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How should we deal with natural disasters?

Considerations looking at the economic effects of the Vaia storm on Italian firms

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Abstract

I exploit differences in the exposure to the storm Vaia to estimate which policy tools are better suited to mitigate the adverse consequences of natural disasters. In 2018 Northern Italy was hit by the most damaging storm since 1970, which provoked serious damages to the territory and the population. Studying how firms reacted to the shock, I find evidence that a strong welfare system cancels the effects of the storm. Moreover, I document that bigger firms attract the financial flows and increase their revenues after the shock. My analysis develops two major policy implications: first, policy makers should ameliorate the welfare system in order to increase firms' resilience; second, they should focus their attention on smaller firms, trying to improve their ability to attract financial aid.

1 Introduction

The economic damages caused by natural catastrophes are significant and expected to increase in the future. Understanding how these events affect the supply side of the economy and how we can make firms more resilient to these shocks is of fundamental interest to policymakers. I estimate the economic effects of one of the strongest European storms on Italian firms. The effects show substantial variability across locations, characteristics, and industries. The results have implications that may be relevant for policymakers.

It is well known and spread opinion that our world is changing and temperatures are rising globally ((Henderson-Sellers et al. (1998); Hsiang (2010))). Among the many consequences of climate change, there is the increase in the number of natural catastrophes such as heavy rainfalls, droughts, and cyclones (Nordhaus (2010); Martin and Pindyck (2021)). The immediate damages caused by extreme weather and the effects of natural disasters on the economy, households and employment have been extensively studied in the literature (Dell et al. (2014)). Studying firms has received less attention but there is consensus among scholars that, after a natural disaster, firms decrease their productivity (Elliott et al. (2019)); firms have a lower probability of surviving (Basker and Miranda (2018)) and have lower profits and assets (Pelli et al. (2023)).

In this work, I focus on a cyclone that hit South-Europe and particularly northern Italy in October 2018. The cyclone is usually referred to as Storm Vaia and was among the most damaging cyclones that hit Italy in the last 50 years. In meteorology, the word cyclone is the broadest term that defines any large air mass that rotates around a strong center of low atmospheric pressure. A cyclone can be called in different ways depending on its characteristics and the place in which it formed. In the following pages, I will use interchangeably the words cyclone and storm. A storm is defined as any disturbed state of the atmosphere and has a broader meaning.

There is scarce empirical evidence on the effects of cyclones on developed countries outside the United States. In Europe, it has been estimated that flooding disasters decrease productivity but increase assets and employment (Leiter et al. (2009)). At the same time, researchers usually tend to estimate the economic effects of an average cyclone (Hsiang and Jina (2014); Pelli et al. (2023)). Focusing on an average effect between storms is as important to policy considerations as capturing cyclone effects that can be termed outliers (i.e. cyclones that are the most damage provoking). Such outlier events are important because they provide a credible upper bound on the effects of storms. Moreover, assuming that the average storm intensity will increase as temperatures rise, these outlier storms can be considered the "future average".

In my empirical analysis, I focus mainly on firms and estimate the consequences of the storm on revenues, profits, and productivity. Moreover, I discuss the effects of disaster aid and ways for policymakers to increase the welfare of society. In order to estimate the effects of a widespread cyclone as Vaia, I exploit the variation in the intensity of the storm across municipalities. The storm hit municipalities with high heterogeneity. Municipalities located at different altitudes or in different valleys were hit differently. I argue that such variability can be considered as good as random after controlling for location fixed effects, and I conclude that using a Difference in Differences estimation strategy yields the average causal effect on the damaged firm.

My results demonstrate that, on average, firms hit by the storm did not reduce their revenues, profits, and wages compared to non damaged firms. The storm caused a small reduction in the productivity of enterprises. I explain that the results do not imply that Vaia had no effect on the supply side of the economy, but rather that Vaia hit in different ways small and medium firms: while small firms decreased their revenues of 260 thousand euros, big firms increased their revenues by 5 million euros. Bigger firms are more resilient and capable of attracting the majority of disaster aid, improving their profits, and taking advantage of the difficulties faced by smaller firms. These conclusions have strong policy implications for politicians and governments in Italy and abroad.

In the next section, I will briefly present the literature review on the effects of catastrophes on economic output. Such a section aims at presenting the general results rather than providing a comprehensive review of the literature (see Dell et al. (2014) for a broad review). Section 3 describes in detail the cyclone Vaia and provides general information of interest for readers that are not familiar with the storm. Section 4 presents the dataset, the assumptions made in the empirical analysis, and the estimating equations. Following, Section 5 presents the results and a broad discussion on robustness, mechanisms, and other interesting takeaways. Finally, in the last section of this thesis, I conclude my discussion with general considerations on the topic and suggestions for future research.

2 Literature Review

In the last decade, climate change has received increasingly more attention not only from scientists but also from the media, politicians, and the public. The discourse on the increasing temperatures is of general interest for various reasons. Climate change increases temperatures, reducing income and deteriorating human capital (Dell et al. (2009); Dell et al. (2012)). Moreover, the increase in temperature causes the sea level to rise, increases migration displacing people (Kaczan and Orgill-Meyer (2020)), and increases the number of extreme weather events (Henderson-Sellers et al. (1998); Knutson et al. (2010)). This thesis will focus mostly on the latter.

Understanding the effects of extreme climatic events gives information on the costs of future events and can suggest possible policy responses. For example, Deryugina (2017) shows that the fiscal costs of hurricanes are typically underestimated. The average disaster-related transfer is estimated to be \$155 − \$160 per capita, while transfers from safety nets such as medical spending or unemployment insurance are estimated between \$780 − \$1150 per capita. With this information, policymakers know that communities hit by hurricanes need an efficient social safety net more than a direct transfer.

In the next pages of this section, I will present the economic literature on the effects of climate change with a focus on those papers that are better aligned with my research[1]. I will talk about the consequences of weather events on the economy, focusing on GDP, growth, and production in both developed and developing countries. The aim of this brief overview of the literature on the economic effects of natural disasters is to provide the reader with a basic, noncomprehensive overview of the literature in order to be able to understand the theories that will be the building blocks of the empirical analysis.

Researchers are typically interested in measuring the damages and economic losses caused by storms. Looking at the US, Nordhaus (2010) studied the economic impact of hurricanes for the period 1900-2008. He found that a 1% increase in the maximum wind speed of the hurricane increases the ratio between damaged and GDP by 9 %. The reason for such a high elasticity is attributed to the estimation strategy: economic damages are related to storm characteristics through stress and rupture relationships. Using the same empirical strategy, but adding as

[1] For a comprehensive review of this literature see Dell et al. (2014).

controls income and population density, Mendelsohn et al. (2011) finds that damages increase with the fifth power of wind speed.

Udali et al. (2021) already analyzed the economic consequences of the storm Vaia. They use various data sources at the regional level to estimate the damages of the storm on the stock and on the prices of the wood market. Destroying wood, the storm increased the available stock of the regions, increasing sales and reducing prices.

Another strand of the literature tries to estimate the effects of weather events on growth rates. Strobl (2011) looks at the growth rates of U.S. coastal counties after a cyclone. He finds that, on average, growth rates decline by 0.45 p.p. after a hurricane. Loayza et al. (2012) estimates that storms don't have a negative effect on output growth worldwide. The only significant and negative effect of storms is on agricultural output growth. Instead, Strobl (2012) focuses on Central American and Caribbean regions and estimates that the average hurricane causes a fall in growth rate by 0.83 percentage points. Naguib et al. (2022) uses an event study design to estimate that, in India, the yearly growth rate decline is comparable with the one found by Strobl (2011). Hsiang and Jina (2015) propose a new way of thinking about extreme climatic events. They argue that capital does not depreciate at a constant rate but, the depreciation rate of capital depends on the geographic location and on the time. For example, the depreciation rate of capital in Trentino in 2018 (the year in which Vaia hit) is different from the depreciation rate in Trentino in 2014 or the depreciation rate in Lazio in 2018. The authors estimate that increasing the average predicted cyclone depreciation rate by 1$ is associated with a decline of long-run average growth by 2.2$ per year.

Yang (2008) constructs an index of storm intensity and uses it to study the effects of storms on disaster damages and deaths worldwide. He then studies how the financial flows after a shock. His results suggest that hurricanes increase damages, deaths, and foreign aid on average. In addition, the paper is among the first to argue that developing countries may suffer more adverse consequences. Among the literature focusing on developing countries, Anttila-Hughes and Hsiang (2013) study the effects of typhoons on Philippine households. They use a Difference in Differences study, taking advantage of year-to-year variation in typhoon exposure of each province. They measure the intensity of a typhoon as its maximum wind speed. The more intense a typhoon, the higher the losses and killings. Typhoons reduce also the available assets of the households one year after the event.

There are not many studies that look at the effects of cyclones on firms. Elliott et al. (2019) estimate the effects of typhoons on manufacturing firms in China. They estimate that the average storm reduces turnover by 1% in the short run. The year after the shock turnover increases slightly. Similarly, Pelli et al. (2023) focus on India and, using micro data on firms, estimate the consequences of cyclones on firms. The analysis exploits the differences among regions in exposure to different storms. For this purpose, they create and use as independent variable a continuous index of firm exposure to storms. The results indicate that higher wind speed causes higher losses of both assets and sales. The effects vary across sectors and regions.

The identification strategy in Pelli et al. (2023) relies on the assumption that the timing and intensity of the storm are exogenous since unexpected. Even though the latter assumption is commonly used in the literature (see for example Hsiang (2010) or Hsiang and Jina (2014)); one objection regards the fact that the probability of being ”hit” is not completely independent of the region in which the firm is located (Pelli and Tschopp (2017)). For example, altitude or distance from the sea are important determinants of the damage that a storm can cause. Such a concern, which is discussed in the paper, could be alleviated by controlling for region fixed effects since these would capture time invariant characteristics of the region such as altitude.

The studies described until this point use variation between storms to estimate the average effect of a storm on economic outcomes. It is important to understand what are the effects of uncommon cyclone. One exceptionally strong natural disaster is capable of inflicting more damage than many average storms. For example, Nordhaus (2010) estimated that annual hurricane costs averaged 0.07 percent of GDP, but, in 2005, the year of Hurricane Katrina, the annual hurricane damages were 1 percent of GDP. One of the major problems of estimating the effects of a single storm consists in defining a reliable comparison group. Defining an appropriate counterfactual may be difficult and is of fundamental importance to estimate causal effects. Studying the effects of Hurricane Katrina, Deryugina et al. (2018) define as counterfactual a group of cities that are similar to the hit city (New Orleans) in terms of pre-treatment variables. The authors estimate that Hurricane Katrina reduced labor income by approximately $2000 in the short run. A few years after the event, those affected by the storm have higher incomes. The authors explain the results saying that the income increase is nominal and that living in New Orleans has become cheaper. One other possibility that was not discussed by the authors is that the hurricane destroyed old physical capital that was substituted through investments in new capital. Also Basker and Miranda (2018) focus on the effects of Hurricane Katrina but look at firms' survival rates. They estimate that the probability of surviving decreases after the hurricane. Small firms were disproportionately affecting, having a lower probability of surviving when damaged compared to bigger firms.

My empirical analysis is closely linked with some papers presented above: I focus on firm level data and estimate the effect of natural disasters on revenues and profits of firms as done by Elliott et al. (2019) and Pelli et al. (2023). I analyze the effects of the storm Vaia on economic outcomes as Udali et al. (2021). I estimate causal effects of a single, ”outlier” storm as done by Deryugina et al. (2018) and Basker and Miranda (2018). My work builds on the previous works in three directions. First, I use a novel dataset at a disaggregated level that will be helpful for tackling different research questions. Second, I estimate a causal parameter using a Difference in Differences methodology, departing from the previous literature that assumed exogeneity. Lastly, I focus on a research question of interest for institutions, providing guidance for future policy.

3 The exogenous shock: The Storm Vaia

The exogenous shock that is study in this thesis is the cyclone (named as Adrian by Météo-France and Vaia by the Freie Universität Berlin) that hit the western Mediterranean between October 27^{th} and November 3^{rd}, 2018 [2].

The Vaia was a Mediterranean cyclone that hit the North-Eastern regions of Italy in October and November 2018 with wind that reached 200 km/h and heavy rains. All this caused serious damage, especially in Veneto and Trentino Alto-Adige. But there were also other extreme events during the same period: heavy rainfall in Liguria, massive hailstorms in Sardinia, wind gusts in central Italy, and several storm surges in various coastal areas. Over 870 mm of rain fell in some areas in just three days, and the Piave and Brenta rivers overflowed, together with Lake Alleghe. On Monday, October 29, Venice registered the worst flooding in a decade: the first tide peaked at 156 cm at 2:40 p.m. while the second, caused by a storm accompanied by strong winds, peaked at 148 cm at 8:25 p.m.

The "Vaia" depression formed on Saturday, October 27, 2018, between the Baltic and western Mediterranean and stationed over the seas between the Gulf of Lion, the Balearic Islands, and Sardinia until the morning of Monday, October 29. During that day, the depressional vortex was fueled by the influx of cold air and by winds coming from the south. On the reliefs, the wind speed reached peaks of 200 km/h. On the morning of October 30, most European newspapers were already reporting the damages and destruction provoked by the event. The end of the storm is dated November 5, 2019.

