural shock and the subsidy scheme on output, assets, employment, productivity, bank credit and liquidity holdings. This section also performs a number of extensions and robustness checks, and the final section concludes with policy remarks.

2 Literature review

Many studies on the effects of natural disasters focus on household behavior, and disregard both corporate employment and output. For example, Gallagher and Hartley (2017) compare the financial outcomes of residents in New Orleans whose home was flooded, with a control group of residents in non-flooded blocks in the aftermath of hurricane Katrina. Their work is similar to Deryugina, Kawano and Levitt (2018), who compare the personal finances of residents in New Orleans with a control group outside the city in the aftermath of hurricane Katrina. These studies highlight the role of private insurance and government subsidies: The former study finds that flooding reduced total debt (presumably because homeowners used insurance payments and subsidies to pay off mortgages rather than rebuild), whereas the latter study finds a fairly modest effect of private and public transfers on personal finances for those individuals living in New Orleans at the time of the flooding.

Many studies relate natural disasters to bank behavior. Some focus on mortgage lending to households (Cortés 2014, Chavaz 2016, Berrospide, Black, and Keeton 2016, Cortés and Strahan 2017), disregarding both corporate employment and output. Some relate bank behavior with firm behavior in the aftermath of natural disasters, focusing on banks' role in mitigating the negative effects of natural disasters on financial fragility (Klomp 2014, Koetter, Noth, and Rehbein 2020). As mentioned before, the Portuguese wildfires had modest size, and it thus unlikely that this shock increased financial fragility.[1]

Our paper relates to a small but growing literature analyzing the relationship between firm behavior and disaster shocks. For example, Barrot and Sauvagnat (2016) use a variety of natural disasters in the U.S. (such as blizzards, earthquakes, floods and hurricanes) to identify how firm-level idiosyncratic shocks propagate in production networks. Koetter, Noth, and Rehbein (2020) show that firms are able to obtain recovery lending in the aftermath of the flooding of the River Elbe in Germany in May 2013. Yet, none of these studies accounts for the ubiquitous official assistance in the aftermath of natural disasters.[2] Our paper adds to this literature in two important ways. First, we exploit the joint effect of the natural disaster and the ensuing government intervention on firm behavior. Second, we use data sets containing detailed information both on firm financial accounts and on bank lending.

Our paper also adds to an empirical literature that examines investment and corporate liquidity management (Almeida, Campello, and Weisbach 2004, Acharya, Almeida, and Campello 2013, Acharya, Almeida, Ippolito, and Perez 2014, Harford, Klasa, and Maxwell 2014, etc.). Our paper differs from these studies in three important ways. First, we obtain a good measure of the *unobservable* investment opportunities that raise so many concerns in empirical studies. Second, we observe the liquidity shocks. Third, we provide a full view of how firms manage liquidity using the asset and the liability sides of their balance sheets.

[1] Cortés and Strahan (2017) document that financially integrated banks reallocate funds towards markets with high credit demand and away from other markets where they lend. This result is in line with Stein (1997) who highlights the role of internal capital markets in moving funds towards the most deserving projects and away from less deserving ones. In our specific setting, Portuguese banks are integrated, and the behavior of bank credit in the aftermath of the wildfires is consistent with headquarters engaging in "winner-picking".

[2] A number of studies highlights the role of government intervention. Froot (2001) and Garmaise and Moskowitz (2009) suggest there are supply restrictions associated with capital market imperfections which prevents the efficient allocation of catastrophic risk. It thus becomes important to assess the role of government insurance during natural disasters, as official aid might explain why some studies find that large economic shocks have little impact on growth. For example, Cavallo, Galiani, Noy, and Pantano (2013) confirm this finding after controlling for political revolutions.

3 The wildfires

Portugal experienced unusual dry conditions during 2017 and, notably, wildfires burned into territories that had never burned before. We focus on the central region of Portugal (*Região Centro*) before and after being hit by the wildfires on 15-16 October 2017. This region covers around one third of Portugal, with an area approximately equal to the area of Belgium.

The wildfires partially or completely destroyed the facilities of 483 firms with an immediate impact on 4238 jobs, causing an estimated loss equal to 260 million euros in property damage (CTI, 2018).[3] Figure 1 illustrates the number of affected firms in each municipality, showing that the region was unevenly affected by the wildfires.

On 3 November 2017, the Portuguese government created a subsidy scheme regulated by the *Decreto-Lei 135-B/2017* (hereafter, the law).[4] The preamble to this law explained that "there is an urgent need to create a specific regime to support the restoration of competitiveness and production capacity, in whole or in part, of the firms affected by the wildfires [...] to allow the rapid restoration of production conditions for firms directly affected with direct losses". The *Comissão de Coordenação e Desenvolvimento Regional da Região do Centro* (CCDRC) managed the subsidy scheme, reporting 372 firms that successfully applied for subsidies. Firms had to satisfy a number of conditions for a successful application, such as having no unpaid wages before the wildfires and guaranteeing at least 85% of employment for six months after finishing their subsidized investment.[5]

Private insurance Private insurance companies recorded the largest chunk of payments ever made in Portugal, covering direct losses in tangible assets (approximately 150 million euros in 728 reported cases) and indirect losses arising from stopped operations in the aftermath of the wildfires (approximately 30 million euros in 102 reported cases) according to the *Associação Portuguesa de Seguradores* (the Portuguese association of insurance companies). These payments, however, concern both the northern and the central regions of Portugal, and sometimes firms file more than one claim to insurance companies.

[3] The wildfires also burned through the northern region of Portugal, but with less significant effects. The wildfires affected 38 firms with an immediate impact on 280 jobs, and causing an estimated 6 million euros loss in property damage (CTI, 2018).

[4] This law was clarified with *Decreto-Lei n.º 31/2018*, published on 7 May 2018.

[5] According to Article 7 of *Decreto-Lei 135-B/2017*, firms must guarantee 85% of their pre-wildfires level of employment for a period of six months after completing their subsidized investment project.

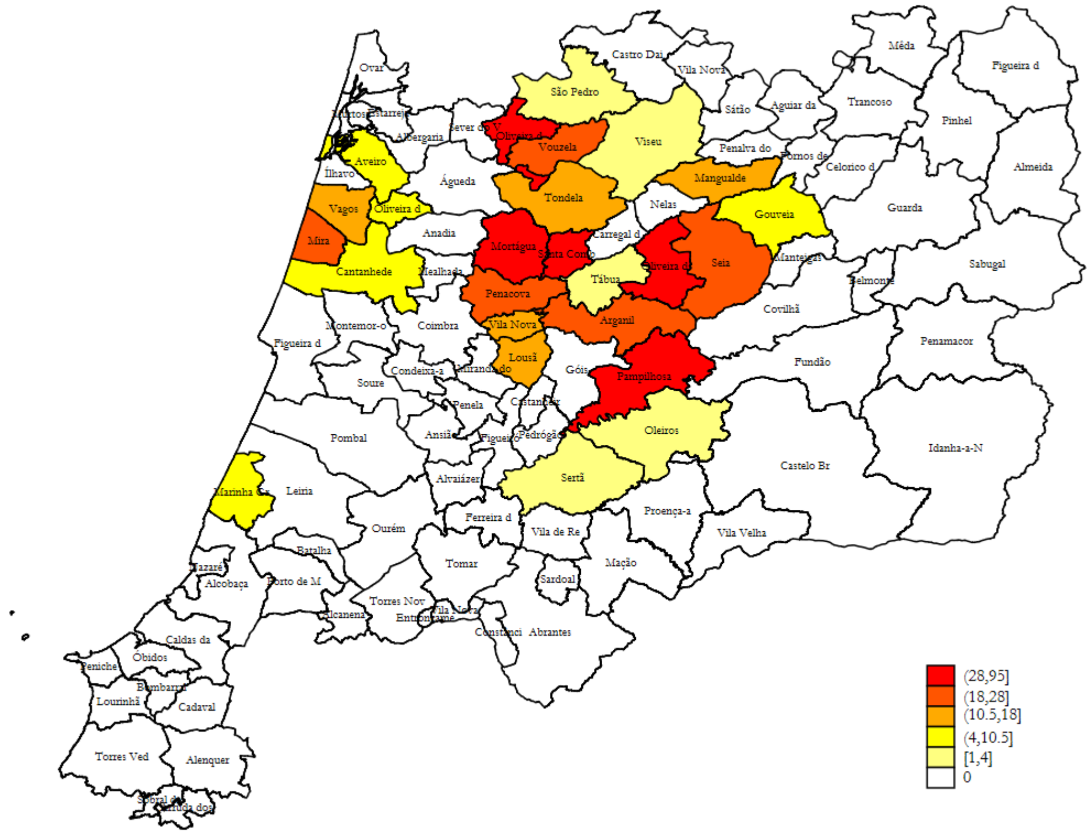


Figure 1: **Number of firms affected by the wildfires in the central region of Portugal** The figure depicts the number of firms affected by the wildfires in each municipality in Região Centro. Source: CTI (2018).

The subsidy scheme Available subsidies amounted to 103 650 386.6 euros, of which 77.57% had been distributed by 15 December 2020 in *Região Centro*. The subsidies covered direct losses in tangible assets, and incidental losses arising from stopped operations in the aftermath of the wildfires. These incidental losses were estimated based on profitability (measured by EBITDA) and wages paid in the past. According to the law, the actual subsidy payments to firms were computed in three steps.

1. The authorities computed the total size of the shock, and then discounted the insurance payments from the total shock. The firm had to secure private funding in advance, before the net value of the shock could be considered as eligible expenses (see Article 7 of *Decreto-Lei 135-B/2017*). For many firms, this rule implied securing bank loans (and being screened by banks) before receiving the subsidy.

2. Central government funding was made available to each firm, equal to a share of the eligible expenses according to Table 1. These funds are called available funding.

<table>
<tr><td>Firm size</td><td>Eligible expenses</td><td>Available funding
(share of eligible expenses)</td></tr>
<tr><td colspan="2">Small and medium enterprises (SME)</td><td>85%</td></tr>
<tr><td rowspan="2">Large firms</td><td>Part of eligible expenses $\leq$ 235000 euros</td><td>85%</td></tr>
<tr><td>Part of eligible expenses $>$ 235000 euros</td><td>25%</td></tr>
</table>

Table 1: **Available funding according to the law**

3. Available funding could only be used to finance the purchase of fixed assets. Hereafter, we call subsidy payments to the actual payments made.[6]

Table 2 reports basic statistics regarding the subsidy scheme, with payments made up to 15 December 2020. The distribution of subsidies was strongly skewed, which is visible in the differences between the mean and the median of the variables.

	Mean	Median
Eligible expenses (€000)	351.754	88.277
Available funding (€000)	278.630	74.043
Subsidy payments (€000)	216.144	57.251

Table 2: **Statistics regarding subsidies** This table reports statistics for the 372 firms that applied successfully to the subsidy scheme. The source of information is CCDRC in 15 December 2020.

4 Data and variables

4.1 Data

We collect data on subsidies made available by CCDRC. According to the information available on 15 December 2020, 372 firms successfully applied for subsi-

[6]Firms could obtain an advance equal to 20% of the available funding before purchasing assets. The remaining subsidy payments could be made as "payment against invoice" or as "payment after delivery". The value of the purchases was typically larger than the available funding, therefore requiring firms to secure funding in advance.

dies, including 95 sole proprietorships. We combine this information with data from the Portuguese credit register, a comprehensive data set available at *Banco de Portugal* (the Portuguese central bank) containing all credit accounts larger than 50 euros for Portuguese firms with monthly frequency. *Banco de Portugal* also makes available information on end-of-year balance sheets, income statements, and number of employees, in a data set known as the Central Balance Sheet Database. This data set does not include information on individual people, and therefore our sample does not include data on firms that are sole proprietorships. After dropping 15 firms with unreliable data on subsidies and matching all data sets, we obtain a sample of 262 firms that received subsidies. We further require complete information on all our regression variables, which leads to a final sample of 244 firms.

There were no large firms with eligible expenses larger or equal to 235 000 euros among the subsidized firms in our sample, and therefore all treated firms have access to the same available funding (85% of eligible expenses, according to Table 1). We thus guarantee a group of firms with homogenous treatment.