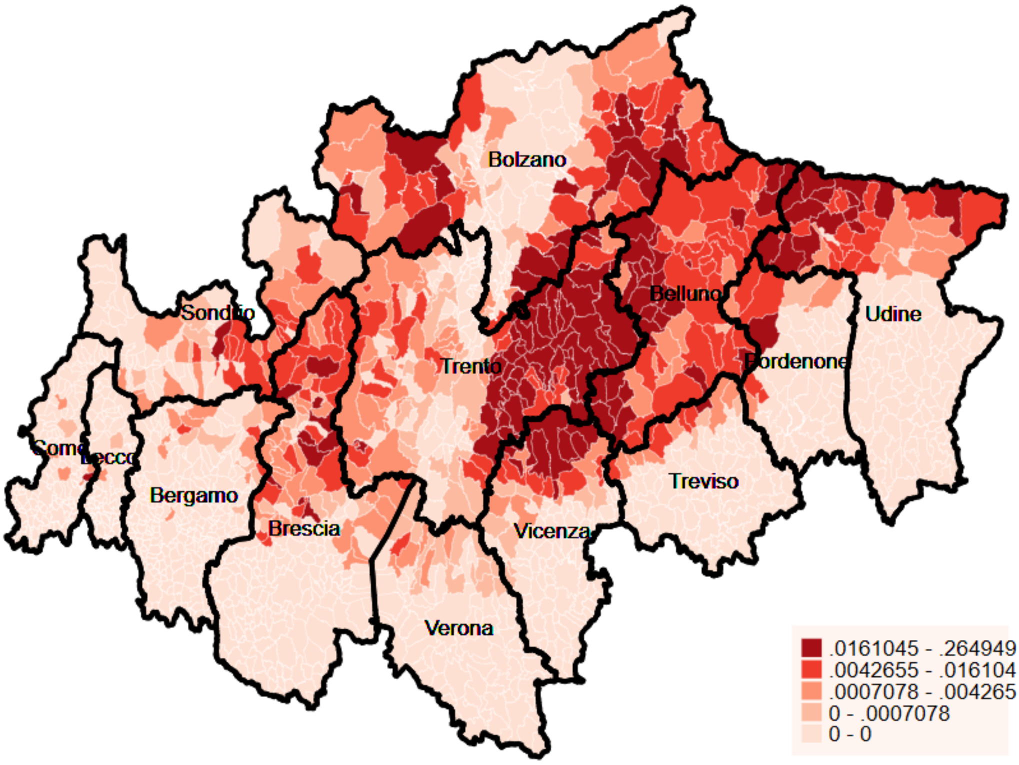
As reported in Chirici et al. (2019); the storm Vaia damaged 494 municipalities, a territory of 2 million of hectares. Of this, 42 thousand hectares of forests were completely razed to the ground, 16 million trees, and 8.6 million cubic meters of wood felled. Figure 1 shows the percentage of the area damaged in municipalities. A municipality is defined as hit if some part of its area had a damage incidence greater than 70%. For a clearer explanation of the dataset used and the definitions, see section 4

Using data from the EM-DAT[3], Figure 2 shows how the storm Vaia ranked among the Italian storms. As already pointed out above, the storm had unprecedented consequences on the Italian territory. The first panel of Figure 2 shows that "Vaia" was the most damaging storm since 1970. Even among the European storms, Vaia ranked fairly high in the EM-DAT, being the 15^{th} most damaging European storm of the century. Moreover, the first panel of Figure 2 highlights that "Vaia" had the highest number of deaths in Italy since the year 2000. The storm Vaia was the most impactful event to forest ecosystems ever recorded to date in Italy and among the most damaging storms in Europe (see Figure B.2).

[2] For a technical description of the storm I reference to the Eumestat website: https://www.eumetsat.int/intense-mediterranean-cyclones-alpine-crossing

[3] The EM-DAT, the International Disaster Database provides information on all the major natural events worldwide. The inclusion criteria for the events in the dataset is that ten or more people were killed, one hundred or more people were affected, an official state of emergency was declared, or a call for international assistance was made.

Figure 1: Percentage of the municipality exposed to Vaia



4 Data

I use data from AIDA - Bureau van Dijk. This dataset tracks all Italian incorporated firms, containing detailed information on revenues, profits, labor costs and a vast set of variables. I created an unbalanced panel that comprehends all firms for which revenues are non missing for at least two years. The panel goes from 2013 until 2019. I decided not to consider more recent periods because in 2020 COVID-19 hit Italy and may cause some distortions in my analysis. If not otherwise specified, the variables in the analysis are in thousands of euros.

The dataset presents also some drawbacks. First, as in the ORBIS dataset, smaller firms and firms in certain sectors are under-represented (Andrews and Cingano (2014)). As a matter of fact, the average firm size in AIDA is 12.8 workers while the population average firm size in the same territory is 4.1 workers[4]. Second, there were some "holes" in the panel. With holes I mean some periods for which the variable of interest was not available. In those cases, I imputed the missing value with the average between the first two adjacent non missing values. For example, if a firm reported revenues for 2014, 2015, 2017 and 2018; I imputed 2016 as the average between 2015 and 2017. Last, in the Aida survey reporting employment is not mandatory. For this analysis I will use the number of employees only to estimate Total Factor Productivity (TFP) and to categorize firms based on their dimension. For this reason, the variable number of employees is defined as the number of employees in the first year in which it is non missing. Therefore, the variable is time constant and in the majority of cases refers to the first year in which the firm is observed.

[4]The data on the average firm size in each province is gathered by the ASIA dataset of ISTAT

Figure 2: All storms that affected Italy in EM-DAT data

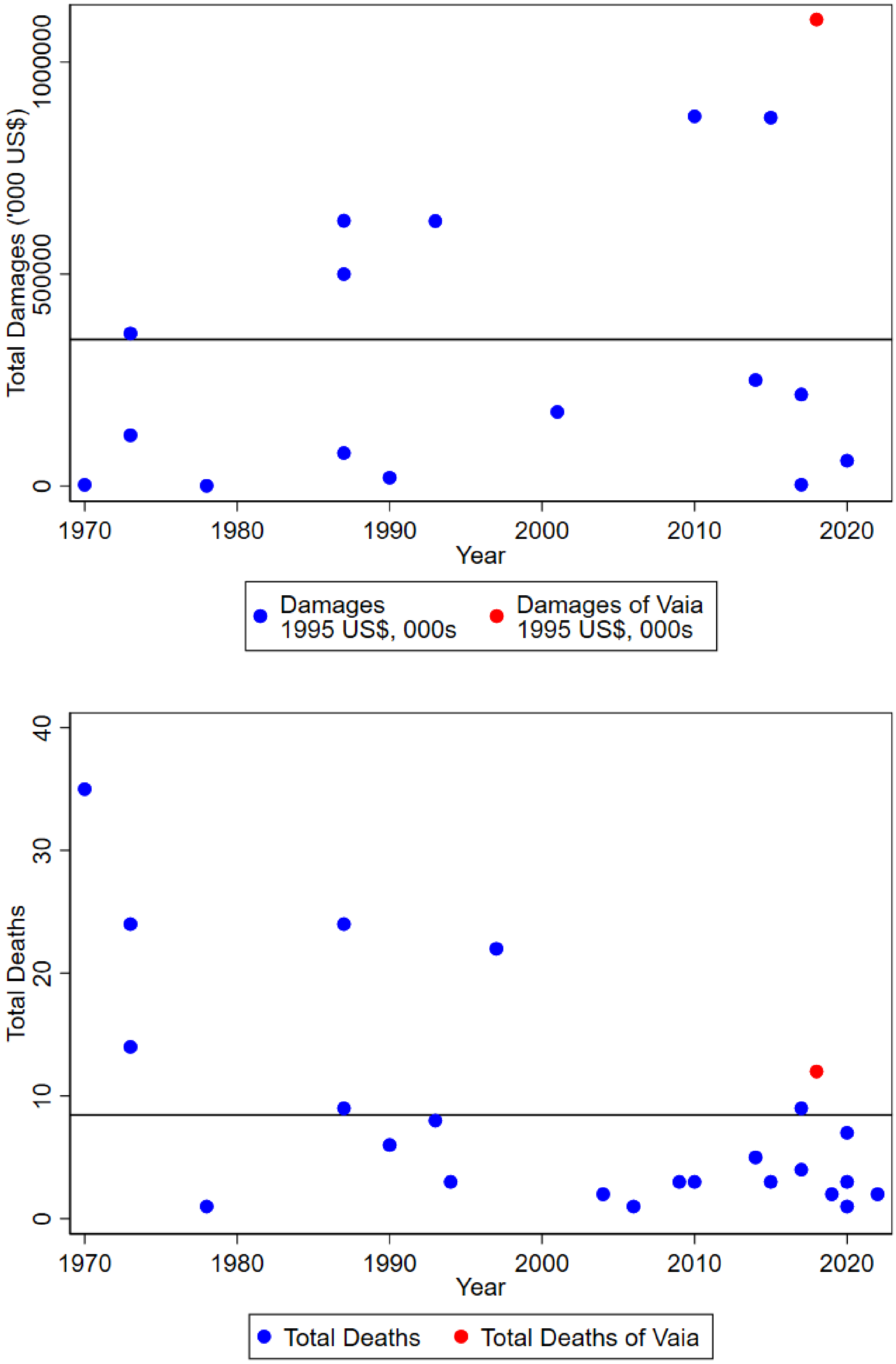


Table 1: Summary statistics

	Mean	SD	Min	Max	N
Treated	0.18	0.38	0.00	1.00	867054
Revenues	3292.55	32368.02	0.00	6372724.00	867054
Profits	95.25	2811.88	-362343.00	1134475.00	867054
Wages	339.72	2456.55	-249.57	392269.00	867054
TFP	6.19	0.44	5.78	14.27	487115
Operating Grants	17.92	436.33	0.00	95961.00	856328
Taxes	53.20	472.00	-11129.94	88527.00	864318

Data obtained from AIDA. The panel dataset has a time span from 2013 to 2019 and includes all firms located in a province in which at least one municipality is treated.

Among the dependent variables that will be used in the empirical part there will be Total Factor Productivity, that was estimated using the approach proposed by Levinsohn and Petrin (2003). Their idea is to estimate a simple Cobb-Douglas production function which takes as inputs labor, capital and intermediate goods. This approach has been used in the past for many economic applications (e.g. Ciani et al. (2018); Brunello et al. (2020); Pelli and Tschopp (2023)). A detailed description of the method and the choices can be found in the appendix B.1.

I match the firm level data described above with a geographical dataset on Vaia taken from Chirici et al. (2019), Chirici et al. (2020) and Vangi et al. (2021)). The match is done at the municipality level. Chirici et al. (2019) defines a polygon as hit if the damaged area is above 70 % of the area of the polygon. Similarly, I define a municipality as damaged if, in some part of its territory, the damage incidence was equal to 70% or more of the surface. This choice is imposed by the available data as polygons with lower incidence are not reported. Chirici et al. (2019) use the damaged incidence threshold of 70% to estimate the stock of wood destroyed in each municipality.

The firm level data is matched at the municipality level. For the analysis I will use only those firms located in a province in which at least one municipality was hit by the storm. This approach may create some significant differences between control and treatment group (as treated units are usually located in mountainous regions). My population of firms is constituted of all the incorporated firms located in the 11 provinces of Como, Sondrio, Bergamo, Brescia, Bolzano, Trento, Verona, Vicenza, Belluno, Treviso, Udine, Pordenone, Lecco.

Finally, I match the dataset with information about the municipality obtained from ISTAT. The variables reported are the number of employees and local units, the total population and the taxable income. In some cases, I will also use the data on institutions and social capital from Buonanno et al. (2022).

Table 1 shows the summary statistics of the outcome variables used in the analyses together with the most important controls. The variable Treated is a dummy equal to one if the firm is in the treatment group, irrespective of the year.

4.1 Identification

The identifying assumption is that, conditional on firm and time fixed effects the probability of being hit is orthogonal to the error term.

The literature on exogenous climatic shocks is costumed to assume exogeneity of natural disasters. The typical argument is that it is very difficult to predict whether, when and where the shock will occur (see for example Hsiang and Narita (2012) or Pelli and Tschopp (2023)). Such an approach has some pitfalls in this application. In the context studied in this thesis, it is true that the storm Vaia was unexpected and surprising; however, it did not hit randomly some municipalities and not others. A storm is not like a lighting but it is a widespread event that lasts for various days and hits with different intensities different places. Vaia was a huge storm that affected all Southern Europe, causing damages not only in Northern Italy but also in Spain, France and Austria. Moreover, Vaia hit different municipalities with different intensities. Table 2 shows that damaged municipalities (defined as those with a damage incidence $\geq 70\%$) are, on average, located at higher altitude, have less population, income and active firms (local units).

Table 2: T-tests across treated and not treated municipalities

	Not Damaged	Damaged	Diff.	s.e.	obs.
Distance from sea	1.2	1.2	-0.0	(0.0)	1485
Distance from river	0.2	0.1	0.0***	(0.0)	1485
Altitude	2.8	6.8	-4.0***	(0.2)	1485
log(Population)	8.1	7.5	0.6***	(0.1)	1485
log(Taxable income)	17.7	17.1	0.6***	(0.1)	1485
log(Local units)	5.5	4.9	0.6***	(0.1)	1485

Note: *** p<0.01, ** p<0.05, * p<0.10. Data at the municipality level only for the year 2017. The variables of distance are in hundreds of kilometers while altitude is in 100 meters.

The evidence discussed above demonstrates that even though the timing was unexpected, the "assignment to the treatment" was not random but varied based on observable characteristics. In other words, it is not possible to define a counterfactual group that is exactly comparable to the damaged group. Having a panel dataset allows for the possibility of controlling for unobservable time constant characteristics: using a fixed effects specification, one can argue that damaged and not damaged municipalities are identical. I prefer to control for firm level fixed effects since these include the municipality FE and capture differences across firms that would not be captured otherwise. This choice is supported by the test for choosing the level of fixed effects in linear panel data models proposed by Papke and Wooldridge (2022) which is discussed in detail in the Appendix B.2.

4.2 Empirical Strategy

In this section I will discuss the estimation strategies used in the analysis. I rely on two different specifications.

First, I employ an event study design to estimate the effect of Vaia on the firms. This approach is useful because it also tests for pretrends. To implement the event study, I regress outcomes on a set of hurricane indicators. All regressions control for firm and year fixed effects. The estimating equation is:

$$Y_{imt} = \sum_{\tau=2013,\tau\neq 2017}^{2021} \mathbf{1}[\tau = t] D_{m\tau}\beta_\tau + \alpha_i + \alpha_t + \epsilon_{imt} \tag{4.1}$$

where Y_{imt} is the outcome of interest of firm i that is located in municipality m, in year t (e.g. revenues, profits, wages or tfp). Only estimating this type of regression, I used data for the years 2020 and 2021. The variable $D_{m\tau}$ is equal to 1 if the municipality was damaged (at least some part of its territory had a damage incidence $\geq 70\%$). I normalize the effect in the year before the hurricane ($\tau = 2017$) to zero.

Second, I estimate a classical Two Way Fixed Effects Regression (TWFE). It is know that such regression estimates a causal, easily interpretable ATT parameter. The estimator applied in this paper does not suffer from the problems recently discussed in the DiD literature because the treatment is not staggered (Goodman-Bacon (2021); de Chaisemartin et al. (2022); Roth et al. (2023)). The estimating equation in this case is:

$$Y_{imt} = \beta_0 + \beta_1 T_{mt} + \alpha_i + \alpha_t + \varepsilon_{imt} \tag{4.2}$$

where T_{mt} is equal to 1 if the municipality was hit and the year is 2018 or 2019. All the other variables are defined as above (4.1).

Lastly, I estimate a TWFE in which the unit of observation is no longer the firm but is the municipality. The estimating equation is:

$$Y_{mt} = \gamma_0 + \gamma_1 T_{mt} + \rho_m + \rho_t + \zeta_{mt} \tag{4.3}$$

where Y_{mt} is the outcome of interest for municipality m in year t; T_{mt} is defined as before; ρ_m and ρ_t are respectively municipality and year fixed effects and ζ_{mt} is the error term.

All the results of the three regressions presented above have heteroskedasticity robust standard errors. The choice of using cluster robust standard errors is usually driven by the misconception that if clustering adjustment matters, one should rely on clustered robust standard errors. Such a claim is not true and depends on the data generating process and the empirical question we want to answer (Abadie et al. (2023)). In this framework, I have a dataset that contains the full sample of firms in the region I am interested into. Henceforth, there is no need to cluster.

5 Results

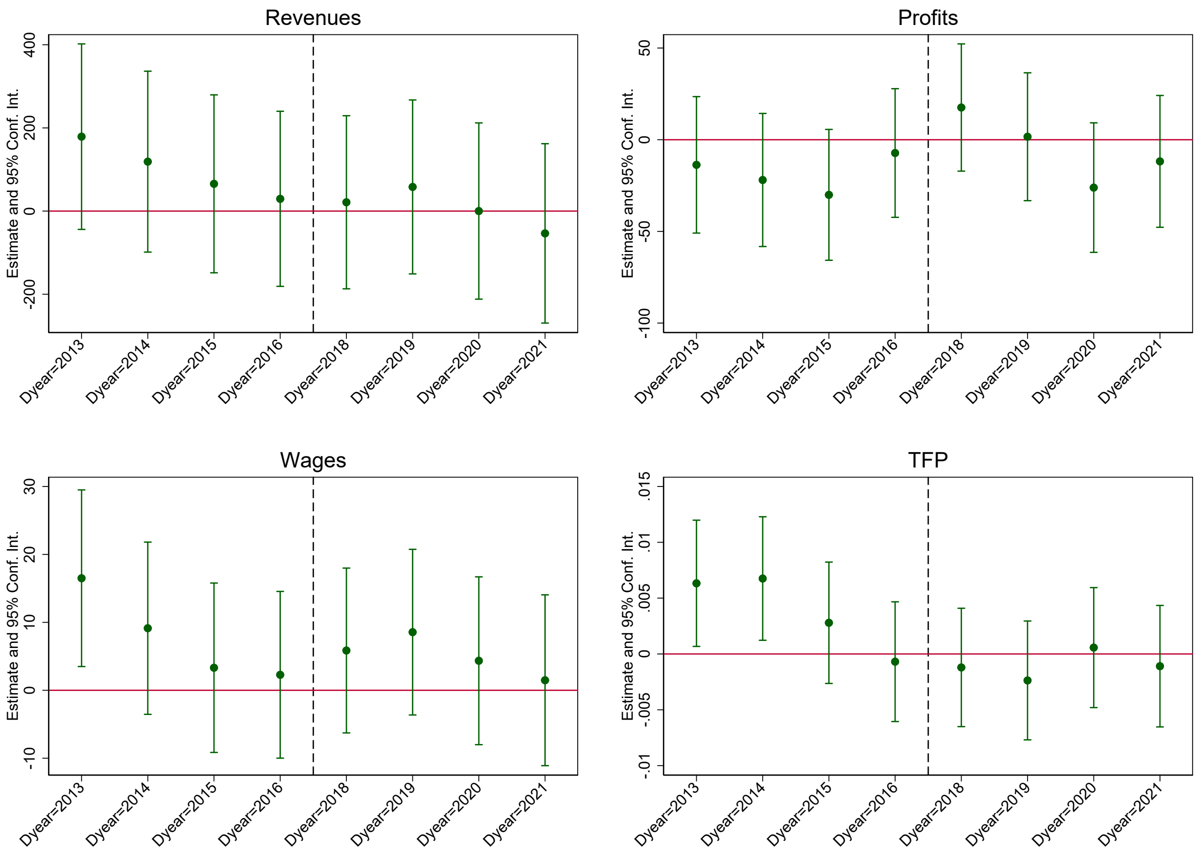
In this section, I will present the results of my analysis. A comprehensive discussion of the estimating strategies is presented in the section 4. I will discuss the results of the event study and of the static DiD. In this part, I will strongly emphasize the robustness of the results to different specifications and choices. After presenting the results, I will discuss possible mechanisms and ways to interpret such results. I will conclude presenting the results of the municipality level regression.

Figure 3 shows the estimates and corresponding 95% confidence intervals of the event study regression based on equation 4.1. Each subgraph corresponds to a different dependent variable, as indicated above each plot. In each graph, the effect in 2017 is normalized to zero and there is a vertical line that divides pre and post-treatment coefficients. The years span from 2013 until 2021. For this specification, years 2020 and 2021 are included even if Covid-19 had already stroke. The reason is that the pandemic hit all Italian municipalities similarly and there is no reason to believe that there were differences across treated and control groups. In the Appendix it is available the same plot excluding the years 2020 and 2021 (Figure B.3).

Looking at the coefficients post 2018, the storm Vaia had, on average, no statistically significant effects on the treated firms. The firms' revenues, profits, and wages of firms located in damaged municipalities are not different than those of the control group. TFP decreased after 2018; even if such an effect is not statistically significant, this trend can be helpful in understanding the findings. These results do not imply that the storm Vaia had no effect on Italian firms but that on average we do not observe any effect. There are many possible explanations for these conclusions. First, it may be that the effect of Vaia was so widespread that also the firms in the control group were negatively affected. This possibility is unlikely to be true as the control group comprehends many municipalities located also in the Po Valley; most of these municipalities did not suffer the negative effects of the storm as the damaged municipalities. One other explanation is that while some firms suffered the negative consequences of the storm, more resilient firms were capable of improving their performance after the disaster. These effects cancel out with each other and result in an average null effect. The last possible explanation is that damaged firms were compensated for the losses through financial aid and tax discounts so that they were as good as if the storm had never hit them. The only production factor that is not possible to compensate with financial flows is the firm's productivity which actually decreased after the storm. In the section 5.2, I will discuss the last two possibilities.

The coefficients before 2018 indicate that the differences between the treatment and control groups are not statistically significant, except for TFP. Such a result is probably due to the differences between treated and control units, as already pointed out. Overall, testing for a null of joint non significance of the pre treatment variables, I can't reject the null hypothesis and conclude that the parallel trends assumption holds. Moreover the results are robust to possible misinterpretations due to violations of the parallel trends assumption (see Appendix B.4).

Figure 3: Event Study (years from 2013 until 2021)



The results of the event study are in opposition to the literature as they demonstrate that the storm Vaia had no effects on firms' sales and productivity. Nevertheless, the results are confirmed by the Difference in Differences regression. Panel A of Table 3 shows the coefficients obtained estimating equation 4.2. The results in this Table are to be interpreted as short run effects. Each column corresponds to a different dependent variable. The mean of the dependent variable is included at the bottom of the table as it is equal across the panels.

On average, an Italian firm which is located in a municipality hit by the storm Vaia has neither higher nor lower revenues compared to any other firm that was not hit. A similar conclusion can be made for wage expenditure. Damaged firms are likely to have higher profits, even though such a claim holds only with a 10% p-value. Finally, Total Factor Productivity of damaged firms is lower than the TFP of non damaged firms. The effect is fairly low but suggests that the effect of the storm may not affect observable outcome but rather affects the productive efficiency of the firms. Such a result is in line with the trend observed while looking at the event study results.

The results of the event study and of the DID are puzzling as they suggest that firms were neither worse nor better off after being hit by the storm Vaia. The cyclone was among the most damaging Italian natural catastrophes of the century. Vaia caused huge damaged not only to the forests but also to the infrastructures, habitations, and communication routes. On the bright side, the results indicate that, on average, the Italian economy is resilient to strong

Table 3: Difference in Differences Results

	(1) Revenues	(2) Profits	(3) Wages	(4) TFP
Panel A				
Damaged	-25.138	25.042*	2.000	-0.004**
	(53.9257)	(15.1782)	(3.4802)	(0.0016)
Panel B				
Damaged=1	-260.579***	-10.459	-27.471***	-0.005***
	(54.8429)	(15.4406)	(3.5356)	(0.0017)
Damaged=1 × Big	5745.212***	866.289***	719.147***	0.018**
	(246.4477)	(69.3855)	(15.8881)	(0.0069)
Panel C				
Damaged=1	-250.036***	21.983	-14.331***	-0.003*
	(75.3980)	(21.2222)	(4.8660)	(0.0017)
Damaged=1 × Autonomous=1	418.356***	5.689	30.379***	-0.011*
	(98.0263)	(27.5913)	(6.3263)	(0.0063)
Mean of dependent variable	3292.550	95.248	339.719	6.192
N	867054	867054	867054	487115

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.10$. Robust standard errors in parenthesis. All regressions have Firm and Time Fixed Effects. Data obtained from AIDA-BVD Database. The panel dataset has a time span from 2013 to 2019. Are included all firms located in a province in which at least one municipality is treated. All variables except TFP are measured in thousands of euros. Details on the estimation of the TFP can be found in Appendix B.1

natural disasters. These results could be driven by differences in the effects of the storm among firms. It could be that smaller firms were negatively affected by the storm while bigger and more resilient firms could benefit from the storm. If this was the case, the average result observed would mask inequalities among firms. If this was the case, policy makers should intervene as the obtained outcome would be Pareto inefficient. Pareto efficiency is obtained in situations in which the benefit of someone worsens off someone else.

Before analyzing possible heterogeneity in the results and discussing the policy implications in the presence of heterogeneity; in the next section I discuss the robustness of my results to different samples and estimators. Discussing the robustness of the general results is important from an econometric point of view and in order to convince the reader of the validity of the results to different choices.

5.1 Robustness checks

The next paragraphs in this section show various robustness checks that support the evidence found in the results above. Each robustness check has its own importance as highlights a possible source of bias and tries to provide evidence that this is not the case. Table 4 shows the estimated coefficients of each of the inspections described below. Each row corresponds to a different robustness check.

All years The first robustness check extends the data period to all the available years, including 2020 and 2021. These two years were excluded from the main specification since these were the years in which COVID-19 hit harder Italy and the world. Including these two years does not change the conclusions of Panel A of Table 3.

Balanced Panel The second robustness check looks at whether the results for the balanced panel (i.e. the panel of firms that are observed every period) are different. This check is closely linked to the one that follows as it is a non formal test of sample selection. The results reported in the second row of Table 4 indicate that balanced and unbalanced sample arrive at the same results.