We collect data for the years 2012 to 2020, and our unit of observation is the firm-year pair. After ensuring that all firms in the sample have data on all variables for all years, we gathered data for a total of 29 167 firms in the central region of Portugal. Following standard procedures, all variables are winsorized at the 1% level in both tails of the distribution.

4.2 Variables

Table 3 lists the variables used in this study and presents descriptive statistics for each variable based on the entire sample of 29 167 firms. In the Appendix, we detail the construction of the various variables that we use in the analysis throughout the paper. Here, we provide a brief explanation for some of the variables. We measure firm output as the value added by the firm. Broadly speaking, value added measures the value of total sales minus the value of intermediate consumption, thus representing the income available for the contributions of labor and capital to the production process. Full-time equivalent is an alternative measure for the number of employees, which converts the effective hours of work in the firm into a surrogate number of workers that would have worked full time. Credit guarantees insure (mostly) long-term bank loans, and are widespread in Portugal. They are partially backed by official institutions called *Sociedades de Garantia Mútua* (SGM), and represent an implicit subsidy to firms. Non-activated credit guarantees back loans that have not defaulted so far. Credit lines is the volume of bank credit granted under the current accounts of firms, and which the bank

	Mean	Std. Dev.	P25	Median	P75
Total Assets (€000)	616.55	1,712.60	63.36	165.58	445.18
Fixed assets (€000)	172.88	623.34	5.10	21.85	98.30
Output (€000)	115.71	339.02	11.11	34.44	92.03
Number of employees	5.68	11.72	1.20	2.80	5.67
Full-time equivalent	4.78	10.10	0.95	2.20	4.74
Total sales (€000)	502.78	1,546.02	46.35	121.31	341.89
Profits (EBITDA, €000)	41.21	343.52	-1.26	6.46	24.19
Total wages (€000)	75.73	374.46	8.01	22.00	55.31
Cash holdings (€000)	46.80	119.58	4.18	12.54	37.85
Total debt (€000)	178.47	617.20	1.95	22.26	99.32
Total bank credit (€000)	170.45	1,904.71	0.11	10.00	58.89
Bank credit lines (€000)	40.02	345.54	0.00	0.00	10.00
Long-term bank credit (€000)	98.74	1,219.17	0.00	2.77	28.76
Total credit guarantees (€000)	13.68	77.80	0.00	0.00	0.98
Non-activated credit guarantees (€000)	12.92	74.21	0.00	0.00	0.75
Overdue credit (€000)	11.60	259.14	0.00	0.00	0.00
Firm age (years)	14.26	11.35	5.00	13.00	20.00
Capital expenditure (€000)	22.36	83.65	0.05	2.38	12.63
Fixed assets growth	-0.06	0.59	-0.22	-0.04	0.10
Sales growth	0.04	0.56	-0.09	0.00	0.14

Table 3: **Summary statistics** This table reports summary statistics for the variables used in the analysis for the entire sample of 29 167 firms. P25 and P75 are the 25th and the 75th percentiles, respectively. The reference period is the year, the sample period is 2012 to 2016, and the sources are *Banco de Portugal* and CCDRC. The growth of variable X is given by $\frac{X_t - X_{t-1}}{\frac{X_t + X_{t-1}}{2}}$.

cannot refuse.

The substantial differences between mean and median in Table 3 suggest skewed distributions for most variables, and therefore recommend distinguishing between average values and the values for the average firm. On average, firms in the central region of Portugal had 5.68 employees and around 616 thousand euros in total assets. Fixed assets represented 28% of total assets on average, and average yearly capital expenditure was 3.6% of firm assets. The average cash position was 7.1% of firm assets, and debt and bank credit were on average 28.9% and 27.6% of firm assets, respectively. On average, long-term credit represents 57.9% of total credit. The average firm makes extensive use of their credit lines.

The average firm in the central region of Portugal have almost three employees, and around 165 thousand euros in total assets. Fixed assets represent 13.2% of total assets, and yearly capital expenditure is 1.4% of firm assets. The cash position is 7.6% of total assets, and debt and bank credit are on average 13.4% and 6% of firm assets, respectively. Long-term credit represents 27.7% of total credit, and 22% of the firms do not rely on bank credit (result not shown).

5 Methodology

5.1 The wildfires as a natural experiment

We examine the effects of the wildfires using a differences-in-differences approach. This approach compares the effect of the wildfires on two groups of firms: A group of firms which was affected by the wildfires and received subsidies (the treated group) and a group of firms that did not receive subsidies (the control group). The differences-in-differences approach measures the differential effect of the wildfires across the two groups of firms.

More specifically, our identification strategy exploits the government program of subsidies to the firms affected by the 15-16 October 2017 Portuguese wildfires (hereafter, the wildfires). We define the treated group as all firms that received subsidies in the aftermath of the wildfires, and the control group as all firms that did not get any subsidies. Accordingly, we define the binary treatment variable $Treated_i$ as an indicator variable that takes the value 1 if firm i received a subsidy.

5.2 Representativeness of treated and control groups

The biggest identification challenge is that the firms in the control group may not represent a proper counterfactual. The first concern is that the wildfires entered business and industrial areas located in the outskirts of cities, but they did not enter city centers. As a result, the fires had a substantial impact on manufacturing industries, but not on firms located in city centers such as stationary shops, pharmacies, restaurants, or bank branches. Moreover, larger firms tend to locate in business and industrial areas, and therefore firms affected by the wildfires are likely to be larger and hire more employees (CTI, 2018, page 108). Table 4 illustrates the industry composition of the treated and control groups for the entire sample, presenting all industries with a weight larger than 5% in any of the groups. The treated group has relatively fewer restaurants, and somewhat more firms in forestry activities; both groups contain many firms in the construction of buildings.

CAE	Industry	Control (%)	Treated (%)	Diff.	P-Value
022	Forestry activities	0.013	0.078	-0.064***	0.000
412	Construction of buildings	0.126	0.168	-0.042**	0.050
452	Maintenance and repair of motor vehicles	0.057	0.025	0.032**	0.030
467	Other specialised wholesale	0.033	0.066	-0.033***	0.004
477	Retail sale of other goods	0.059	0.033	0.026*	0.084
494	Freight transport by road	0.079	0.090	-0.011	0.538
561	Restaurants	0.068	0.008	0.060***	0.000

Table 4: **Industry composition of control and treated groups** This table reports the industry composition of control and treated firms, for all industries with weight larger than 5% in the total number of firms in either of the two groups. We use the CAE industry classification. The treated group contains 244 firms that obtained subsidies in the aftermath of the 15-16 October 2017 wildfires, and the control group contains 20 923 firms that did not obtain subsidies. The sources are *Banco de Portugal* and CCDRC. Differences in means are assessed with the t-test, and *, **, *** denote statistical significance at the 5%, 1%, and 0.1% levels, respectively.

The second concern is that the design of the subsidy scheme induced selection into treatment. On the one hand, the scheme provided incentives for applications by profitable firms with a large wage bill, and therefore it is likely that firms in the treated group have higher EBITDA and larger payroll than the average firm in the control group. On the other hand, most firms applying for subsidies had to be screened by banks, and therefore it is more likely that banks hold good (soft and hard) information on these firms—86% of the firms that obtained subsidies had been granted bank credit before the wildfires.

Table 5 compares firm characteristics between affected firms and unaffected firms for the entire sample. As would be expected, treated firms are larger, hire more workers, are more profitable, have more credit, and had less overdue credit before the wildfires. The differences in these variables are substantial, and raise the concern that the control group simply constructed from the unaffected firms may not be an appropriate counterfactual. To guarantee that treatment and control groups are comparable/balanced, we seek "high quality observations" by performing matching on:

- Industry, fixed assets, and number of employees, as the wildfires may have created selection bias.
- Profitability (measured by EBITDA/total assets) and the value of overdue credit, because the law and bank screening may have induced selection into treatment.

The matching is performed for the average of the period 2012-2016 among the firms located in the central region of Portugal. To prevent matching two firms with the same average fixed assets but different growth rates, we also match on the average growth rate of fixed assets during the period 2012-2016. The initial sample contains 244 treated firms and 28 923 control firms, which is an appropriate setting for our approach as matching is desirable when there is a small treated group with a large reservoir of potential controls. For each treated firm, we select control firms that share the same economic activity by exact matching at the three-digit level of the CAE industry classification, thereby insuring that the treated and control groups have similar industry composition.[7] We implement coarsened exact matching for the continuous variables.

[7]CAE stands for classification of economic activities in Portugal, and it is similar in function to NAICS and SIC. We use the third revision, made in 2007. To illustrate the level of detail at the three-digit level, "accommodation, and food and beverage service activities" encompasses industry codes 55 and 56. The classification system further divides code 56 "food and beverage service activities" into "restaurants and mobile food service activities" (561), "event catering and other food service activities" (562), and "beverage serving activities" (563). Our matching at the three-digit level means that we do allow for firms working in "conventional restaurants"

	Control	Treated	t-statistic	P-Value
Total Assets (€000)	610.933	1282.510	-3.949	0.000
Fixed assets (€000)	170.764	423.969	-3.792	0.000
Output (€000)	114.244	289.801	-4.961	0.000
Number of employees	5.624	12.783	-5.897	0.000
Full-time equivalent	4.727	11.055	-5.777	0.000
Total sales (€000)	496.219	1281.061	-4.618	0.000
Profits (EBITDA, €000)	40.634	109.497	-4.183	0.000
Total wages (€000)	75.057	155.703	-4.168	0.000
Cash holdings (€000)	46.597	70.886	-2.595	0.010
Total debt (€000)	177.107	339.932	-2.998	0.003
Total bank credit (€000)	169.357	300.115	-2.539	0.012
Bank credit lines (€000)	39.667	82.369	-2.632	0.009
Long-term bank credit (€000)	98.039	181.623	-2.621	0.009
Total credit guarantees (€000)	13.384	48.724	-3.635	0.000
Non-activated credit guarantees (€000)	12.627	48.000	-3.653	0.000
Overdue credit (€000)	11.684	1.690	5.666	0.000
Firm age (years)	14.260	14.779	-0.735	0.463
Capital expenditure (€000)	21.942	71.774	-4.475	0.000
Fixed assets growth	-0.060	0.032	-4.466	0.000
Sales growth	0.044	0.094	-2.465	0.014

Table 5: **Summary statistics for the treated and control groups for the entire sample** This table reports means for some variables used in the analysis. The treated group contains 244 firms that obtained subsidies in the aftermath of the 15-16 October 2017 wildfires, and the control group contains 28 923 firms that did not obtain subsidies. The sample period is 2012 to 2016 and the sources are *Banco de Portugal* and CCDRC. Differences in means are assessed with the t-test.

Coarsened exact matching temporarily coarsens the data, and then matches exactly on these coarsened data. We apply automated coarsening according to Blackwell, Iacus, King, and Porro (2009). We restrict the matching solution to a k-to-k match to avoid the inconvenience of using weights, and because we match the treated firms with firms belonging to a sizeable control group (the results obtained with a k-to-k match were broadly similar to the k-to-n match).[8] We run our analysis on the uncoarsened matched data.

After matching over the entire sample, we dropped observations on 2 treated firms that do not obtain a good match in the control group, thereby obtaining a final sample of 242 treated firms. Table 6 provides sample means of the main variables for the treated and the control groups, as well as difference-in-means tests. The two groups are fairly comparable after being matched and the differences between groups are not statistically different from zero, except for sales growth.

Table 7 reports basic statistics regarding the subsidy scheme for the 242 firms in our sample. The data on subsidies shows differences to the values reported in Table 2, which includes data on all firms that successfully applied for a subsidy. After matching, the distributions for the variables related with subsidies have higher mean values and are likely to be more skewed. This is likely to happen because sole proprietorships are often micro firms, and are not available in our sample.

5.3 Empirical specification

We apply a dynamic version of the differences-in-differences estimator to exploit the rich time-series variation in the data. We estimate by OLS regression models of the form

$$y_{i,t} = \sum_{k=2012,k\neq 2016}^{2020} \iota_k \times year_{k,t} + \sum_{k=2012,k\neq 2016}^{2020} \delta_k \times year_{k,t} \times Treated_i + \eta_i + \varepsilon_{i,t} \quad (1)$$

(56101) to be matched with firms active in "take away food" (56106). Many industries have few four-digit level codes. In the case of Table 4, industry codes 022, 412, and 452 only have one four-digit level code each, and the industry code 494 only has two four-digit codes (4941 "freight transport by road", and 4942 "removal services"). The full sample of firms affected by the wildfires contains 80 different three-digit level industries, and our sample after matching contains 63 three-digit level industries.