Sample Selection and Survival Analysis One of the major issues with the estimation strategy described above is the possible self-selection out of the dataset: if a firm closes it exits the sample and it is not part of the estimating sample anymore. It could be that the null effects observed above are due to self selection out of the sample of damaged firms. In other words, if a firm was damaged by the storm and closed, it would not report negative or zero revenues because it left the sample. The econometrics literature has developed various ways to deal with this problem. In an unbalanced panel dataset Semykina and Wooldridge (2010) proposes a two-step estimator that can is asymptotically consistent in the presence of sample selection bias. More on the estimator and the choices are available in Appendix B.3. The results of the estimator are displayed in Table 4 and are aligned with those in Table 3. The only difference regards the TFP, which is not statistically significant with this estimator.

Municipalities with a Damaged Area $>$ 1 ha This test wants to evaluate whether the threshold chosen for the analysis is valid. Would the results have changed if a different threshold was chosen? For this test, I chose as a threshold whether a municipality had more than 1 hectare with an incidence of damage above 70%. Recall that the previous threshold was 0. Row 4 of Table 4 shows that the results do not change if a different threshold was chosen. I tried different thresholds and the results did not change (except for extremely high values).

Only municipalities above 100 meters Row 5 of Table 4 shows the estimates of equation 4.2 when the sample is reduced to only those municipalities above 100 meters above the sea level. As already explained in Section 4, hit and non hit municipalities are different in the sense that hit municipalities are, among other things, located at higher altitudes.

Table 4: Different Robustness checks

	(1) Revenues	(2) Profits	(3) Wages	(4) TFP
All years	-60.840	16.291	-0.263	-0.004***
	(55.5855)	(12.2206)	(3.2395)	(0.0014)
Balanced	-48.547	31.592	1.172	-0.005***
	(60.2065)	(30.2949)	(6.6137)	(0.0016)
Sample Selection	-3344.188	-447.147	-30.232	0.038
	(3169.5738)	(301.2273)	(157.0934)	(0.0649)
Damaged area $> 1ha$	11.803	8.094	4.053	-0.005***
	(56.0046)	(15.7646)	(3.6144)	(0.0018)
Above $100m$	2.307	18.988	5.982	-0.004**
	(53.3043)	(17.6926)	(3.6665)	(0.0018)
IPW	-333.269	-4.775	-14.399	-0.009**
	(226.6255)	(17.2236)	(10.6602)	(0.0041)

Note: *** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parenthesis. All regressions have Firm and Time Fixed Effects. Data obtained from AIDA-BVD Database. The panel dataset has a time span from 2013 to 2019. Are included all firms located in a province in which at least one municipality is treated. All variables except TFP are measured in thousands of euros. Details on the estimation of the TFP can be found in Appendix B.1

This test excludes all those municipalities in the Po Valley since these municipalities are more likely to be different from mountainous towns. Excluding those municipalities does not change significantly the results.

Inverse Probability Weighting It has already been pointed out that treated and control municipalities are not identical based on observable characteristics. This test has the same spirit as the last check but uses an econometric tool to make treatment and control groups comparable. In a similar fashion as Deryugina et al. (2018), I rely on inverse propensity score weighting to make treated and control units comparable (Hirano et al. (2003)). The inverse propensity score weighting allows to compare the outcomes of damaged firms to control units while accounting for differences in their observable characteristics. The results are shown in the last row of Table 4. Even if the estimated coefficients are not exactly identical, the interpretation of the results is similar to the main specification.

Continuous treatment To conclude the discussion on the robustness of the results I will discuss how the estimation changes when a continuous treatment is used. Among the recent discoveries in the econometric Difference in Differences literature, it has been pointed out that interpreting coefficients of a DiD specification with a continuous treatment can be troublesome (Callaway et al. (2021), de Chaisemartin et al. (2022)). I use as a continuous treatment an estimate of the volume of wood destroyed by the storm. The estimation procedure of the continuous treatment is taken from Chirici et al. (2019). To estimate easy-to-interpret treatment effects I resort on the estimator proposed by de Chaisemartin et al. (2022). The results indicate that the treatment effects are not statistically different from zero (see Figure B.7).

5.2 Mechanisms

I document how the storm Vaia did not affect firms' observable outcomes such as revenues and profits, on average. The first possible explanation for these results is that the storm had no effect on the firms. If this was the case, it would mean that Italian firms are actually sufficiently resilient to not be affected by a cyclone of the magnitude of Vaia. This is likely to be implausible as it contradicts the majority of the literature analyzed in section 2. One other possibility is that the Italian government and regional institutions gave sufficient financial support to the firms to make them work as if the storm never happened. Such a possibility is not novel to the literature but has been already considered (Deryugina (2017)). It is likely that bigger firms are capable of attracting more resources and therefore cope better with the damages caused by the storm. The same reasoning can be made with institutions: firms located in places with stronger institutions receive more disaster aid both directly and indirectly (since communication routes are restored faster). To test these hypotheses, I will look at whether the results differ based on firms' dimension and location. Moreover, I will analyze whether damaged firms receive financial support through grants and tax deductions.

Dimension One of the most important peculiarities of Italy is the disproportionate number of micro and small enterprises. The results observed in Panel A of Table 3 may be heterogeneous by dimension. The idea is that small firms usually have more difficulties in attracting financial flows and suffer the most from adverse natural events like cyclones or earthquakes (Bańkowska et al. (2020); Basker and Miranda (2018)). To test this hypothesis, Panel B of Table 3 shows how the effects change across dimensions. The reference category in Panel B is micro and small firms (those with less than 50 employees). The coefficient of the reference category captures how much the micro firms' dependent variable changed after the shock. The results for the other category is to be interpreted as how much the dependent variable of the category changed compared to the reference group.

The dimension classification used here is taken from the one used by the European Commission. In the European community, micro firms are those with less than 10 employees; small firms have between 10 and 50 employees, while medium firms have a number of employees between 50 and 250. Finally, big firms are those with more than 250 employees. In my analysis, I created a dummy variable equal to 1 if the firm is a medium or big firm. Interacting such a dummy with the regressor "damaged" shows the differences across firms' dimensions.

Column (1) of Panel B, Table 3 shows that micro and small firms had their revenues decreased after the shock. As the dimension of the firm increases, the effect of the storm goes to zero and becomes positive, indicating that medium and big firms were positively affected by the storm Vaia (The results with the interactions for all four dimension classifications are available in Table B.3). This result strengthens the hypothesis that the bigger the firm, the higher the probability of receiving disaster aid. All the other variables behave in a similar way, except for profits which are not affected for small firms.

One important caveat that must be considered is that the average causal effect of Vaia on the population of all Italian firms is likely to be negative. Remember that the Aida dataset is composed of incorporated firms only. These firms are on average bigger than the average Italian firm. Since we discovered that the null effect in Panel A of Table 3 is due to a cancelling out effect between small and big firms, it is likely that estimating the same equation with a representative panel of the population of Italian firms would yield different results. In particular, since the Aida dataset contains bigger firms and since smaller firms were negatively affected by the storm, we can hypothesize that the average effect of the storm Vaia on the population of Italian damaged firms is negative.

Regional Differences One other possible source of heterogeneity is the location. The Italian peninsula is incredibly heterogeneous across regions (Putnam et al. (1992)). Italy is divided into 20 administrative regions. Among these 20 regions, 5 are defined as Special or Autonomous (Aosta Valley, Friuli-Venezia Giulia, Sardinia, Sicily, and Trentino-Alto Adige/Südtirol). These regions became autonomous in order to take into account cultural differences and protect linguistic minorities. Article 116 of the Italian Constitution, depending on their specific statute, gives to these areas varied degrees of legislative, administrative, and financial power.

Among the regions in my sample, two out of four are special regions (Friuli-Venezia Giulia and Trentino-Alto Adige/Südtirol). These regions are renowned for having strong institutions and one of the most efficient welfare system in Italy (Putnam et al. (1992)). Such institutions are likely to have helped firms located in these regions both directly (through disaster aid) and indirectly (for example through social cooperation and rapid reconstruction after the storm).

Panel C of Table 3 shows the results of the TWFE regression when the regressor is interacted with a dummy equal to 1 if the firm is located in an autonomous region. This estimating equation should capture the differences in resilience to the shock for firms in different institutional contexts. The results indicate that firms in non-special regions had their revenues decreased after the shock, while firms in special regions saw an increase in their revenues. A similar pattern is observed for wages. Looking at the profits, these did not increase for all firms, independently of their location. Finally, looking at the productivity, firms in autonomous regions were affected as firms in non autonomous regions (both decreased the TFP of the same amount).

Financial Aid To understand whether firms received financial aid after the shock, I will use the regression equation 4.2. Figure 5 column (1) has as dependent variable operating grants. In Italian accounting legislation, whenever financial aid is received, such a grant must be inserted in the income statement under the voice *A5 - Contributi in Conto esercizio*, which can be translated as operating grants. The dependent variable in Column (2) is the amount of taxes paid by the firm. The results of the regression are in Panel A. Damaged firms receive on average 9,000 euros after being hit and have a reduction in taxes of about 3,000 euros. These results support the hypothesis that damaged firms are compensated for their losses after Vaia.

Table 5: DiD with financial variables

	(1) Operating Grants	(2) Taxes
Panel A		
Damaged	9.660***	-3.220*
	(3.4240)	(1.6514)
Panel B		
Damaged=1	4.953**	-0.109
	(2.0279)	(0.8740)
Damaged=1 × Big	116.079*	-77.384**
	(69.4072)	(35.0744)
Panel C		
Damaged=1	-1.872**	-2.459*
	(0.8727)	(1.4630)
Damaged=1 × Autonomous=1	21.460***	-1.418
	(6.3323)	(2.9396)
Mean of dependent variable	17.915	53.200
N	856328	864318

Note: *** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parenthesis. All regressions have Firm and Time Fixed Effects. Data obtained from AIDA-BVD Database. The panel dataset has a time span from 2013 to 2019. Are included all firms located in a province in which at least one municipality is treated. All variables except TFP are measured in thousands of euros. Details on the estimation of the TFP can be found in Appendix B.1

Panel B shows how the results vary based on dimension (in a similar way as Panel B of Table 3). The results indicate that while small firms received on average 5 thousand euros when damaged; medium and big firms received 116 thousand euros. There is no reason to believe that medium firms faced higher damages than small firms and therefore there is no clear explanation for such a disproportion in the results other than the idea that the bigger the firm the easier it is to gather resources. Column (2) supports the hypothesis above as it shows that only medium and big damaged firms had a tax reduction while small enterprises did not have any fiscal discounts compared to the control group.

Panel C of Table 5 demonstrates that the financial aid received by the firms is heterogeneous by location: firms located in autonomous regions received positive disaster aid while firms in non autonomous regions received fewer grants. Looking at taxes, firms in non autonomous regions had a fiscal discount of 2 thousand euros (not statistically significant) while firms in autonomous regions has a fiscal discount of 4 thousand euros (statistically significant).

This section aimed at answering the two hypotheses originated by looking at the results of the event study. The first hypothesis was whether the results observed in Panel A of Table 3 were due to heterogeneity in firms' characteristics. Looking at Panels B and C of the Table, I found that while small firms saw their profits decrease after the shock, big firms saw a significant increase in their profits and TFP. Similarly, firms located in autonomous regions drew positive revenues after the shock while other firms were negatively affected. Small firms located in non autonomous regions were the more damaged by the storm (see Table B.5). Overall, the results support the claim that the null results observed in the basic specification are due to a canceling out effect among different firms.

After having answered the first hypothesis, it is reasonable to ask why there is such heterogeneity in the results. The first channel of these differences is the source of the heterogeneity in dimension: small firms are less consolidated, have limited access to private and public funding, and are more vulnerable to unexpected economic shocks. A second channel is the institutional quality in which the firm is located. Firms located in regions with better services, resilient infrastructures are capable of reorganizing in less time and are likely to suffer less the negative effects of a natural catastrophe. The last channel is disaster aid. Receiving more financial resources definitely helps the firm overcome the shock. For example, financial resources can be used to restore damaged capital and make investments. As a matter of fact, two years after the shock damaged firms increase the value of their assets (see Figure B.4). The fourth channel is a combination of the previous three. Small firms are unable to be noticed and to attract financial aid from governments and do have not collateral as strong as a big firm when asking for a loan from a bank. Similarly, autonomous regions enjoy more disaster aid from the government and have stronger institutions and tax reliefs chosen by the regional administration.

All the channels discussed above must be taken into consideration when designing policies that aim at reducing inequalities among firms.

Industry One other source of heterogeneity in the results is the sector. Firms that operate in different industries are likely to be affected in different ways. In particular, I expect the real estate sector to be among the most damaged as the value of housing property is likely to have decreased due to damages caused by the storm and higher maintenance costs. This is observed also in the data (see Table B.6). In the Table the sectors follow the NACE 2007 classification. The reference category is composed of all the firms that are not in one of the sectors showed in the table. While the real estate sector was damaged by the storm, other sectors like manufacturing and trade were positively affected. The reason is that the cost of wood decreased (Udali et al. (2021)) and made it cheaper to produce furniture and made the Italian wood convenient for other regions.

5.3 Looking at the effects of storm Vaia on the Municipalities

Thus far I have focused my attention on firms. However, to complement my analysis, I am looking at municipalities in this section. The reasons for focusing on an aggregate level are threefold: first, this kind of analysis could confirm and provide additional evidence on the strength of the results discovered in the previous sections. Second, such analysis could shed light on the dynamics discovered by looking at firms. Last, the data used for the analysis at the municipality level is representative of the whole population and does not focus only on incorporated firms. The estimating equation used in this section is equation 4.3.