[8]The Internet Appendix shows that the estimates are almost indistinguishable between the k-to-k matching and the k-to-n matching, but the confidence intervals narrow down in the k-to-n matching.

	Control	Treated	t-statistic	P-Value
Total Assets (€000)	1170.288	1198.941	-0.127	0.899
Fixed assets (€000)	348.701	370.145	-0.281	0.779
Output (€000)	279.126	261.615	0.350	0.727
Number of employees	10.533	11.900	-0.886	0.376
Full-time equivalent	8.976	10.242	-0.934	0.351
Total sales (€000)	1187.955	1225.083	-0.153	0.879
Profits (EBITDA, €000)	106.938	96.679	0.417	0.677
Total wages (€000)	160.158	143.648	0.572	0.568
Cash holdings (€000)	82.828	71.236	0.714	0.475
Total debt (€000)	312.706	323.297	-0.139	0.889
Total bank credit (€000)	287.048	284.001	0.040	0.968
Bank credit lines (€000)	66.642	78.439	-0.562	0.575
Long-term bank credit (€000)	183.994	169.893	0.267	0.790
Total credit guarantees (€000)	41.717	44.174	-0.168	0.867
Non-activated credit guarantees (€000)	41.674	43.444	-0.121	0.903
Overdue credit (€000)	2.526	1.704	0.427	0.669
Firm age (years)	15.522	14.682	0.810	0.418
Capital expenditure (€000)	55.964	64.454	-0.653	0.514
Fixed assets growth	0.037	0.032	0.153	0.878
Sales growth	0.029	0.094	-1.759	0.079

Table 6: **Summary statistics for the treated and control groups after matching** This table reports means for some variables used in the analysis. The initial sample contains the treated group with 244 firms that obtained subsidies in the aftermath of the 15-16 October 2017 wildfires, and the control group with 20 923 firms that did not obtain subsidies. We perform matching on industry, fixed assets, growth of fixed assets, number of employees, profitability, and overdue credit. The matching is performed for the average of the period 2012-2016. We apply automated coarsening and restrict the matching solution to a k-to-k match, thereby obtaining 242 firms in each of the groups of firms. The sample period is 2012 to 2016 and the sources are *Banco de Portugal* and CCDRC. Differences in means are assessed with the t-test

	Mean	Median
Eligible expenses (€000)	438.016	102.487
Available funding (€000)	356.788	84.985
Subsidy payments (€000)	274.958	63.286

Table 7: **Statistics regarding subsidies after matching** This table reports statistics for the 242 firms in our sample (after matching) that applied successfully to the subsidy scheme. The source of information is CCDRC in 15 December 2020.

where i indexes firms and t indexes year, y_{it} is the value of the dependent variable, $Treated_i$ is the treatment variable, η_i are firm fixed effects, and $year_{k,t}$ are year dummies (which take the value one when $k = t$ and zero otherwise). The reference year is 2016 and is omitted from the estimation. We estimate the ι's and the δ's, and the coefficients of interest are the δ's. Standard errors are heteroscedasticity-consistent and clustered at the firm level, following Bertrand, Duflo, and Mullainathan (2004). If firm i exits the market at date τ, then we set the dependent variable y_{it} equal to zero for $t \geq \tau$.

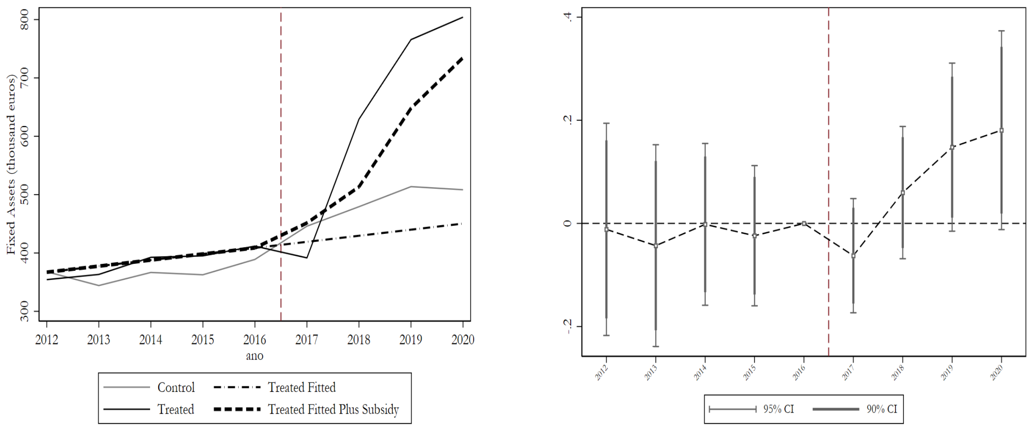
A key assumption for the differences-in-differences specification is that treated and control groups would have behaved similarly in the absence of the wildfires. There are two indicators that shed light on the validity of this assumption. The first indicator is the similarity between control and treated firms with respect to the observable characteristics presented in Table 6. The second, more important, indicator is the similarity between the evolutions of the two groups before the wildfires—aka parallel trends. With Specification (1) it is possible to test for parallel trends by comparing the values of the coefficients δ_k before the wildfires. By way of preview, both groups behave similarly before the wildfires, thereby supporting our identification strategy.

6 Empirical results

The wildfires had a mixed impact. On the one hand, the wildfires destroyed tangible assets, forcing many firms to stop their operations. On the other hand, firms received government subsidies equal to 85% of their losses to restore production capacity and employment. The estimates of the causal effect encompass the direct effect of the wildfires and the indirect effect of the official aid, with these two effects working in opposite directions.

6.1 Scale: Fixed assets, output, and employment

Figure 2 depicts the evolution of fixed assets and output, and Table 8 presents the estimates of coefficients δ_k obtained from Specification (1).



(a) Fixed assets (€000) (b) ln(Output+1)

Figure 2: **Wildfires, fixed tangible assets, and output** Panel (a) plots average values of fixed assets for the treated and control groups, and Panel (b) plots the point estimates and the 90% and 95% confidence intervals for the coefficients δ_k associated with the variable $Treated_i$ in Specification (1) for output. The horizontal axis displays time in years, with variables measured in December and with the wildfires happening in 15-16 October 2017. The units on the vertical axis are measured in thousand euros for fixed assets, and are measured in natural logarithms for output. The treated group contains firms that obtained subsidies in the aftermath of the 15-16 October 2017 wildfires, and the control group contains firms that did not obtain subsidies. We perform matching on industry, fixed assets, growth of fixed assets, number of employees, profitability, and overdue credit. The matching is performed for the average of the period 2012-2016, restricting the matching solution to a k-to-k match. The sample period is 2012 to 2020 and the sources are *Banco de Portugal* and CCDRC.

Panel (a) in Figure 2 plots the time series of average fixed assets measured in euros. The panel depicts parallel trends for the outcome variable before 2017, thus lending credibility to the research design. The solid and the dotted lines represent the treated and the control groups, with the dotted-dashed line representing the fitted behavior of the treated group if there had been no wildfires (i.e. a counterfactual) and with the dashed line representing the sum of these fitted values and average subsidy payments. The effect of the wildfires and the associated fiscal transfers manifests themselves after 2017, as the average difference between groups increases above the 2016 average. This increase is larger than the average value of the subsidy payments, which is consistent with private funding complementing the 85% subsidy. The fall in the book value of fixed assets for treated firms in December 2017 is relatively small, suggesting that some of the fixed assets damaged during the wildfires had low salvage value. The subsequent evolution of fixed assets suggests that the reconstruction value of the fixed assets is substantially larger than their salvage value, for example because damaged assets are replaced be expensive new assets.

Panel (b) in Figure 2 plots the point estimates and the 90% and 95% confidence intervals for the coefficients δ_k obtained from Specification (1) for output measured in natural logarithms.[9] There is an immediate negative response in the output of treated firms in the aftermath of the wildfires (which is not statistically significant) followed by a protracted increase in the following years, which indicates that the negative impact of the wildfires is limited and is quickly reversed. The joint evolution of fixed assets and output suggests that official assistance enlarges the set of investment opportunities—recall that subsidies had to be spent in the purchase of fixed assets—with firms taking the opportunity to purchase new capital.

The differences-in-differences estimates in Table 8 confirm the diagnosis obtained from Figure 2. The statistically insignificant coefficients for the period between 2012 and 2015 support the existence of parallel trends, and the table shows economically large and statistically significant coefficients δ_k for both outcome variables in 2020, which is consistent with the results reported in Figure 2. The magnitude of the effects is huge. Treated firms increase fixed assets more than control firms by $[exp\,(1.051)-1]\times 100 = 198.02\%$ on average from 2016 until 2020. The average increase in the difference in output is more moderate. The average accumulated difference in output between the two groups equals 41.98% $(= 6.18\% + 15.95\% + 19.84\%)$ in the period 2018-2020.

The extraordinary discrepancies between the growth in the book value of fixed assets and the growth of output hints that the increase in the book value of fixed assets is much larger than the increase in the economic value of these assets. These discrepancies also suggest that the fixed assets damaged during the

[9] We measure variables in natural logarithms for two reasons. First, there is substantial cross sectional heterogeneity in the size of the firms affected by the wildfires, and measuring the variables in levels would overly weigh large firms. Second, the estimates of the coefficients δ_k obtained from Specification (1) yield the percent changes in the response of the dependent variable to the wildfires. Treatment effects estimated with logarithms and zero-valued outcomes depend arbitrarily on the units of the outcome, and therefore should not be interpreted as percentage effects (Chen and Roth, 2023). This feature is not a concern since our variables seldom take zero values.

Treated ×	(1) ln(Fixed Assets+1)	(2) ln(Output+1)	(3) ln(Employment+1)
2012	0.061	-0.012	-0.032
	(0.118)	(0.105)	(0.048)
2013	-0.034	-0.043	0.004
	(0.102)	(0.100)	(0.041)
2014	-0.085	-0.002	-0.027
	(0.078)	(0.080)	(0.033)
2015	-0.041	-0.024	-0.014
	(0.063)	(0.069)	(0.025)
2017	-0.059	-0.063	-0.018
	(0.064)	(0.056)	(0.021)
2018	0.735***	0.060	0.001
	(0.090)	(0.065)	(0.030)
2019	0.998***	0.148*	0.059*
	(0.105)	(0.083)	(0.034)
2020	1.092***	0.181*	0.077*
	(0.113)	(0.098)	(0.040)
Firm Chars × Year	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	4142	3944	4141
Adjusted R^2	0.865	0.858	0.927

Table 8: **Baseline results** This table reports estimates of coefficients δ_k in Specification (1) for a range of outcome variables. The regressors are indicator variables equal to 1 when the firm received a subsidy, interacted with a year dummy (2016 is the reference year and is omitted). The estimates result from panel regressions, and the standard errors are heteroscedasticity-consistent and clustered at the firm level. Standard errors are in parentheses and *, **, *** denote statistical significance at the 5%, 1%, and 0.1% levels, respectively. We perform matching on industry, fixed assets, growth of fixed assets, number of employees, profitability, and overdue credit. The matching is performed for the average of the period 2012-2016, restricting the matching solution to a k-to-k match. The sample period is 2012 to 2020 and the sources are Banco de Portugal and CCDRC.

wildfires had low salvage value but still possessed substantial economic value.

Figure 3 plots the distribution of the growth rates of the value of fixed assets for treated and control firms separately for 2016, 2017 and 2018. The distributions of the two groups are broadly comparable in 2016. The mean of the growth rates remains similar between the two groups in 2017, but there is a substantial increase in the dispersion of growth rates among treated firms. This increase in dispersion in 2017 is consistent with the view that:

- Some treated firms purchased expensive new capital between 15-16 October 2017 and 31 December 2017, thus showing up on the right-hand side of the 2017 distribution.
- Some firms did not purchase capital immediately, thus lying on the left-hand side of the 2017 distribution.

The impact of the wildfires on damaged assets is fully visible on the two distributions of fixed assets in 2018, with the distribution of treated firms shifting rightwards.

Next, we examine the evolution of employment. Figure 4 plots the point estimates and the 90% and 95% confidence intervals for the coefficients δ_k obtained from Specification (1). Two outcome variables are considered: employment measured as ln(1+ number of employees) and employment measured as ln(1+ full time equivalent). Table 8 presents the results for the coefficients δ_k obtained from the differences-in-differences Specification (1) for employment measured as ln(1+ number of employees). The two panels of Figure 4 suggest that the wildfires have a mild immediate negative impact on employment, which is quickly reversed. Thus, the municipalities of *Região Centro* are unlikely to be vulnerable to the out-migration patterns existing in other natural disasters (see Strobl 2011, or Boustan, Kahn, Rhode, and Yanguas 2020). According to the estimates in Table 8, treated firms increased employment (measured as number of employees) more than control firms by 8% on average, from 2016 until 2020. Yet, this effect is milder and is not statistically significant when the measure of employment takes into account the full-time equivalent.

Overall, these estimates corroborate the previous diagnosis. The increase in the book value of fixed assets was much larger than the increase in output and employment, thereby strongly suggesting that the increase in the economic value of fixed assets was lower than the increase in the book value of these assets. To examine this hypothesis, we now turn to other variables that allow us to assess the evolution in sales, distribution of added value, and productivity.

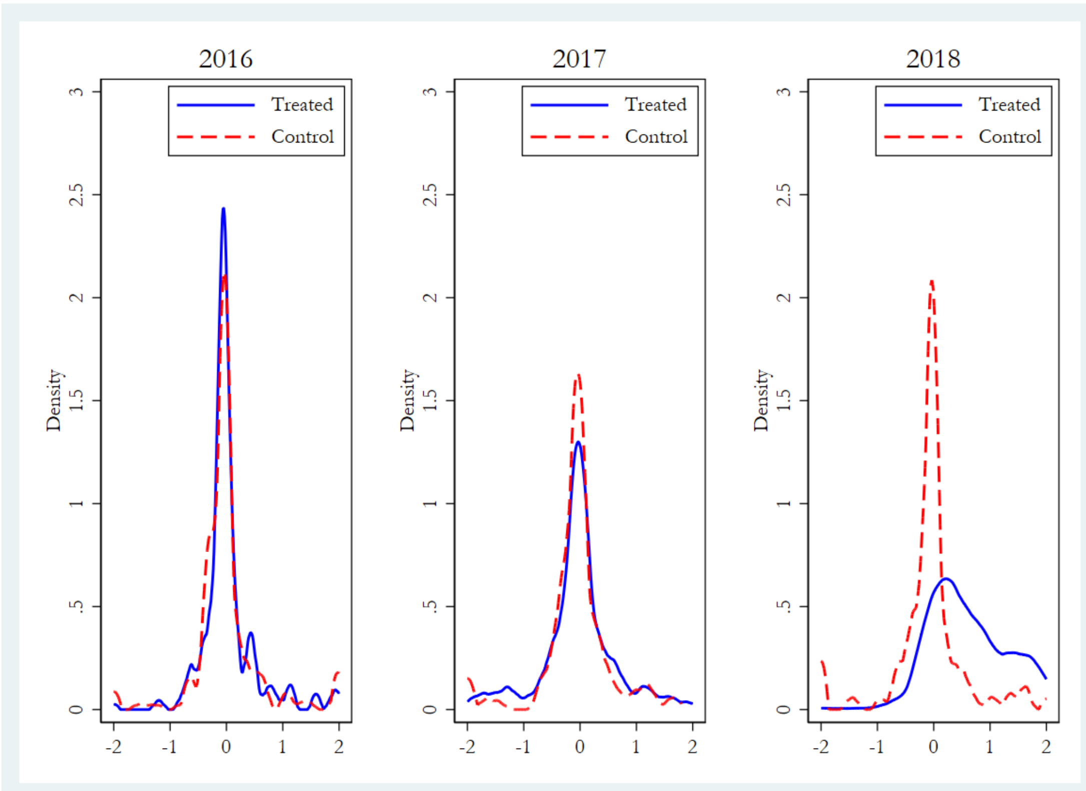
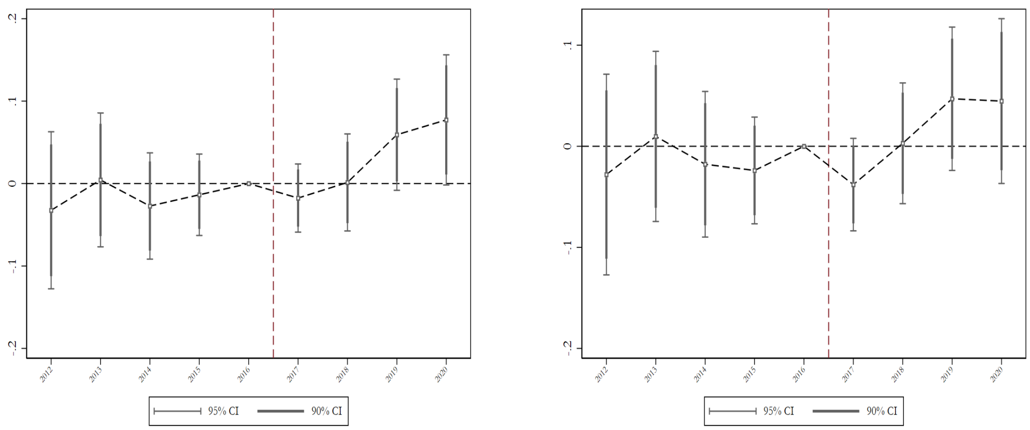


Figure 3: **Wildfires and the distribution of the variation of fixed assets** This figure plots the densities of the symmetric growth rate in fixed tangible assets, shown separately for the treated and control firms. The symmetric growth rate of fixed assets in 2016 equals the difference between the value of fixed assets in 31 December 2016 and in 31 December 2015 divided by average of these two values. This growth rate definition is bounded in the range [-2,2] and can accommodate entry and exit, and limit the influence of outliers. We plot the densities separately for 2016, 2017, and 2018. The units in the horizontal axis are rates of growth (0.5 corresponds to a rate of growth of 50%), and the units in the vertical axis are densities. The treated group contains firms that obtained subsidies in the aftermath of the October wildfires in 2017, and the control group contains firms that did not obtain subsidies. We perform matching on industry, fixed assets, growth of fixed assets, number of employees, profitability, and overdue credit. The matching is performed for the average of the period 2012-2016. The matching is performed for the average of the period 2012-2016, restricting the matching solution to a k-to-k match. The sample period is 2012 to 2020 and the sources are *Banco de Portugal* and CCDRC.



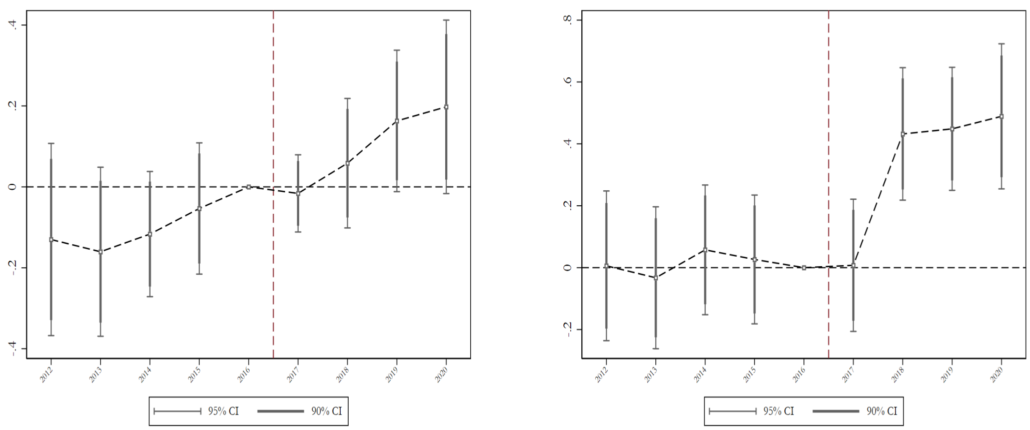
(a) ln(Employment+1) (b) ln(FTE+1)

Figure 4: **Wildfires and employment** This figure plots the point estimates and the 90% and 95% confidence intervals for the coefficients δ_k associated with the variable $Treated_i$ in Specification (1) for two outcome variables, number of employees and full time equivalent. The horizontal axis displays time in years, with the wildfires happening in 15-16 October 2017. The units on the vertical axis are measured in natural logarithms. The treated group contains firms that obtained subsidies in the aftermath of the 15-16 October 2017 wildfires, and the control group contains firms that did not obtain subsidies. We perform matching on industry, fixed assets, growth of fixed assets, number of employees, profitability, and overdue credit. The matching is performed for the average of the period 2012-2016, restricting the matching solution to a k-to-k match. The sample period is 2012 to 2020 and the sources are Banco de Portugal and CCDRC.

6.2 Productivity: Sales, profitability, and wages

The analysis in Section 6.1 suggests that firms interpreted the subsidy scheme as an opportunity to make new investments, thereby increasing investment and output in the aftermath of the wildfires. Following the same approach as in the previous section, we investigate if the purchase of new fixed assets has a positive impact on variables such as sales, profitability, interest payments, wages and labor productivity.

We trace the propagation of the shock along time in Figure 5 and in Table 9 for the variables total sales and EBITDA (with both variables measured in logarithms). The figure plots the point estimates and the 90% and 95% confidence intervals for the coefficients δ_k obtained from Specification (1). We observe an increase in sales of treated firms when compared with control firms (in the aftermath of the wildfires) but the hypothesis of parallel trends is debatable. We observe an unambiguous increase in profitability in the aftermath of the shock. Unlike Barrot and Sauvagnat (2016) we do not find evidence that the natural disaster imposed severe losses or a decrease in sales growth. This may happen because the firms in our sample are able to outsource production or replace assets quickly. Table 9 shows that the economic impact of the wildfires is substantially larger for EBITDA than for sales, with the impact on EBITDA being higher than the impact on output (but much lower than the impact of fixed assets).



(a) ln(Sales+1) (b) ln(EBITDA+1)

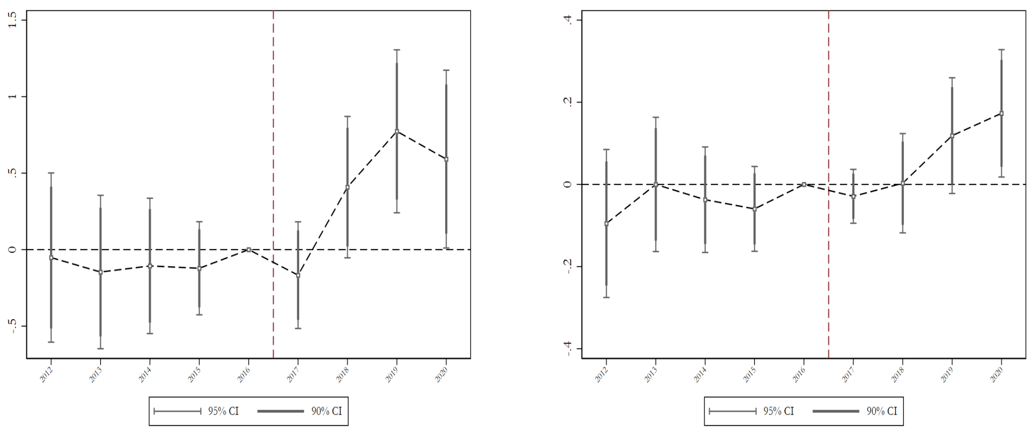
Figure 5: **Wildfires, sales and profitability** This figure plots the point estimates and the 90% and 95% confidence intervals for the coefficients δ_k associated with the variable $Treated_i$ in Specification (1) for two outcome variables, total sales and profitability (measured by EBITDA). The horizontal axis displays time in years, with the wildfires happening in 15-16 October 2017. The units on the vertical axis are measured in natural logarithms. The treated group contains firms that obtained subsidies in the aftermath of the 15-16 October 2017 wildfires, and the control group contains firms that did not obtain subsidies. We perform matching on industry, fixed assets, growth of fixed assets, number of employees, profitability, and overdue credit. The matching is performed for the average of the period 2012-2016, restricting the matching solution to a k-to-k match. The sample period is 2012 to 2020 and the sources are Banco de Portugal and CCDRC.