Table 6 presents the results for various dependent variables at the municipality level. Panel A presents the results without any interaction while Panel B shows how the results change across autonomous and non autonomous regions.

The first column has as dependent variable the number of active local units. The storm Vaia did not reduce the number of local units in the short run. Such a result is different from what I observe in the Aida dataset. Table B.8 estimates the probability of closing for a firms after the shock. The fact that the probability of closing increases does not supports the result found in Table B.8. This result is interesting for various reasons but it mainly suggests that the firm level dataset is not representative of the whole population of firms. Looking at Panel B of Figure 6, municipalities that were damaged and were in an autonomous region increased the number of local units, while municipalities that were not in an autonomous region lost on average 3 active local units compared to non damaged municipalities. This result is partially supported by the firm level analysis. Column (3) of Table B.8 estimates how the probability of closing changes in the Aida dataset by region type. Firms located in non autonomous regions have an estimated probability of closing of 1% if hit. Firms located in autonomous regions have still a positive probability of closing but significantly lower (0.5%). Column (2) of Table B.8 estimates how the probability of closing changes by firm dimension. The results are in line with those estimated looking at Hurricane Katrina (Basker and Miranda (2018)).

Column (2) has as dependent variable the number of individuals that are working in the municipality. The coefficient indicates that damaged municipalities lose on average 43 employees. This can be interpreted as a reduction of 2% in employment after the shock. The number of employees decreased significantly for municipalities in both autonomous and non autonomous regions. On average, municipalities in autonomous regions decreased their unemployment even though the difference is not statistically significant. It would be interesting to see whether this result is due to an increase in unemployment in the municipalities or it is due to migratory flows caused by displaced individuals.

The variable income is defined as the reported income by those individuals in the municipality who compile their taxes. The variable is in thousands of euros. As shown in Column (3), municipalities that were hit by the storm lost, on average, 2 million euros of household income.

Table 6: Difference in Differences at the Municipality level

	(1) Local Units	(2) Employees	(3) Income	(4) Welfare Spending
Panel A				
Damaged	-0.106	-43.862***	-2369.748***	-37.565**
	(0.8074)	(9.3819)	(291.8150)	(19.0165)
Panel B				
Damaged=1	-3.075***	-54.719***	-3106.567***	-112.806***
	(0.8747)	(9.0400)	(297.5038)	(16.8763)
Damaged=1 × Autonomous=1	5.913***	21.617	1467.028***	149.807***
	(1.0338)	(13.9281)	(437.9570)	(27.0980)
Mean of dependent variable	458.884	1850.710	82414.763	1374.574
N	11944	11944	11944	11944

Note: *** p<0.01, ** p<0.05, * p<0.10. Number of observations and constant are the same in both panels.

This effect is heterogeneous across municipalities, with municipalities in non autonomous regions losing, on average, 1 and a half million euros more than municipalities in autonomous regions.

Finally, Welfare Spending is defined as the amount spent by municipalities on every kind of welfare assistance. The variable is in thousands of euros. Interestingly, damaged municipalities spent less money on welfare compared to non hit municipalities. Differently from what happened in New Orleans after hurricane Katrina, Italian municipalities decreased their welfare spending. Probably, these municipalities had to restrict their spending to balance off the increase in the maintenance and safety costs of the affected areas. Looking at Panel B, the previous conclusions hold for non autonomous regions since autonomous regions actually increased their welfare spending. As a matter of fact, autonomous regions received more disaster aid than other regions (art. 1, paragraphs 663 and 664 of the law of 30 December 2018, n. 145; order n. 1 e 2 of 23 November 2018, Veneto Region).

To conclude, I discuss how the storm Vaia affected the composition of the population in damaged municipalities. The literature studying how migratory flows change over time after a cyclone focuses mostly on developing countries and there is limited evidence for developed countries. One exception is Deryugina et al. (2018) which estimates that residents were 29% more likely to change residence after hurricane Katrina. Table B.10 shows the results of the analysis looking at population changes. Foreign residents are those individuals that live in a municipality but do not have Italian citizenship. I find that after the storm the resident population of damaged municipalities decreased of 5% on average. Interestingly, hit municipalities attract foreign residents, probably because there is a cheaper housing market and migrants are less risk averse than Italian citizens (Jaeger et al. (2010); Böhme and Kups (2017)). Interestingly, from Panel B we can notice that the foreigners migrate to municipalities hit but that are in autonomous regions while Italian citizens move when they are residents of non autonomous regions. Furthermore, while the movement of Italian citizens is more or less identical by gender, damaged municipalities attract more male foreigners than female (see Table B.11).

Overall, the results indicate that the storm Vaia affected the Italian municipalities, causing significant losses in households' income in the short run. There is also strong heterogeneity across regions. Households living in autonomous regions experienced fewer adverse consequences after the storm. These findings strengthen the considerations made in the previous sections: policies should take into account the heterogeneity of the population and make also redistributive considerations when dealing with climatic shocks.

6 Conclusions

I study the effects of the storm Vaia on Italian incorporated firms. I find that the cyclone had, on average, no impact on firms' revenues, profits, and wages. There is a small, negative effect on Total Factor Productivity. I demonstrate that small firms suffer the negative consequences of the cyclone while medium and big firms enjoy an increase in revenues, profits, and TFP. At the same time, firms located in autonomous regions (which are regions with more administrative flexibility and stronger institutions) are not worse after being hit by the storm while firms in other regions have negative performances. Future research should understand whether the results found in Italy can be generalized to other countries and to other types of natural disasters.

Disaster aid, received by the firms as operating grants or tax deductions, is an important policy tool that can improve firms' resilience to natural disasters. Financial inflows are an alternative source of income when a demand shock causes lower revenues and can be used to invest in new capital in order to replace older and destroyed capital. The ability of firms to receive such grants varies based on their characteristics, creating strong inequalities among Italian firms. Small firms have more difficulties in attracting funds both from public and private sources. This could cause a long run divergence between those firms capable of attracting funding and the other enterprises.

The findings imply that there are strong inequalities among Italian firms in accessing financial aid. If the social objective is to achieve Pareto efficiency, there is a need to develop new policy tools in order to modify the current situation. In the future, researchers should understand which policy tools can be used to reduce the inequalities in access to disaster aid in a cost effective manner.

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A Theoretical model supporting my claims

Consider a firm with a simple Cobb-Douglas production funcion:

$$Y = F[K, L] = AK^{\alpha}L^{1-\alpha} \tag{A.1}$$

Profits are:

$$\Pi = AK^{\alpha}L^{1-\alpha} - wL - rK \tag{A.2}$$

With no uncertainty, the equilibrium is defined by:

$$\begin{aligned} \frac{\partial \Pi}{\partial K} &= \alpha AK^{\alpha-1}L^{1-\alpha} - r = 0 \\ &\rightarrow \alpha AK^{\alpha-1}L^{1-\alpha} = MPK = r \end{aligned} \tag{A.3}$$

$$\begin{aligned} \frac{\partial \Pi}{\partial L} &= (1-\alpha)AK^{\alpha}L^{-\alpha} - w = 0 \\ &\rightarrow (1-\alpha)AK^{\alpha}L^{-\alpha} = MPL = w \end{aligned} \tag{A.4}$$

Define the ratio between the equation for marginal product of labor and marginal product of capital as the efficient Marginal Rate of Techincal substitution. The ratio between the two optimality equations derived above gives the following equality:

$$MRTS^{*}_{L,K} = \frac{MPL}{MPK} = \left(\frac{1-\alpha}{\alpha}\right)\frac{K}{L} = \frac{w}{r} \tag{A.5}$$

A.1 Add Uncertain shock on capital

Now I add an uncertain shock which happens with probability p. If the shock happens, a quantity D of the capital will be destroyed. At the same time, the government can give the firm a disaster aid FK. The financial aid is given with probability f. Notice that the government can give financial aid also to non damaged firms. This captures asymmetries in the information of the actual damages. The Table below shows the probabilities and possible outcomes:

		Disaster aid f	Not Disaster Aid (1-f)
Destroyed	p	(K-D+F)	(K-D)
Not Destroyed	(1-p)	(K+F)	K

Table 7: Table of Probabilities

It is assumed that institutions work well, and can identify whether a firm is damaged or not. They have limited resources and cannot reimburse all firms. They have to decide f which yields the most efficient outcome.

Thus, the expected capital is:

$$\begin{aligned} E[K] &= pf(K - D + F) + p(1 - f)(K - D) + (1 - p)f(K + F) + (1 - p)(1 - f)K \\ &= (K - pD + fF) \end{aligned} \tag{A.6}$$

Moreover, the probability of receiving financial aid f can depends on the dimension L. Thus $f = f(L)$. Obviously, this is not the aim of the government, but it is likely that bigger firms are capable of attracting more resources (for example winning public contests for disaster aid or through loans). If this is the case then $f'(L) = \partial f(L)/\partial L > 0$.

The expected profits are:

$$E[\Pi] = A(K - pD + f(L)F)^{\alpha} L^{1-\alpha} - wL - r(K - pD + f(L)F) \tag{A.7}$$

The optimal choices of K and L are obtained as follows:

$$\begin{aligned} \frac{\partial E[\Pi]}{\partial K} &= A\alpha(K - PD + f(L)F)^{\alpha-1} L^{1-\alpha} - rK = 0 \\ &\to A\alpha(K - PD + f(L)F)^{\alpha-1} L^{1-\alpha} = r \end{aligned} \tag{A.8}$$

$$\begin{aligned} \frac{\partial E[\Pi]}{\partial L} &= A\alpha(K - pD + f(L)F)^{\alpha-1} f'(L)FL^{1-\alpha} + A(K - pD + f(L)F)^{\alpha}(1 - \alpha)L^{-\alpha} - w - rf'(L)F = 0 \\ &\to A(K - pD + f(L)F)^{\alpha}(1 - \alpha)L^{-\alpha} \end{aligned} \tag{A.9}$$

Taking the ratio of the two equations obtained gives the following equality. For simplicity I define the LHS as $EMRTS$.

$$EMRTS_{L,K} = \frac{(K - pD + f(L)F)}{L} \left(\frac{1 - \alpha}{\alpha} \right) = \frac{w}{r} \tag{A.10}$$

A.2 Evaluate different policies

My claim is that government should provide financial aid to firms and should give this financial aid equally to different firms (i.e. $f'(L) = 0$).

To justify this claim, I need to measure how much a policy is close to an efficient one. My measure of economic efficiency is the Marginal Rate of Technical Substitution (MRTS). The reason is that if firms chose L and K in order to reach an efficient MRTS, then the supply side of the economy is working efficiently (the relative price of inputs is at the efficient level).

Therefore, policy makers aim at minimizing the distance:

$$|MRTS^*_{L,K} - EMRTS_{L,K}| \tag{A.11}$$

With the help of some calculus it is easy to demonstrate that to minimize the distance A.11, policymakers should set:

$$f(L) = \frac{pD}{F} + c_1 L \tag{A.12}$$

Where c_1 is a constant. To find the value of c_1 and therefore the optimal $f(L)$, we need a cauchy condition. In this setting, the most reasonable condition is $f(1) = 0$ implying that if the firm is very small the probability of receiving funds is 0 (the same result holds with limits).

Therefore the optimal solution is:

$$f(L)F = pD \tag{A.13}$$

and $f'(L) = 0$.

B Appendix

This appendix contains all the material and the theoretical discussion that was left for the reader in the main text.

B.1 Estimating Total Factor Productivity

The production function is a fundamental concept in economics that connects the inputs that are used in the firm's production with the output produced. Total Factor Productivity is a measure of productivity that remains after having measured the productivity of the inputs.

Economists have developed various methods to measure the TFP. In the following I will discuss the approach used in my work to estimate the TFP. My notes are taken from Mollisi and Rovigatti (2017). The idea in Levinsohn and Petrin (2003) is to estimate a Cobb-Douglas production function of the form:

$$y_{it} = \alpha + \mathbf{w}_{it}\beta + \mathbf{x}_{it}\gamma + \omega_{it} + \epsilon_{it} \tag{B.1}$$

Where w_{it} and x_{it} are vectors of free and state variables respectively. ω_{it} is the total factor productivity which is unobservable. It is frequently assumed that that productivity evolves according to a first-order Markov process such that: $\omega_{it} = g(\omega_{it-1}) + \zeta_{it}$

The literature proposed different two step estimators to estimate ω_{it}. Levinsohn and Petrin (2003) propose to use intermediate inputs m_{it} as a proxy for ω_{it}. The idea is that firms adjust their demand function for intermediate inputs after observing their productivity. In particular, define the intermediate input function: $m_{it} = f(\omega_{it}, \mathbf{x}_{it})$; with $f()$ invertible and monotonically increasing in ω. As long as $E[m_{it}|\mathbf{x}_{it}] = 0$ it holds that $\omega_{it} = f^{-1}(m_{it}, \mathbf{x}_{it})$. Plugging this into equation B.1:

$$y_{it} = \alpha + \mathbf{w}_{it}\beta + \mathbf{x}_{it}\gamma + f^{-1}(m_{it}, \mathbf{x}_{it}) + \epsilon_{it} \tag{B.2}$$

Equation B.2 can be estimated using non linear estimators. Consistently estimating the residuals of the equation allows to obtain a proxy of the productivity ω. Unfortunately, nonlinear least squares would yield biased estimates since the intermediate output are correlated with the error term given the firms'response to the technology efficiency shock ζ_{it}. Therefore, we need to rely on *GMM* estimators.