Figure 6 plots the point estimates and the confidence intervals for the coefficients δ_k obtained from Specification (1) for the variables interest payments and wages, with both variables measured in logarithms. We observe parallel trends before the wildfires, and an increase in the difference between the two groups for both variables afterwards. The economic magnitude of the increase in interest payments is larger than the increase in wages, and suggests that much of the

Treated ×	(1) ln(Total Sales+1)	(2) ln(EBITDA+1)	(3) Output/FTE	(4) Wage/FTE
2012	-0.130	0.006	126.789	72.621
	(0.121)	(0.123)	(115.753)	(75.376)
2013	-0.160	-0.033	-183.961	18.437
	(0.106)	(0.117)	(337.138)	(110.743)
2014	-0.117	0.057	125.768	83.951
	(0.079)	(0.107)	(129.605)	(84.570)
2015	-0.053	0.026	128.420	83.976
	(0.083)	(0.106)	(130.115)	(84.958)
2017	-0.016	0.008	123.384	84.528
	(0.049)	(0.109)	(130.601)	(85.144)
2018	0.059	0.432***	-138.581	17.918
	(0.081)	(0.109)	(309.872)	(103.560)
2019	0.163*	0.449***	102.143	-5.889
	(0.089)	(0.101)	(141.259)	(129.082)
2020	0.198*	0.489***	129.011	76.953
	(0.109)	(0.119)	(135.606)	(88.913)
Firm Chars × Year	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	4142	3487	3929	3929
Adjusted R^2	0.865	0.809	0.110	0.046

Table 9: **Sales, profitability and productivity** This table reports estimates of coefficients δ_k in Specification (1) for a range of outcome variables. The regressors are indicator variables equal to 1 when the firm received a subsidy, interacted with a year dummy (2016 is the reference year and is omitted). The estimates result from panel regressions, and the standard errors are heteroscedasticity-consistent and clustered at the firm level. Standard errors are in parentheses and *, **, *** denote statistical significance at the 5%, 1%, and 0.1% levels, respectively. We perform matching on industry, fixed assets, growth of fixed assets, number of employees, profitability, and overdue credit. The matching is performed for the average of the period 2012-2016, restricting the matching solution to a k-to-k match. The sample period is 2012 to 2020 and the sources are Banco de Portugal and CCDRC.

increase in EBITDA was absorbed by the payment of financial expenses.



(a) ln(Interest payment+1) (b) ln(Wages+1)

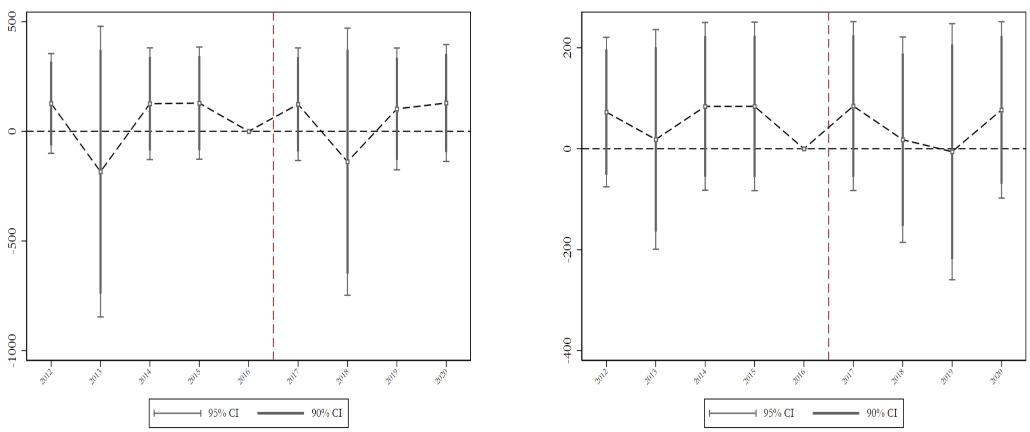
Figure 6: **Wildfires, interest payments and wages** This figure plots the point estimates and the 90% and 95% confidence intervals for the coefficients δ_k associated with the variable $Treated_i$ in Specification (1) for two outcome variables, total interest payments and total wages. The horizontal axis displays time in years, with the wildfires happening in 15-16 October 2017. The units on the vertical axis are measured in natural logarithms. The treated group contains firms that obtained subsidies in the aftermath of the 15-16 October 2017 wildfires, and the control group contains firms that did not obtain subsidies. We perform matching on industry, fixed assets, growth of fixed assets, number of employees, profitability, and overdue credit. The matching is performed for the average of the period 2012-2016, restricting the matching solution to a k-to-k match. The sample period is 2012 to 2020 and the sources are Banco de Portugal and CCDRC.

We now turn to the impact on productivity. Figure 7 plots the point estimates and the confidence intervals for the coefficients δ_k obtained from Specification (1) for the ratio of output to full time equivalent, and for the average wage (computed with the full time equivalent). Both Figure 7 and Table 9 paint a rather bleak picture, suggesting that investment in fixed assets has no clear impact on productivity. Treated firms have not become more productive than control firms in the aftermath of the wildfires, and the difference in the average wage between the two groups has not changed either.

There is no evidence of the "build back better" effect, given the inertia in productivity. Together with the evolution of fixed assets, output and employment, this evolution is consistent with:

- The purchase of new assets being mainly driven by the official subsidies, and not by innovation, more productive investment opportunities, or new business opportunities.

- The fast economic recovery, which was probably the main concern of the Portuguese government. It seems as if government assistance induces firms to increase their scale, instead of inducing firms to adopt more productive technologies.



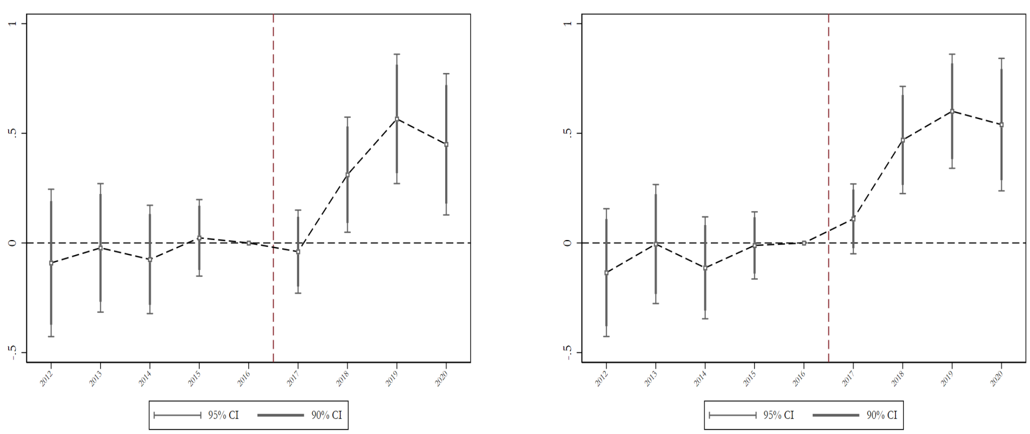
(a) Output/FTE

(b) Wage/FTE

Figure 7: **Wildfires and productivity** This figure plots the point estimates and the 90% and 95% confidence intervals for the coefficients δ_k associated with the variable $Treated_i$ in Specification (1) for two outcome variables, the ratio of output to full time equivalent and the ratio of total wages to full time equivalent. The horizontal axis displays time in years, with the wildfires happening in 15-16 October 2017. The units on the vertical axis are measured in natural logarithms. The treated group contains firms that obtained subsidies in the aftermath of the 15-16 October 2017 wildfires, and the control group contains firms that did not obtain subsidies. We perform matching on industry, fixed assets, growth of fixed assets, number of employees, profitability, and overdue credit. The matching is performed for the average of the period 2012-2016, restricting the matching solution to a k-to-k match. The sample period is 2012 to 2020 and the sources are Banco de Portugal and CCDRC.

6.3 Debt and bank credit

We now turn to the issue of how the corporate sector financed the investment in fixed assets. Figure 8 plots the point estimates and the 90% and 95% confidence intervals for the coefficients δ_k obtained from Specification (1) for the variables total debt and total bank credit, with both variables measured in natural logarithms. The panels show parallel trends before the shock, and an unambiguous protracted increase in the difference between treated and control firms for both variables in the aftermath of the wildfires, suggesting that debt and bank credit financed the increase in scale of the firms affected by the wildfires. The growth in both variables is broadly identical, and is consistent with the pattern of recovery lending in the aftermath of natural disasters reported by Koetter, Noth, and Rehbein (2020). The increase in debt and bank credit is likely to be responsible for the increase in interest payments depicted in Figure 6.



(a) Ln(Debt+1) (b) Ln(Bank credit+1)

Figure 8: **Wildfires, debt and bank credit** This figure plots the point estimates and the 90% and 95% confidence intervals for the coefficients δ_k associated with the variable $Treated_i$ in Specification (1) for two outcome variables, total debt and total bank credit. The horizontal axis displays time in years, with the wildfires happening in 15-16 October 2017. The units on the vertical axis are measured in natural logarithms. The treated group contains firms that obtained subsidies in the aftermath of the 15-16 October 2017 wildfires, and the control group contains firms that did not obtain subsidies. We perform matching on industry, fixed assets, growth of fixed assets, number of employees, profitability, and overdue credit. The matching is performed for the average of the period 2012-2016, restricting the matching solution to a k-to-k match. The sample period is 2012 to 2020 and the sources are Banco de Portugal and CCDRC.

6.4 Liquidity: cash, credit lines, and long-term credit

Firms build up liquidity buffers to protect themselves against negative cash flow shocks, since liquidity holdings reduce the potential costs stemming from refinancing risk. When refinancing, firms face the risk that lenders underestimate the continuation value of the firm and do not refinance the firm, leading to the inefficient termination of ongoing projects. Firms with more cash holdings, credit lines, and debt with longer maturity face refinancing risk less frequently.

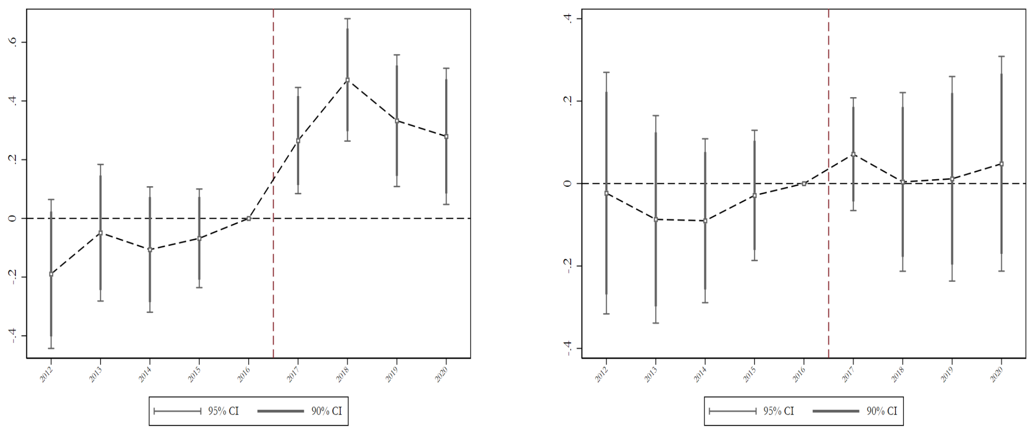
The wildfires represent an appropriate setting to study corporate liquidity management in the aftermath of a shock. At first sight, one would expect that firms would reduce their cash holdings, would draw down their credit lines, and would activate their credit guarantees to offset the liquidity shock *immediately* after the wildfires. This would likely be the case without the government subsidy scheme. But government assistance supplied *outside* liquidity to firms, thereby complementing the *inside* liquidity held by the corporate sector on the eve of the wildfires.[10] In what follows, we investigate how the corporate sector used up its *inside* liquidity to offset the shock caused by the wildfires. By way of preview, we find that the fresh funds provided by the subsidy scheme and new debt were enough to finance the liquidity shock, without the need for cash holdings or credit line drawdowns. To our knowledge, our setting is unique in the literature since we observe the size of the liquidity shock.

The wildfires also represent an appropriate setting to study corporate liquidity management, as official assistance induced the purchase of fixed assets in the aftermath of the wildfires. Credit rationed firms inevitably face a critical trade-off between investment in scale versus investment in liquidity (Holmström and Tirole, 1998). In what follows, we investigate if the increase in size also induced an increase in the demand for liquidity. By way of preview, we find that firms invested *both* in scale *and* in liquidity (in the form of cash holdings). To our knowledge, our setting is unique in the literature since the set of new investment opportunities is (partially) *observable* in our setting—the new opportunities were mostly driven by the subsidy equal to 85% of the losses.

Next, we analyze how the joint effect of the natural disaster together with the subsidy scheme affected a number of variables related with corporate liquidity. Figure 9 plots the point estimates (with the point estimate for 2016 normalized to zero) and confidence intervals for the coefficients δ_k obtained from Specification (1) for cash holdings and credit line drawdowns measured in logarithms.

Firms affected by the wildfires increase their cash holdings immediately and

[10] We apply the terminology in Holmström and Tirole (2013) and in Kahn and Wagner (2021).



(a) ln(Cash holdings+1) (b) ln(Credit lines+1)

Figure 9: **Wildfires, cash holdings and credit lines** This figure plots the point estimates and the 90% and 95% confidence intervals for the coefficients δ_k associated with the variable $Treated_i$ in Specification (1) for two outcome variables, cash holdings and credit line drawdowns. The horizontal axis displays time in years, with variables measured in December and with the wildfires happening in 15-16 October 2017. The units on the vertical axis are measured in natural logarithms. The treated group contains firms that obtained subsidies in the aftermath of the 15-16 October 2017 wildfires, and the control group contains firms that did not obtain subsidies. We perform matching on industry, fixed assets, growth of fixed assets, number of employees, profitability, and overdue credit. The matching is performed for the average of the period 2012-2016, restricting the matching solution to a k-to-k match. The sample period is 2012 to 2020 and the sources are Banco de Portugal and CCDRC.

unambiguously after the shock, when compared with control firms, thereby indicating that (*i*) firms do not use existing cash holdings to offset the liquidity shock caused by the natural disaster, and (*ii*) the demand for cash holdings after the wildfires is driven mostly by the new investments. There is a mild increase in credit line drawdowns immediately after the liquidity shock, but the variation is not statistically significant.

Regarding the evolution of cash holdings, Figure 10 plots the distribution of the growth rates of cash holdings for treated and control firms separately for 2016, 2017 and 2018. The figure shows a shift rightwards in the distribution of cash holdings from 2016 to 2018, and an increase in the dispersion of cash holdings. This evolution confirms treated firms do not use cash holdings to offset the liquidity shortages caused be the wildfires.

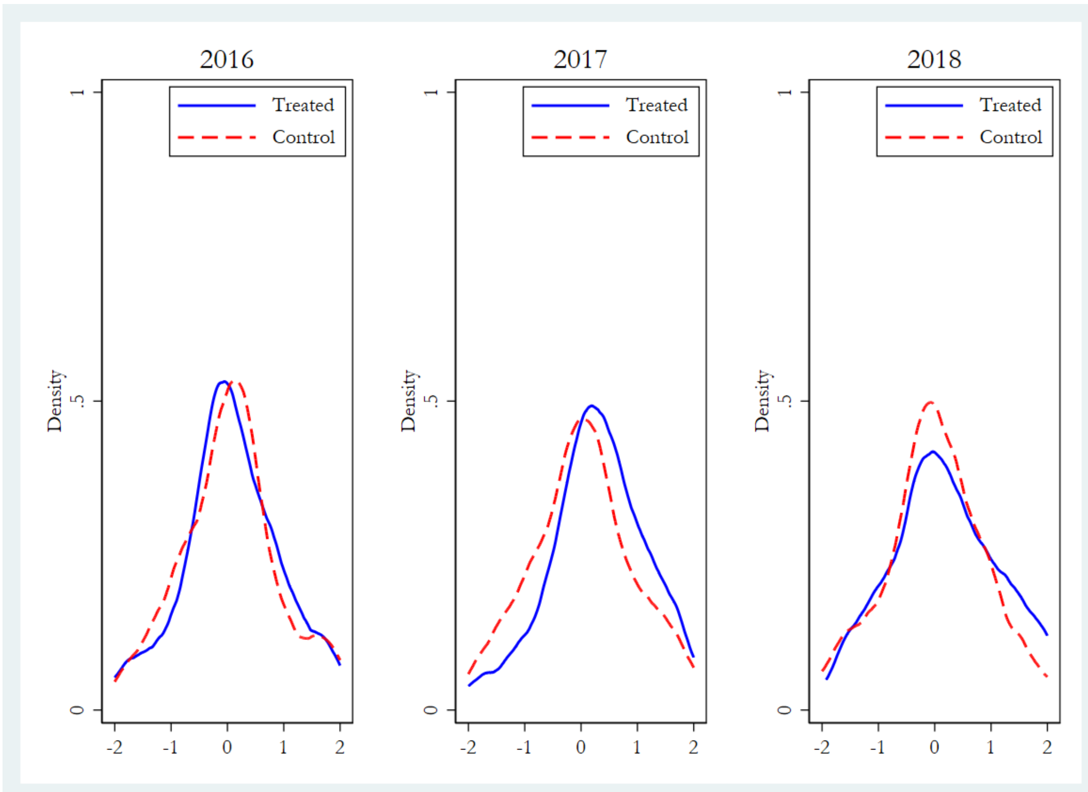


Figure 10: **Wildfires and the distribution of the variation of cash holdings** This figure plots the densities of the symmetric growth rate in cash holdings, shown separately for the treated and control firms. The symmetric growth rate of cash holdings in 2016 equals the difference between the value of cash holdings in 31 December 2016 and in 31 December 2015 divided by average of these two values. This growth rate definition is bounded in the range [-2,2] and can accommodate entry and exit, and limit the influence of outliers. We plot the densities separately for 2016, 2017, and 2018. The units in the horizontal axis are rates of growth (0.5 corresponds to a rate of growth of 50%), and the units in the vertical axis are densities. The treated group contains firms that obtained subsidies in the aftermath of the October wildfires in 2017, and the control group contains firms that did not obtain subsidies. We perform matching on industry, fixed assets, growth of fixed assets, number of employees, profitability, and overdue credit. The matching is performed for the average of the period 2012-2016, restricting the matching solution to a k-to-k match. The sample period is 2012 to 2020 and the sources are *Banco de Portugal* and CCDRC.

The differences-in-differences estimates for the coefficients δ_k obtained from Specification (1) in Table 10 confirm the diagnosis in Figure 9 for cash holdings. The table shows economically large and statistically significant coefficients δ_k for cash holdings in the aftermath of the wildfires. In the period between 2016 and 2020, treated firms increase their cash holdings more than control firms by 32.18% on average.

Next, we examine the evolution of other contingent assets and liabilities. Figure 11 plots the point estimates with the confidence intervals for the coefficients δ_k obtained from the differences-in-differences Specification (1) for overdue credit and activation of credit guarantees, with both variables measured in logarithms. The panels show that firms affected by the wildfires did not rely on these alternatives to offset the liquidity shock caused by the wildfires. Moreover, it seems that additional investment did not increase delinquency or the activation of credit guarantees. Like Koetter, Noth, Rehbein (2020), we find no evidence that recovery lending entails excessive risk-taking by firms.

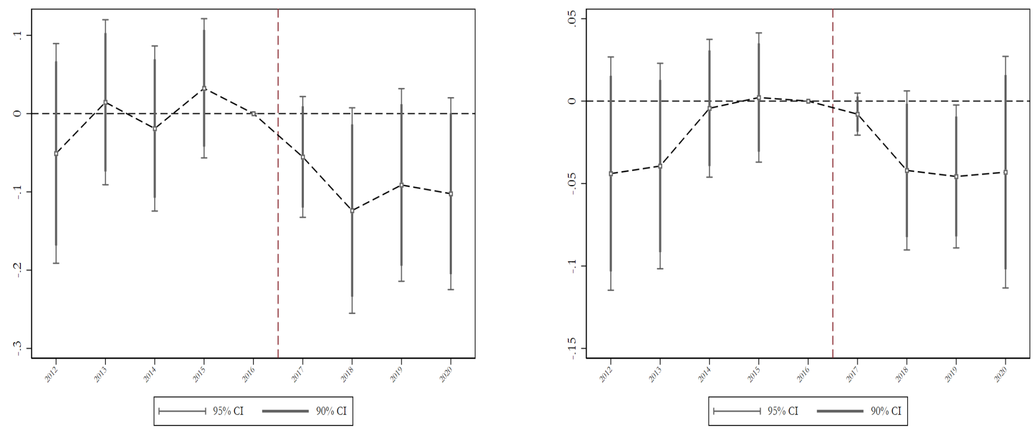
We now turn to the issue of how the corporate sector financed the increase in cash holdings. The protracted increase in the variables depicted in Figure 8 suggests that debt and bank credit financed both the increase in scale and the increase in cash holdings of the firms affected by the wildfires. Figure 12 plots the point estimates for the coefficients δ_k obtained from Specification (1) for the total value of long-term bank credit and the total value of credit guarantees, with both variables measured in logarithms.

Regarding the value of long-term bank credit, the average difference between the treated and the control groups increased, thereby suggesting that firms financed their investment in fixed assets and in cash holdings with long-term debt. Regarding the value of credit guarantees, the average difference between the two groups also increased, although at a slower pace than long-term credit. These guarantees represent contingent liabilities that provide liquidity insurance, thereby representing an additional source of liquidity.

The differences-in-differences estimates in Table 10 confirm this diagnosis, showing economically large and statistically significant coefficients δ_k for both outcome variables in 2020. Treated firms increased long-term credit more than control firms by 66.53% on average from 2016 until 2020, and increased their use of credit guarantees by 31.39% on average for the same period (although the result is not statistically significant).

Treated ×	(1) ln(Cash Holding+1)	(2) ln(LT Credit+1)	(3) ln(SGM+1)
2012	-0.189	-0.331*	-0.125
	(0.129)	(0.177)	(0.146)
2013	-0.049	-0.150	-0.031
	(0.118)	(0.171)	(0.124)
2014	-0.106	-0.177	0.023
	(0.109)	(0.153)	(0.107)
2015	-0.068	-0.021	0.022
	(0.086)	(0.115)	(0.085)
2017	0.265***	0.108	-0.098
	(0.092)	(0.106)	(0.069)
2018	0.472***	0.539***	0.171
	(0.106)	(0.162)	(0.108)
2019	0.333***	0.598***	0.209*
	(0.114)	(0.184)	(0.127)
2020	0.279**	0.510**	0.273
	(0.118)	(0.205)	(0.166)
Firm Chars × Year	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	4142	4142	4142
Adjusted R^2	0.743	0.755	0.755

Table 10: **Liquidity** This table reports estimates of coefficients δ_k in Specification (1) for a range of outcome variables. The regressors are indicator variables equal to 1 when the firm received a subsidy, interacted with a year dummy (2016 is the reference year and is omitted). The estimates result from panel regressions, and the standard errors are heteroscedasticity-consistent and clustered at the firm level. Standard errors are in parentheses and *, **, *** denote statistical significance at the 5%, 1%, and 0.1% levels, respectively. We perform matching on industry, fixed assets, growth of fixed assets, number of employees, profitability, and overdue credit. The matching is performed for the average of the period 2012-2016, restricting the matching solution to a k-to-k match. The sample period is 2012 to 2020 and the sources are Banco de Portugal and CCDRC.