The estimator discussed above was implemented using the *prodest* command in Stata. Following Ciani et al. (2018) and Brunello et al. (2020) I use labor costs are a proxy for labor as this variable captures differences in labor quality. The estimated coefficients of the production function are 0.2937 for labor, 0.0795 for capital and 0.2578 for intermediate goods. The coefficients of labor and capital are slightly higher than those estimated by Van Beveren (2012) but are overall in line with the literature. The variable TFP has less non missing observations than the other variables used in the sample because of missingness in the intermediate inputs variable. This missing value should not bias the results as the attention dedicated in compiling the survey is captured by the firm fixed effects.

B.2 Test for choosing the level of fixed effects in linear panel data models

In all the regression that I present, I control for firm level Fixed Effects. Even though from a theoretical point of view this is the reasonable thing to do, there is not a definitive convention in the literature. This section wants to support the theoretical reasoning with a simple empirical test developed by Papke and Wooldridge (2022).

Consider the following model for an unbalanced panel dataset (as it is the case in the application above):

$$y_{it} = x_{it}\beta + \alpha_i + \alpha_{g(i)} + d_t\gamma + \epsilon_{it} \tag{B.3}$$

Where y_{it} is the outcome of interest for individual i in group g at time t; x_{it} is the independent variable and α_k are the fixed effects. Notice that $\alpha_{g(i)}$ is the group level FE and $d_t\gamma$ are time FE.

Define the time demeaned variables as: $\ddot{z}_{it} = z_{it} - T^{-1}\sum_{r=1}^{T} x_{ir}$.

The test develops on the idea of an Hausman test. The idea is to use correlated random effects such that $\alpha_i = \eta + \bar{x}_i\zeta + \rho_i$ to estimate the regression (η and ρ are dropped from the statistical software because of collinearity):

$$y_{it} = x_{it}\beta + \bar{x}_i\zeta + +\alpha_{g(i)} + +d_t\gamma + \bar{d}_i\lambda + v_{it} \tag{B.4}$$

The null hypothesis is

$$\textbf{H0}: \quad \zeta = 0, \lambda = 0 \tag{B.5}$$

and can be tested using an appropriate Wald Statistic. Notice that the test of $\lambda = 0$ is more of a test of endogenous sample selection and would not be part of the test in the balanced case.

The F-type statistic, obtained clustering at the municipality level, gives $F_{9,1468} = 42.40$; (p-value =0.0000). Such a test rejects the null and favors a firm FE specification. Such statistic is preferred to the estimated t-statistic obtained while testing for a single coefficient (which is -0.5281 (p-value = 0.5974)). There are two main reasons for this preference. First the test for a single coefficient is presented for balanced panel data and is based on a different null hypothesis (it excludes the test on λ which would be important also for capturing endogenous sample selection issues). Second, in this application the effect of the independent variable is not statistically significant different from zero. It would be preferable to have additional controls at the firm level to control for the firm level FE using CRE.

B.3 Controlling for sample selection in Panel Datasets

Since Heckman's sample selection model, economists and econometricians posed a lot of attention on sample selection issues in econometrics specifications. There exist some estimators that have been developed to take into account unobserved heterogeneity in $N \to \infty$, T fixed contexts. The most popular parametric estimators are Wooldridge (1995) and Semykina and Wooldridge (2010). In this work, I relied on the parametric estimator proposed by Semykina and Wooldridge (2010).

Consider a simple TWFE regression as the one in equation 4.2:

$$y_{it} = x_{it}\beta + c_{i1} + u_{it1}, \quad t = 1...T \tag{B.6}$$

Where $x_{it} = (1, T_{mt}, d_t')'$, d_t is a $T \times 1$ vector of time indicators, x_{it} is a $1 \times K$ vector ($K = 2+T$). With the assumptions of correlation between unobserved heterogeneity and regressors and $E[u_{it1}|x_i, c_{i1}] \neq 0$. Moreover, define z_{it} as a vector of L instruments (i.e. exogenous conditional on c_{i1}). The vector of instruments contains all exogenous regressors of x_{it}, including the time dummies.

Define the selection indicator (z_{it} is always observed while (x_{it}, y_{it}) is observed when $s_{it} =$ 1):

$$s_{it} = 1[s_{it}* > 0] = 1[z_{it}\delta_t + c_{i2} + u_{it2} > 0] \tag{B.7}$$

Then, model the unobserved heterogeneity as proposed in Mundlak (1978): $c_{i1} = \bar{z}_i\eta + a_{i1}$. Notice that in this case, with an unbalanced panel dataset, the way in which the unobserved heterogeneity is modelled is similar to the fixed effects but it is free of selection bias. Substitute the last equation into the model:

$$Y_{it} = x_{it}\beta + \bar{z}_i\eta + E[a_{i1} + u_{it1}|z_i, s_{it}] + e_{it1} \tag{B.8}$$

In a similar way define $c_{i1} = \bar{z}_i\zeta + a_{i2}$; and $a_{i2}|z_i \sim Normal(0, \sigma_a^2)$. Therefore:

$$s_{it} = 1[z_{it}\delta + \bar{z}_i\zeta_t + a_{i2} + u_{it2}] \quad \text{where} \quad a_{i2} + u_{it2}|z_i \sim Normal(0, 1 + \sigma_a^2) \tag{B.9}$$

Moreover assume that selection occurs through equation B.9 and assume that $E[a_{i1}+u_{it1}|z_i, v_{it2}] = E[a_{i1} + u_{it1}|v_{it2}] = \gamma v_{it2}$. The estimating equation becomes:

$$\begin{aligned} Y_{it} &= x_{it}\beta + \bar{z}_i\eta + \gamma E[v_{it2}|z_i, s_{it}] + e_{it1} \\ &= x_{it}\beta + \bar{z}_i\eta + \gamma\lambda_{it} + e_{it1} \end{aligned} \tag{B.10}$$

The equation B.10 can be consistently estimated under the assumptions stated above using the following procedure:

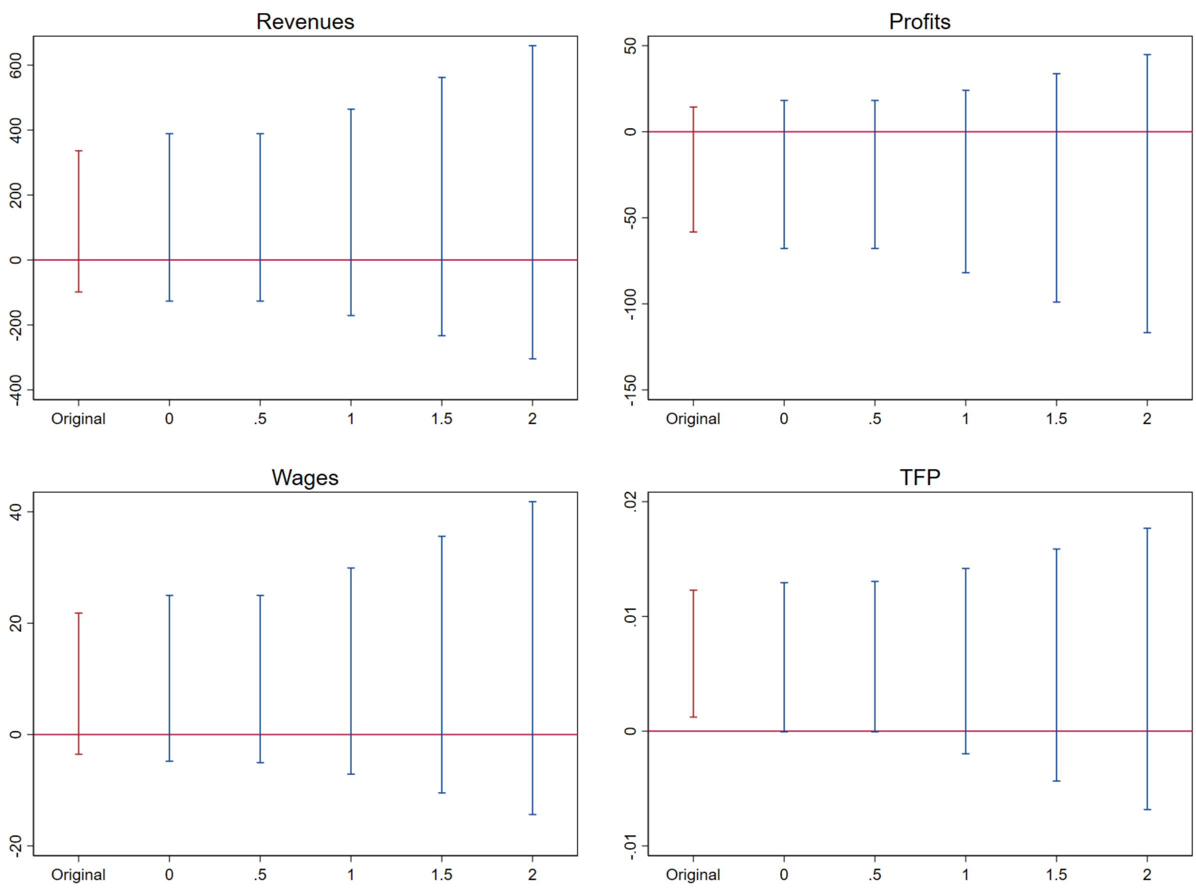
1. $\forall t$; use probit to estimate $P(s_{it} = 1|z_i)$. Estimate $\hat{\lambda}_{it}$.
2. For those observations with $s_{it} = 1$, use pooled 2SLS to estimate equation B.10.

B.4 Robust inference in presence of violations of parallel trends assumption

Usually, imposing that the parallel trends assumption holds exactly is too strong or is rejected by the parallel trends tests. Imposing restrictions on how different the post-treatment violations of parallel trends can be from the pre-treatment differences in trends ("pre-trends") can be a solution to the problem.

Figure B.1 shows that the treatment effects estimated using OLS are robust to non parallel pre trends (i.e. the treatment effects are statistically non different from zero). The procedure used to implement such a test was developed by Rambachan and Roth (2023). The idea is to create confidence sets for the treatment effect that are valid under the assumption that the counterfactual differences in trends in pretreatment and posttreatment periods is not larger than some value M.

Figure B.1: Honestdid (years from 2013 until 2021)



B.5 Additional figures and tables

Figure B.2: All storms that affected Europe in EM-DAT data

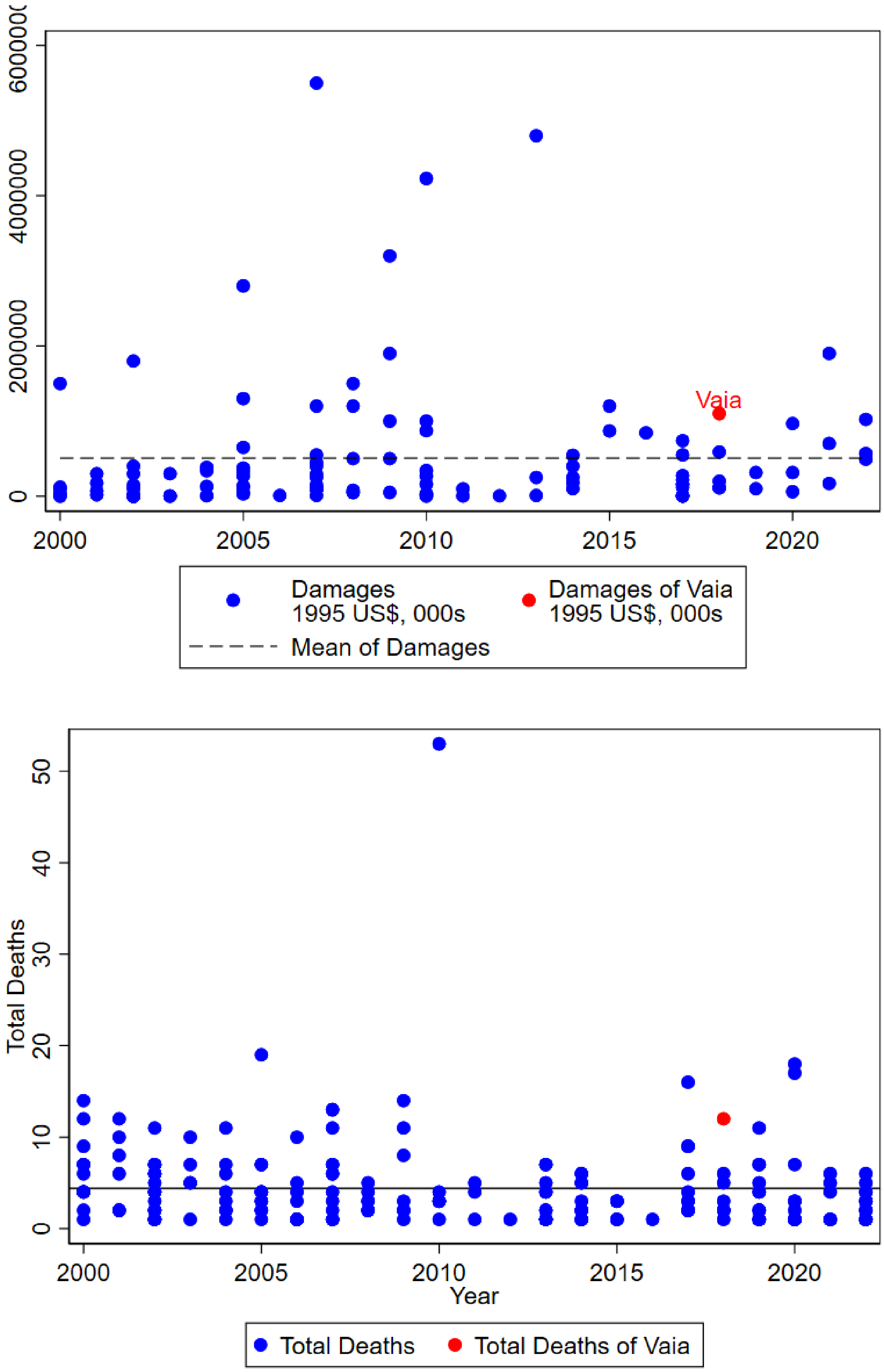


Figure B.3: Event Study (years from 2013 until 2019)