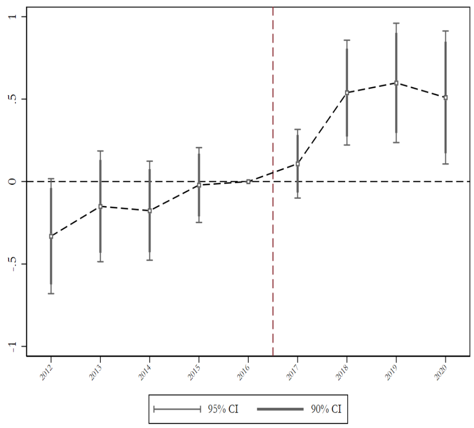


(a) ln(Overdue credit+1) (b) ln(Activated credit guarantees+1)

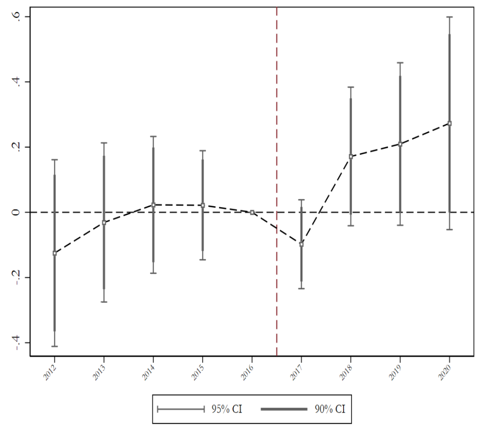
Figure 11: **Wildfires, overdue credit and activation of credit guarantees** This figure plots the point estimates and the 90% and 95% confidence intervals for the coefficients δ_k associated with the variable $Treated_i$ in Specification (1) for two outcome variables, overdue credit and activated credit guarantees. The horizontal axis displays time in years, with the wildfires happening in 15-16 October 2017. The units on the vertical axis are measured in natural logarithms. The treated group contains firms that obtained subsidies in the aftermath of the 15-16 October 2017 wildfires, and the control group contains firms that did not obtain subsidies. We perform matching on industry, fixed assets, growth of fixed assets, number of employees, profitability, and overdue credit. The matching is performed for the average of the period 2012-2016, restricting the matching solution to a k-to-k match. The sample period is 2012 to 2020 and the sources are Banco de Portugal and CCDRC.

6.5 The role of credit guarantees

The evolution of the official credit guarantees is jointly determined with the evolution of long-term credit, since these guarantees back mostly long-term bank loans. The Portuguese credit guarantee scheme is a mitigated mutualism scheme with strong government support. The official goal of the scheme is to reduce credit rationing arising from the informational asymmetries that plague small firms. The operational activity is carried out both by private banks and by the SGM, and we present a brief description of a typical operation. Three parties are engaged in the transaction of a credit guarantee in Portugal: the borrowing firm, the bank, and the SGM. To obtain guaranteed loans, the firm must present a project to its bank, which conducts a preliminary screening before filing an application to the SGM on behalf of the firm. The bank does not send any credit



(a) ln(Long-Term Credit+1)



(b) ln(Credit guarantees+1)

Figure 12: **Wildfires, long term credit and credit guarantees** This figure plots the point estimates and the 90% and 95% confidence intervals for the coefficients δ_k associated with the variable $Treated_i$ in Specification (1) for two outcome variables, long term credit and credit guarantees. The horizontal axis displays time in years, with the wildfires happening in 15-16 October 2017. The units on the vertical axis are measured in natural logarithms. The treated group contains firms that obtained subsidies in the aftermath of the 15-16 October 2017 wildfires, and the control group contains firms that did not obtain subsidies. We perform matching on industry, fixed assets, growth of fixed assets, number of employees, profitability, and overdue credit. The matching is performed for the average of the period 2012-2016, restricting the matching solution to a k-to-k match. The sample period is 2012 to 2020 and the sources are Banco de Portugal and CCDRC.

score to the SGM. Next, the SGM examines the application and takes a credit decision. The SGM has no privileged information about the firm, and mostly verifies the eligibility of the firm. Anecdotal evidence suggests that the rejection rate is extremely low, probably reflecting an endogenous response from banks to the behavior of the SGM. If the decision is favorable, the bank extends a loan to the firm at an interest rate set by the SGM. There is no official guarantee premium, but the firm must buy shares of the SGM, which can be resold later when the guarantee expires. The value of the guarantee, the share of the loan backed by the SGM, and the loan rate depend on the official size classification of the firm.

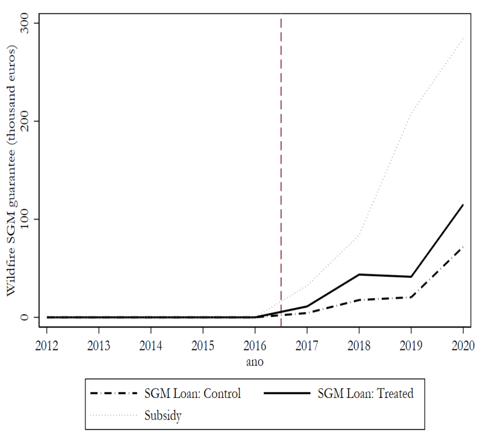
The SGM credit guarantees were a second ingredient of the official assistance. The Portuguese government complemented the official subsidy scheme described in Section 3 with a newly created official credit guarantee, designed specifically for the firms affected by the wildfires and available after 20 November 2017 (PME Investimentos, 2017a). This new credit guarantee is an important complement to the official subsidy scheme because firms must secure private funding before applying for the subsidy. Since this rule requires bank financing for many firms, the new credit guarantee enticed banks to finance healthy firms affected by the wildfires. There were two key changes to the existing credit guarantees: the size of the bank loan, and the share of the loan backed by the official credit guarantee. The two types of guarantees and the details of the changes are as follows:

- The "old" credit guarantees targeting micro/small/medium sized firms had broad conditions applying during 2017, 2018, and 2019 ("Linha Capitalizar"; PME Investimentos 2017b, PME Investimentos 2018). Firms have access to bank loans backed by 50% to 60% guarantees up to 1 500 000 euros until 31 July 2018, and 1 000 000 euros afterwards. Micro/small sized firms also have access to guarantees with more generous conditions. More specifically, micro firms and small firms have access to bank loans backed by a 70% official credit guarantee, up to 25 000 euros or 50 000 euros, respectively, until 31 July 2018 (50 000 euros or 100 000 euros, respectively, afterwards).
- The new credit guarantee targeting *all* firms affected by the wildfires introduced more favorable credit conditions, namely access to bank loans backed by an 80% official credit guarantee, up to the limit of 750 000 euros.

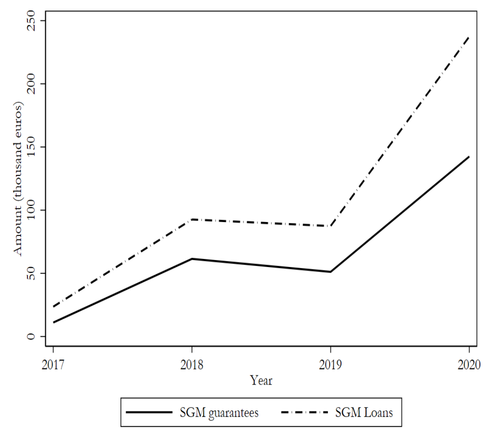
The combined increase in the size of the bank loan and in the share of the loans backed by the official guarantee have substantially reduced the credit rationing for those firms affected by the wildfires. Arguably, the more favorable conditions in the new official guarantees led banks to extend credit to firms, thereby (*i*) facilitating access to the official subsidies and (*ii*) financing the increase in cash holdings and fixed assets. Yet, it is hard to disentangle the joint effect of the new credit guarantee scheme and the official subsidy scheme.

- On the one hand, the official subsidy scheme might have failed without the newly created credit guarantees, as many firms had to secure bank credit before applying for the subsidy. Hence, the new credit guarantees are likely to play an *indirect* role in the recovery.
- On the other hand, we refrain from including the value of the guarantees obtained in the aftermath of the wildfires as a regression variable in Specification (1), as this approach would suffer from the bad control problem (as we would be conditioning our results on ex-post outcome variables).

For the sake of completeness, we provide additional information on the SGM guarantees issued after October 2017. Panel (a) in Figure 13 depicts the time series of the average loans backed by credit guarantees issued after the wildfires measured in euros. The solid and the dotted-dashed lines represent the treated and the control groups, and the dotted line represents the average value of subsidies obtained by treated firms. It is plausible to assume that most treated firms obtained loans backed by the "new" guarantees with more favorable conditions (loans backed by 80% guarantees, up to 750 000 euros), whereas control firms obtained the conventional credit guarantees (mostly loans backed by 70% or 50% guarantees, depending on the size of the loan).



(a) Loans backed by SGM guarantees (€000): Treated versus Control firms



(b) Loans and SGM guarantees obtained by treated firms that obtained guarantees (€000)

Figure 13: **SGM credit guarantees** Panel (a) plots average values of bank loans backed by credit guarantees issued after the wildfires for the treated and control groups, and Panel (b) plots average loans backed by credit guarantees and average credit guarantees measured in euros for the treated firms that obtained SGM guarantees. The horizontal axis displays time in years, with variables measured in December and with the wildfires happening in 15-16 October 2017. The units on the vertical axis are measured in thousand euros. The treated group contains firms that obtained subsidies in the aftermath of the 15-16 October 2017 wildfires, and the control group contains firms that did not obtain subsidies. We perform matching on industry, fixed assets, growth of fixed assets, number of employees, profitability, and overdue credit. The matching is performed for the average of the period 2012-2016, restricting the matching solution to a k-to-k match. The sample period is 2012 to 2020 and the sources are *Banco de Portugal* and CCDRC.

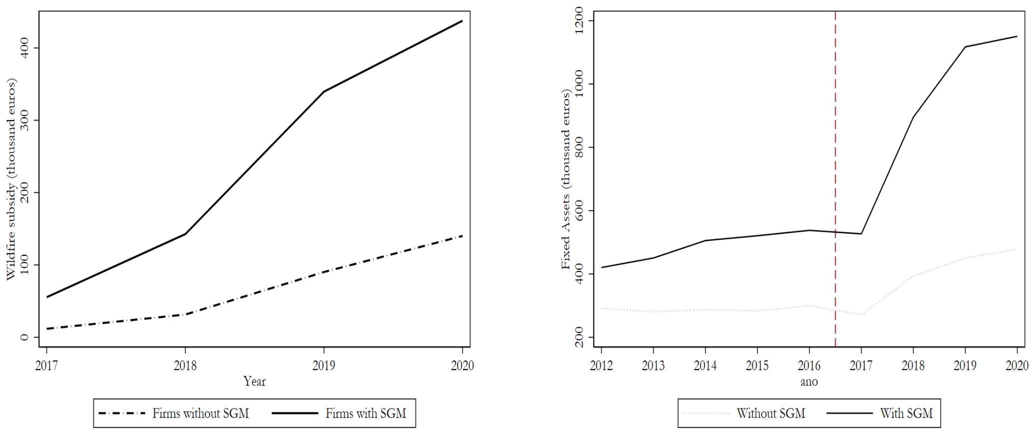
The panel shows a sharp increase in SGM guarantees in 2020 for both groups, caused by COVID-19 economic policy measures which relied heavily on official credit guarantees. The panel shows that treated firms obtained more loans backed by official guarantees than control firms. Yet, the loans backed by the official guarantees were lower than the value of the subsidies, thereby suggesting that additional sources of private funding were needed to apply for the subsidy scheme.

We now focus on the SGM guarantees obtained by the 242 treated firms available in our sample. There were 114 firms that got a credit guarantee in the aftermath of the wildfires and 128 that did not. The two sets are not balanced: On average, firms that obtained credit guarantees are twice as large in terms of assets, number of employees, and profitability, but have less overdue credit (results not shown). These differences suggest self-selection in applications for credit guarantees in the aftermath of the wildfires.

Panel (b) of Figure 13 plots the time series of the average loans backed by credit guarantees and of the average credit guarantees measured in euros for the treated firms that obtained SGM guarantees. We observe a sharp increase in COVID-19 related SGM guarantees in 2020 as in Panel (a). The two panels in Figure 13 also suggest the SGM guarantees played a limited role in the aftermath of the wildfires, as about half of the firms did not obtain loans backed by official guarantees and the remaining firms relied on additional sources of funding to apply for the subsidy scheme.

We now turn to the distinctive features of the two groups of firms affected by the wildfires. Panel (a) in Figure 14 depicts the time series of subsidies received by firms with and without credit guarantees. There is a correlation between the value of subsidies and having obtained SGM guarantees or not, but the direction of causality is unclear. On the one hand, the subsidy is a proxy for the value of the damage caused by the wildfires, and the panel could suggest that more damage leads to applications for official guarantees. On the other hand, it may also be the case that larger subsidies lead to applications to SGM guarantees, as applying for the subsidy scheme requires prearranged bank loans for many firms. Panel (a) confirms that the effects of this second channel are limited, since about half of the firms did not obtain loans backed by official guarantees and the remaining firms obtained subsidies that were substantially larger than the value of the loans backed by the official guarantees.

Finally, Panel (b) in Figure 14 plots the evolution of average fixed assets measured in euros separately for treated firms with and without SGM guarantees. Firms with credit guarantees invested substantially more in the aftermath of the wildfires. Since treated firms that invest more also obtain more subsidies, we are unable to figure out what is causing what: if firms that invest more apply for official guarantees, or if larger subsidies lead to more applications for SGM



(a) Subsidies obtained (€000): Treated firms with and without SGM guarantees

(b) Fixed assets (€000): Treated firms with and without SGM guarantees

Figure 14: **Treated firms with and without SGM credit guarantees** Panel (a) plots average values of subsidies received by the 114 treated firms that obtained SGM guarantees and of subsidies received by the 128 treated firms that did not obtain SGM guarantees, and Panel (b) plots average values of fixed assets treated firms that obtained SGM guarantees and received by treated firms that did not obtain SGM guarantees. The horizontal axis displays time in years, with variables measured in December and with the wildfires happening in 15-16 October 2017. The units on the vertical axis are measured in thousand euros. Treated firms obtained subsidies in the aftermath of the 15-16 October 2017 wildfires. The sample period is 2012 to 2020 and the sources are *Banco de Portugal* and CCDRC.

guarantees. Still, it is clear from the figures that the increase in fixed assets is substantially larger than the value of the subsidies and the value of the official guarantees, suggesting that a substantial amount of private funding was involved in the recovery. It seems as if SGM guarantees played a role in the recovery for those firms most severely affected by the wildfires, but played little role for those firms less affected by the natural disaster.

6.6 The full picture

Figure 15 plots the evolution of some components of the balance sheet of treated and control firms between 2016 and 2020. The figure suggests that the private sector is also responsible for the investment in fixed assets among treated firms. Equity financing (through subscribed capital) plays a relatively minor role in the recovery. The figure also confirms that treated firms hoarded substantial amounts of cash.

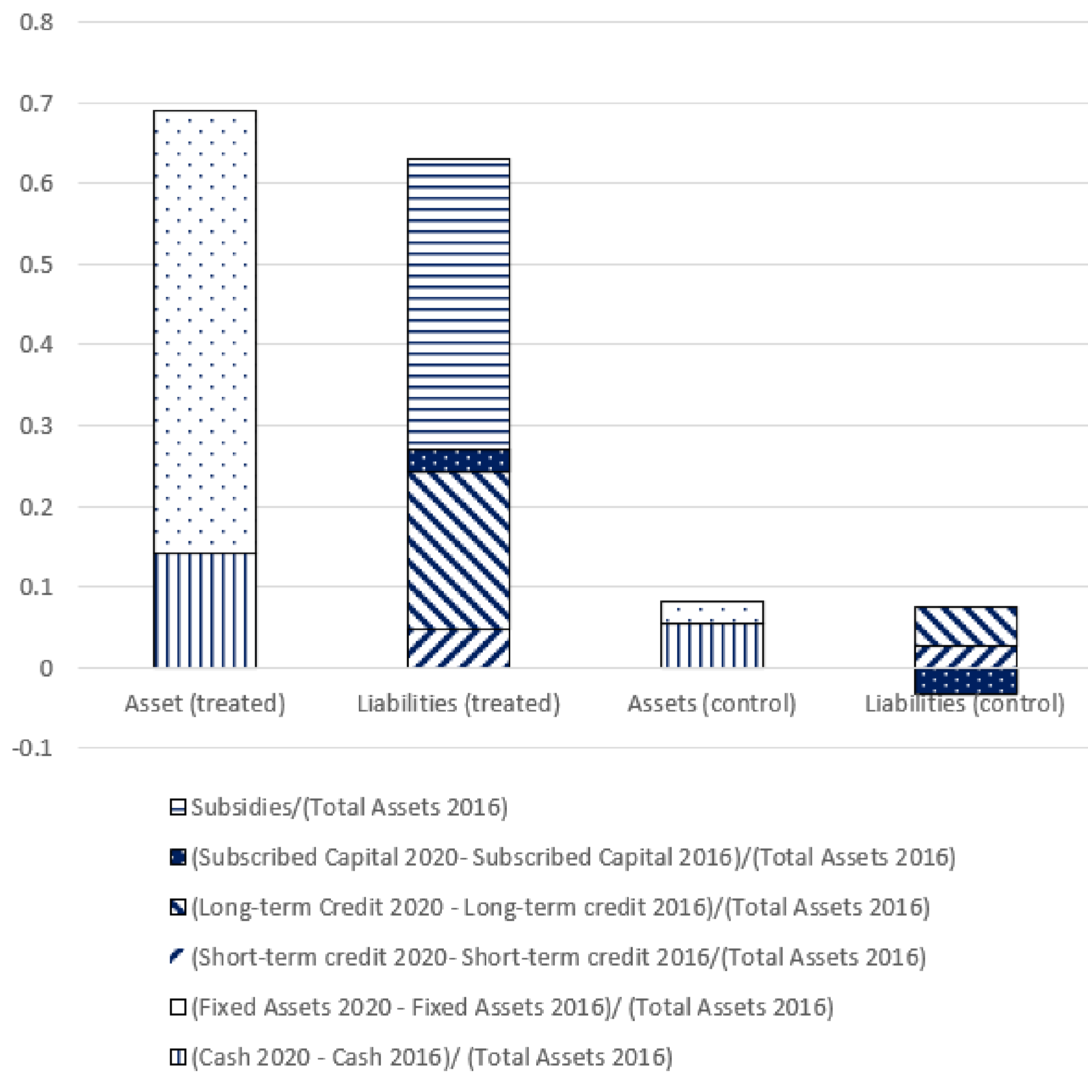


Figure 15: **Evolution of balance sheets between 2016 and 2020** The figure depicts changes in the components of the balance sheets of treated and control firms, standardized by the total assets in 2016.

6.7 The broken window fallacy

The assistance by the Portuguese government in the aftermath of the 15-16 October 2017 wildfires encompassed three official programs.[11] The first was the subsidy scheme described in Section 3, and the second was the new credit guarantees described in Section 6.5. The third program, regulated by *Decreto-Lei 142/2017* on 14 November 2017, subsidized housing reconstruction. According to the latter program, CCDRC subsidized the reconstruction of 823 dwellings and 23 cases in which households purchased furniture or other domestic utensils damaged by the wildfires. Arguably, the reconstruction of buildings by firms and households may have benefitted the construction industry in *Região Centro*. To exclude the effects of this industry, we remove all firms with activities belonging to codes 412 ("construction of buildings") and 431 ("demolition and site preparation") according to the CAE industry classification, ending up with 198 firms in the treated group.

The effects on firms are broadly similar to the baseline results, except that the existence of parallel trends before the shock is more debatable for a number of variables, namely employment, full-time equivalent, wages, and credit guarantees (results available in the Internet Appendix).

6.8 Insurance payments

The basis of our empirical strategy is that the treated group contains firms affected by the wildfires, and the control group represents the remaining firms. To identify the control group, we assume that firms applied for official assistance if and only if they had been affected by the wildfires. Yet, one may conceive the possibility that some affected firms did not apply for subsidies, for example because all damage caused by the wildfires was fully insured. If this were the case, the control group would contain firms affected by the wildfires, thus jeopardizing our empirical strategy. As a robustness check, we exclude firms located in municipalities affected by wildfires from the control group. After this preliminary procedure, we match firms unambiguously affected by the wildfires (as they had access to the "85% subsidy") with similar firms located in non-affected municipalities in *Região Centro*. In the Internet Appendix, we show that the results

[11] A full description of all measures undertaken by the Portuguese government is available in IAPMEI (2017). Apart from the three programs presented in this paper, there were a number of minor measures, such as the extension of deadlines for paying taxes and social security, and for ongoing projects that benefitted from official subsidies at the time of the wildfires. Firms with stopped operations may not pay social security while their operations are stopped. There were also a number of measures that apply to all firms in *Região Centro*.

with the preliminary procedure are similar to the results obtained without the preliminary procedure, except for the behavior of output. There is suggestive evidence of parallel trends in the growth rates of output before the natural disaster and there is an increase in the difference in growth rates between the treated and the control groups (but it is not statistically significant).

6.9 Sales growth

Table 6 reports different sales growth between the treated and the control groups, and Panel (a) in Figure 5 shows that the hypothesis of parallel trends is debatable. We thus match the two groups on an additional variable: we perform coarsened exact matching on the average annual sales growth rate between 2012 and 2016. As would be expected, the two groups become comparable in terms of sales growth rates (9% versus 9.4%) after the new matching. We observe parallel trends in sales growth before the shock, and an unambiguous increase in the difference in the growth rates among the two groups in the aftermath of the wildfires. The evolution of the remaining variables is broadly identical to their evolution in the baseline matching approach (results available in the Internet Appendix).

7 Conclusion

Official assistance is an essential feature of recovery in the aftermath of natural disasters. However, the impact of official assistance on firm investment, employment, bank credit, and liquidity has received little attention in the academic literature. First, the intricate nature of official assistance imposes complex identification challenges. Second, accurate data on subsidies and firm real and financial variables have typically not been available.

Our empirical strategy combines two key ingredients that enable us to make progress in empirically assessing the impact of natural disasters. First, we have precise measures of official assistance. Second, we employ a comprehensive data set from the Portuguese central bank that contains detailed information about loan contracts, credit lines, balance sheet variables, and profit and loss accounts.

We study the impact of the 15-16 October 2017 Portuguese wildfires using a differences-in-differences approach. We find that the (economic) value of the damage is smaller than the value of the reconstruction. The value of fixed assets, output, and employment increase after the natural disaster. Thus, *Região Centro* was unlikely to be vulnerable to the out-migration patterns existing in other natural disasters. There is no evidence of the "build back better" effect as productivity does not increase, which is consistent with the fast economic recovery. Long-term borrowing increases with firms hoarding cash, and there is no evidence of excessive risk-taking in the aftermath of the shock.

Our results suggest that official assistance spurs production capacity and preserves employment. These results are likely due to the specificities of the Portuguese wildfires and the details of government assistance. On the one hand, the impact of the wildfires was relatively small when compared with Portuguese GDP, thus allowing for substantial government assistance (a feature common to Park and Wang 2017, and Heger and Neumayer 2019) and highlighting the role of fiscal space in the aftermath of natural disasters. On the other hand, it seems as if the government favored a fast recovery instead of taking the opportunity to rebuild firms with better productive processes than what they had before the wildfires.

Our results also hold lessons regarding the design of the subsidy scheme. First, our results depend on the specific size of the subsidy (equal to 85% of uninsured losses). Second, the subsidy scheme relied heavily on bank screening. These two features are relevant for extrapolating our estimates to other natural disasters and subsidy schemes. Firms invest both in scale and liquidity in our setting, which is consistent with the standard corporate liquidity management model of Holmström and Tirole (1998) and with banks selecting safe investment projects and forsaking risky projects.

Appendix

Variable definitions: Codes in parentheses refer to the code in the data sets *Central de Balanços—Harmonized Panel Data* provided by *Banco de Portuga*l.

VBP = Turnover (D001) + Variation in production (D006) + Capitalized production (D007) + Supplementary income (DL043) + Operating subsidies (D005)

CI = Costs of goods sold and material consumed (D025) + Supplies and external services (D026) + Indirect taxes (DL047)

Firm output = VBP - CI

Full-time equivalent = Number of hours worked by paid and unpaid employees (E011)/2080

Interest payments = Interest expenses (D053); interest expenses include principal repayments and interest, according to the definition in the data sets.

Credit lines is the value of drawdowns/overdrafts obtained under the current accounts of firms.

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