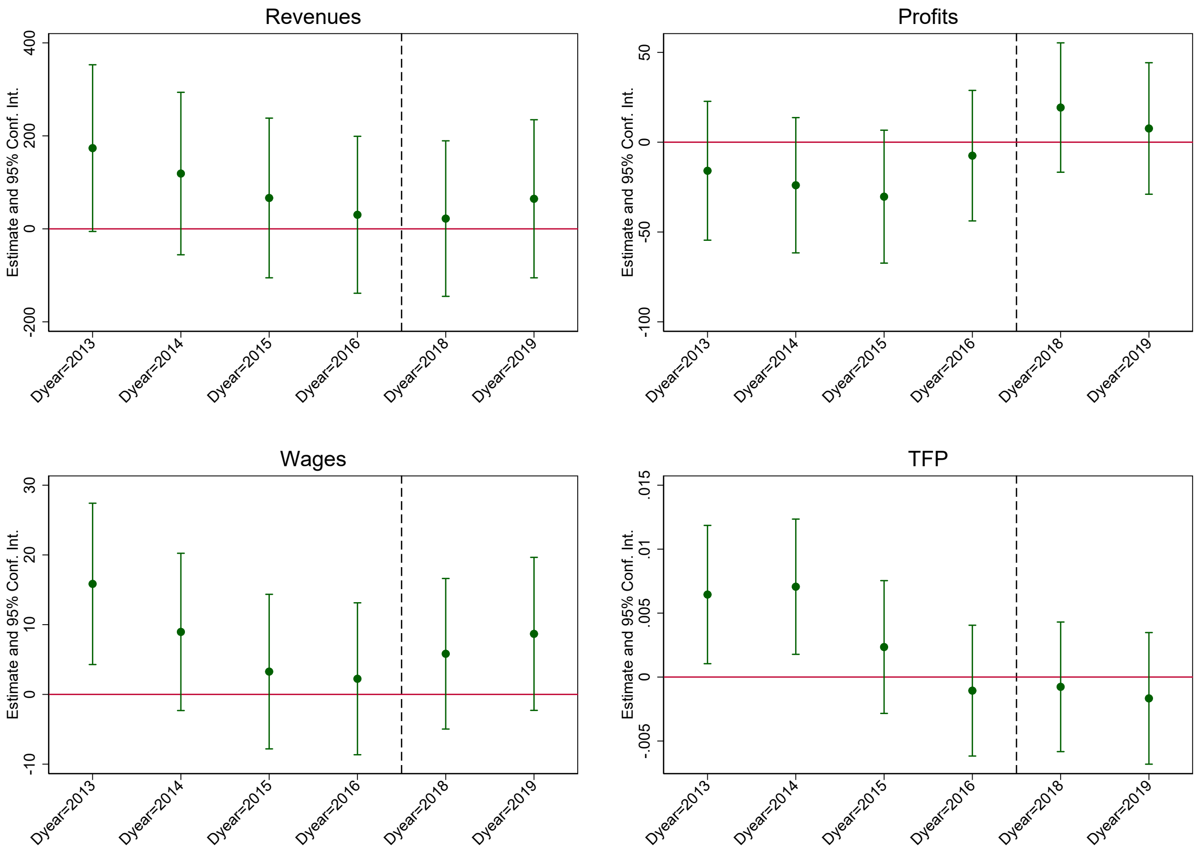


Figure B.4: Event Study for Total Assets (right years from 2013 until 2019 only)

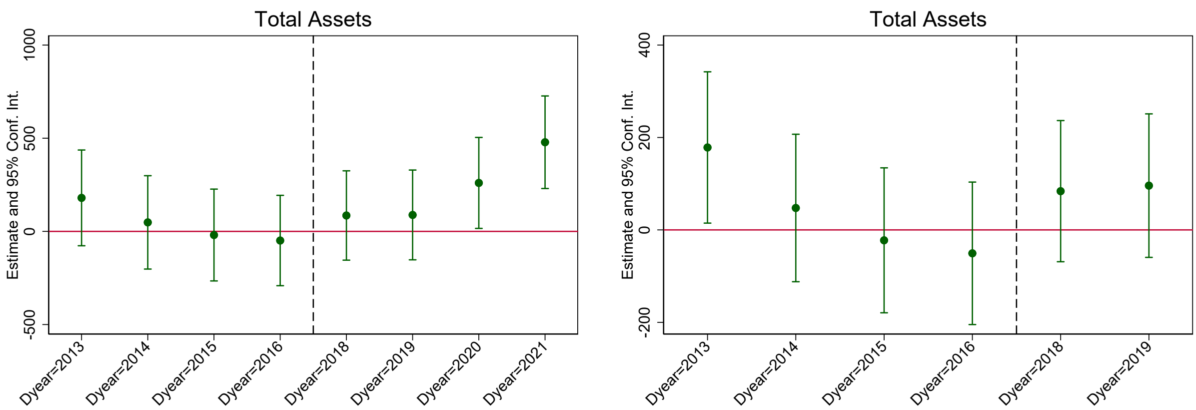


Figure B.5: Event Study for Operating Grants and Taxes

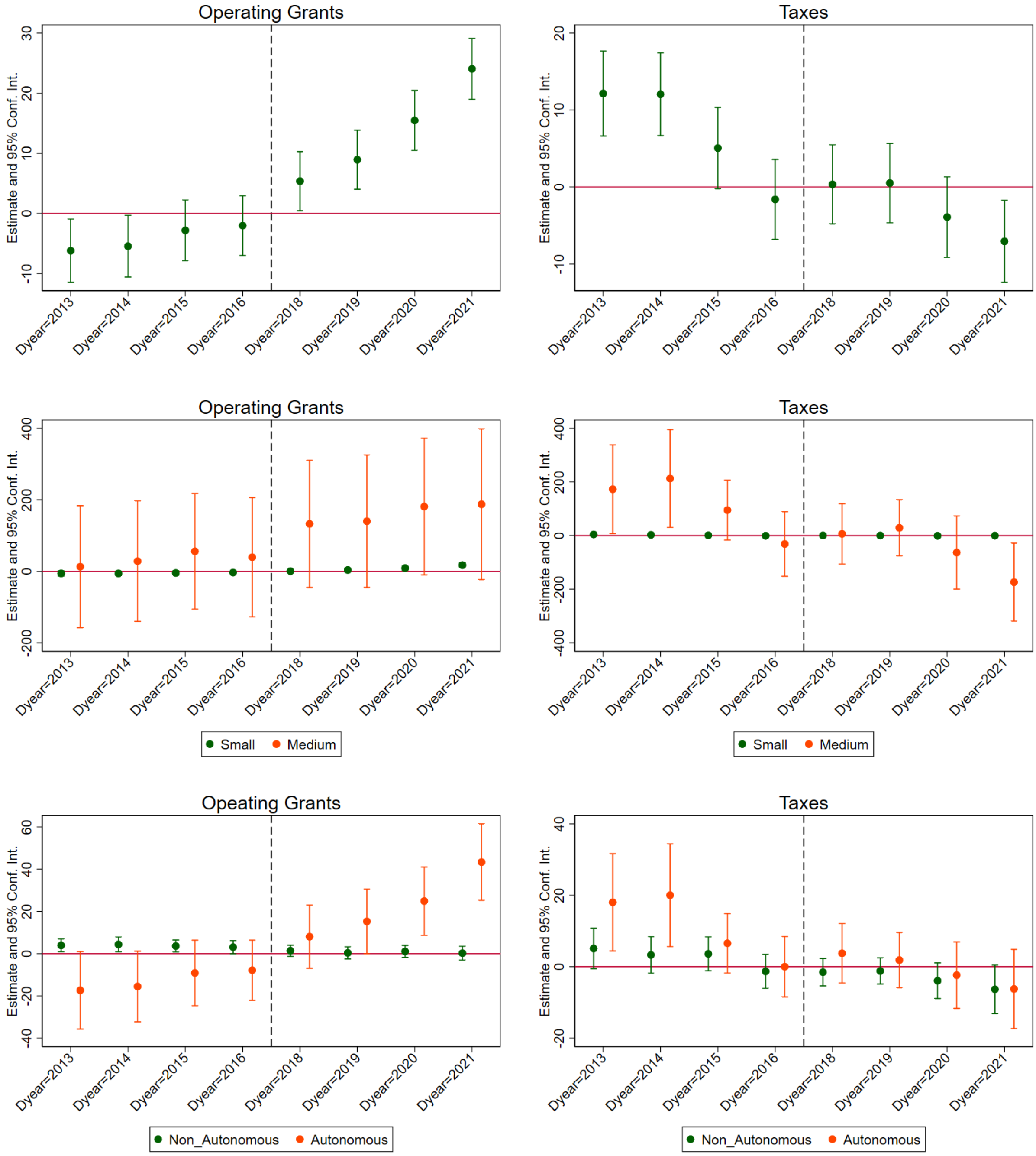


Figure B.6: Difference in Differences with Continuous Treatment. Estimator of de Chaisemartin et al. (2022)

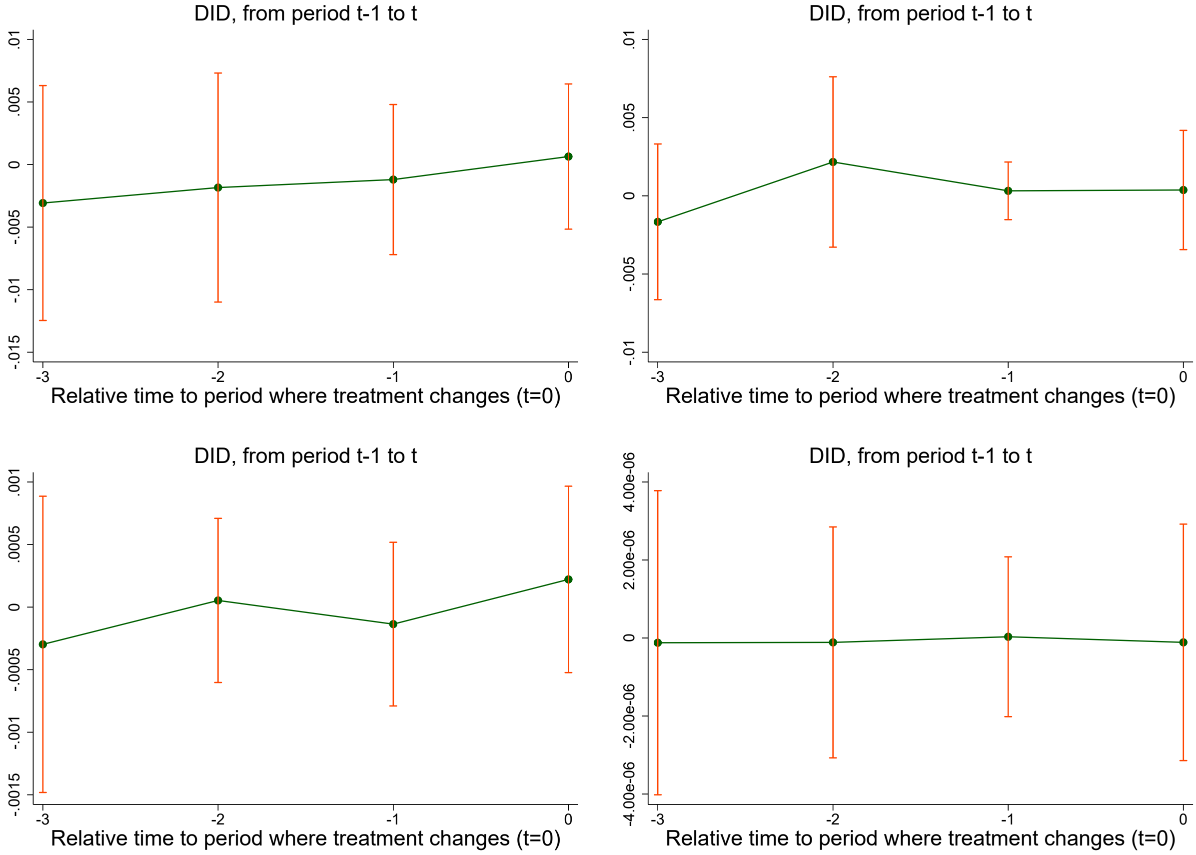


Figure B.7: Correlation between dependent variables and dimension

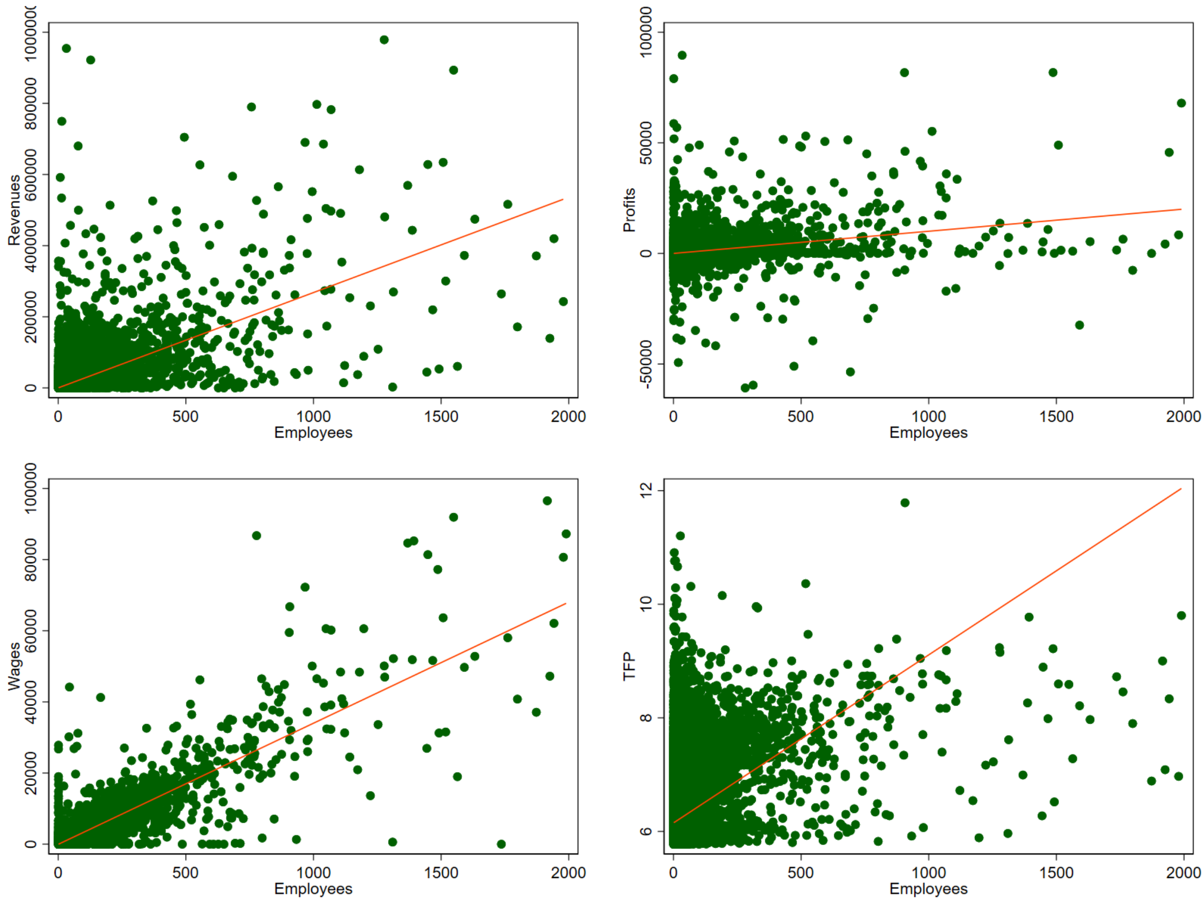


Table B.1: Correlation matrix

	Revenues	Profits	Wages	Operating Grants	Taxes	TFP
Revenues	1					
Profits	0.289	1				
Wages	0.724	0.255	1			
Operating Grants	0.0450	0.0314	0.118	1		
Taxes	0.576	0.375	0.577	0.0724	1	
TFP	0.367	0.125	0.337	0.0776	0.314	1

Table B.2: Difference in Differenceswith municipality fixed effects

	(1) Revenues	(2) Profits	(3) Wages	(4) TFP
Damaged	-29.649	13.679	-1.255	-0.002
	(197.0715)	(17.1610)	(14.9293)	(0.0049)
Mean of dependent variable	3292.550	95.248	339.719	6.192
N	867054	867054	867054	487115

Note: *** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parenthesis. All regressions have municipality and year fixed effects.

Table B.3: Difference in Differences with EU classification

	(1) Revenues	(2) Profits	(3) Wages	(4) TFP
Damaged=1	-166.003	67.963**	-18.357***	-0.008***
	(102.3498)	(28.8141)	(6.6008)	(0.0026)
Damaged=1 × Small	-254.603**	-112.741***	-26.610***	0.003
	(116.6294)	(32.8342)	(7.5217)	(0.0034)
Damaged=1 × Big	2925.382***	294.099***	359.326***	0.016***
	(180.7170)	(50.8765)	(11.6548)	(0.0047)
Mean of dependent variable	3292.550	95.248	339.719	6.192
N	867054	867054	867054	487115

Note: *** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parenthesis. All regressions control for firm and year fixed effects. This Table presents the results when the variable damaged is interacted with the four categories of firms (micro, small, medium and big)

Table B.4: Difference in Differences with Regional interactions

	(1) Revenues	(2) Profits	(3) Wages	(4) TFP
Damaged=1	-340.014**	76.790**	-22.196***	-0.000
	(132.0060)	(37.1556)	(8.5193)	(0.0027)
Damaged=1 × FRIULI	535.898***	-48.704	39.010***	
	(146.8269)	(41.3272)	(9.4758)	
Damaged=1 × TRENTINO	-79.805	-57.937	21.922	-0.013**
	(340.8276)	(95.9323)	(21.9960)	(0.0066)
Damaged=1 × VENETO	129.565	-78.920*	11.326	-0.004
	(156.0279)	(43.9169)	(10.0696)	(0.0033)
Mean of dependent variable	3292.550	95.248	339.719	6.192
N	867054	867054	867054	487115

Note: *** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parenthesis. All regressions control for firm and year fixed effects. This Table presents the results when the variable damaged is interacted with the regions

Table B.5: Difference in Differences with Triple Interactions

	(1) Revenues	(2) Profits	(3) Wages	(4) TFP
Damaged=1	-376.414***	-8.635	-31.282***	-0.004**
	(76.7029)	(21.5964)	(4.9444)	(0.0017)
Damaged=1 × Big	3333.345***	807.525***	447.112***	0.017**
	(376.1289)	(105.9027)	(24.2458)	(0.0071)
Damaged=1 × Autonomous=1	216.071**	-3.403	7.110	-0.011*
	(100.0336)	(28.1654)	(6.4483)	(0.0065)
Damaged=1 × Big × Autonomous=1	4202.089***	102.927	475.043***	0.010
	(497.9022)	(140.1891)	(32.0955)	(0.0298)
Mean of dependent variable	3292.550	95.248	339.719	6.192
N	867054	867054	867054	487115

Note: *** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parenthesis. All regressions control for firm and year fixed effects. This Table presents the results when the variable damaged is interacted with both dimension and autonomous region dummies

Table B.6: Difference in Differences with Industry interactions

	(1) Revenues	(2) Profits	(3) Wages	(4) TFP
Damaged=1	-250.840**	81.098***	2.349	-0.012***
	(97.9029)	(27.5582)	(6.3171)	(0.0034)
Damaged=1 × AGRICULTURE=1	438.532	-92.184	-29.469	-0.010
	(392.1156)	(110.3748)	(25.3007)	(0.0134)
Damaged=1 × MINING=1	20.625	-26.545	-37.000	-0.002
	(705.2264)	(198.5108)	(45.5038)	(0.0211)
Damaged=1 × MANUFACTURING=1	736.736***	-31.137	94.714***	0.014***
	(149.0861)	(41.9656)	(9.6196)	(0.0042)
Damaged=1 × ELECTRICITY SUPPLY=1	448.304*	-99.485	-49.984***	-0.052***
	(229.4876)	(64.5974)	(14.8074)	(0.0194)
Damaged=1 × WASTE MANAGEMENT=1	86.375	-102.736	33.343	0.041**
	(618.4328)	(174.0797)	(39.9035)	(0.0176)
Damaged=1 × CONSTRUCTION=1	-166.748	-114.275**	-38.404***	0.023***
	(167.1460)	(47.0491)	(10.7849)	(0.0056)
Damaged=1 × TRADE=1	1077.793***	-57.638	6.753	0.005
	(168.5672)	(47.4492)	(10.8766)	(0.0055)
Damaged=1 × TRANSPORT=1	771.000***	-19.761	129.361***	0.002
	(287.6390)	(80.9661)	(18.5595)	(0.0091)
Damaged=1 × ACCOMODATION=1	-71.173	-107.528*	-10.363	0.001
	(213.3998)	(60.0689)	(13.7693)	(0.0066)
Damaged=1 × REAL ESTATE=1	-583.820***	-107.464**	-111.049***	-0.005
	(168.0429)	(47.3016)	(10.8427)	(0.0106)
Mean of dependent variable	3292.550	95.248	339.719	6.192
N	867054	867054	867054	487115

Note: *** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parenthesis. All regressions control for firm and year fixed effects.

Table B.7: Difference in Differences with social capital interactions

	(1) Revenues	(2) Revenues	(3) Revenues	(4) Revenues	(5) Revenues	(6) Revenues
Damaged=1	312.885***	-144.042**	119.294	-1680.398***	-880.131***	36.431
	(118.9724)	(61.5882)	(101.0418)	(524.1037)	(223.0230)	(77.3803)
Damaged=1 × (mean) instability	-29.116***					
	(7.0891)					
Damaged=1 × (max) organdonation=1		277.521**				
		(118.5084)				
Damaged=1 × (mean) sc			-16.906***			
			(5.2773)			
Damaged=1 × (mean) fc				23.965***		
				(7.3657)		
Damaged=1 × (mean) pd					128.193***	
					(37.6623)	
Damaged=1 × (mean) mutualhelp						-364.861***
						(136.8838)
constant	3296.519***	3296.595***	3297.283***	3296.605***	3296.868***	3296.957***
	(3.7635)	(3.7675)	(3.7727)	(3.7551)	(3.7697)	(3.7571)
N	865904	865904	864922	865904	865808	865800

Note: *** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parenthesis. All regressions control for firm and year fixed effects.

Table B.8: Estimating probability of closing after the storm

	(1) Closed	(2) Closed	(3) Closed
Damaged	0.016***		
	(0.0007)		
Damaged=1		0.016***	0.012***
		(0.0007)	(0.0010)
Big		-0.013***	
		(0.0007)	
Damaged=1 × Big		-0.012***	
		(0.0028)	
Autonomous=1			-0.005***
			(0.0004)
Damaged=1 × Autonomous=1			0.010***
			(0.0014)
Mean of dependent variable	0.034	0.034	0.034
N	1363682	1363682	1363682

Note: *** p<0.01, ** p<0.05, * p<0.10.Robust standard errors in parenthesis. Dependent variable is a dummy equal to 1 if the firms stopped being observed in the sample.

Table B.9: Replicating results in Basker and Miranda (2018)

	(1) Closed b/se
Damaged=1	0.015***
	(0.0024)
log(Firm Dimension)	-0.006***
	(0.0001)
Damaged=1 × log(Firm Dimension)	-0.005***
	(0.0005)
log(Firm Age)	0.003***
	(0.0002)
Damaged=1 × log(Firm Age)	-0.003***
	(0.0009)
N	1363664

Note: *** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parenthesis. Municipality and year fixed effects are included. Dependent variable is a dummy equal to 1 if the firms stopped being observed in the sample.

Table B.10: Difference in Differences Municipality Results for migration outcomes

	(1) Residents	(2) Italian	(3) Foreign
Panel A			
Damaged	-233.990***	-249.647***	15.657***
	(35.2582)	(34.4652)	(2.4549)
Panel B			
Damaged=1	-289.757***	-291.798***	2.041
	(30.9233)	(30.6437)	(2.9115)
Damaged=1 × Autonomous=1	111.034**	83.923*	27.110***
	(47.1939)	(46.3596)	(3.3428)
Mean of dependent variable	5535.324	4989.192	546.132
N	11944	11944	11944

Note: *** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parenthesis. All regressions control for municipality and year fixed effects.

Table B.11: Difference in Differences Municipality Results for migration outcomes

	(1) Italian Females	(2) Foreign Females	(3) Italian Males	(4) Foreign Males
Panel A				
Damaged	-120.108***	5.040***	-129.539***	10.618***
	(17.3154)	(1.1815)	(17.1842)	(1.5219)
Panel B				
Damaged=1	-144.075***	-0.978	-147.723***	3.019*
	(15.3723)	(1.4355)	(15.3332)	(1.7016)
Damaged=1 × Autonomous=1	47.718**	11.981***	36.205	15.129***
	(23.3350)	(1.7045)	(23.0645)	(2.1093)
Mean of dependent variable	2536.441	282.966	2452.751	263.166
N	11944	11944	11944	11944

Note: *** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parenthesis. All regressions control for municipality and year fixed effects.