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The impact of floods on firms' performance

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Abstract

We estimate the short-run impact of a major flood that hit the region of Veneto in 2010 on firms' performance. Using firm level data and a difference in difference approach we compare the value added growth of hit firms to the one of a control group of companies that are not exposed to the flood. The results indicate that the value added growth of affected firms is 6.9% higher two years after the flood. We further investigate the role of aid transfers in the aftermath of the disaster event. Considering both the flood and the aid treatment, we construct four mutually exclusive and exhaustive groups. The results indicate that, among firms exposed to the flood, both the ones that benefit from financial aid and the ones that don't grow faster than the reference groups of firms that neither are exposed to the flood, nor receive financial aid. We also find a 2% additional growth effect that is attributable to the contribution of aid in the recovery phase.

Keywords: Natural disasters, flood, firm growth, difference in differences, financial aid

JEL classification: D24, Q54, R10, C23

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Introduction

Natural disasters are not a new phenomenon. Human societies have always been hit by calamities such as floods, hurricanes, storms and earthquakes that resulted in human, social, economic and environmental losses. Some recent catastrophes, such as the December 2004 tsunami, hurricane Katrina in 2005 and the earthquake in Haiti in 2010, brought the issue of the human and material costs of these events to the forefront of public attention and fueled a debate about the influence that a warming climate could have on the frequency and intensity of climate- and weather-related disasters. In the last years, indeed, the consensus that climate change could be worsening weather and climate extremes has increased. In its 2012 Special Report the Intergovernmental Panel on Climate Change (IPCC) notes that *a changing climate leads to changes in the frequency, intensity, spatial extent, duration, and timing of extreme weather and climate events, and can result in unprecedented extreme weather and climate events* (Field, Barros, Stocker, & Dahe, 2012, p. 7).

According to the IPCC (Field et al., 2012) floods are the most frequent natural disaster in Europe and data from the International Disaster Database (EM-DAT)[1] show that floods, immediately followed by storms, caused the highest total and average annual damages among the reported natural disasters between 1990 and 2012 in Europe (Fig.1). In the recent *Climate Change, impacts and vulnerability in Europe 2012* report the European Environmental Agency (EEA, 2012) reports that hydro-meteorological events (storms, floods, and landslides) represent 75% of the natural disasters that occurred in Europe since 1980 and account for 64% of the reported damage costs. The report (EEA, 2012) also analyzes the impact of extreme-precipitations-related disasters on society, environment, agriculture, industry and ecosystem services due to both climatic and non-climatic factors. Taking into account both climate change and socio-economic changes, the EEA calculates the Gross Value Added (GVA) affected by floods for the 'Economy First'[2] scenario and concludes that *for many parts of Europe the GVA affected by floods for the 2050s is larger than for the baseline scenario* (EEA, 2012, p. 214).

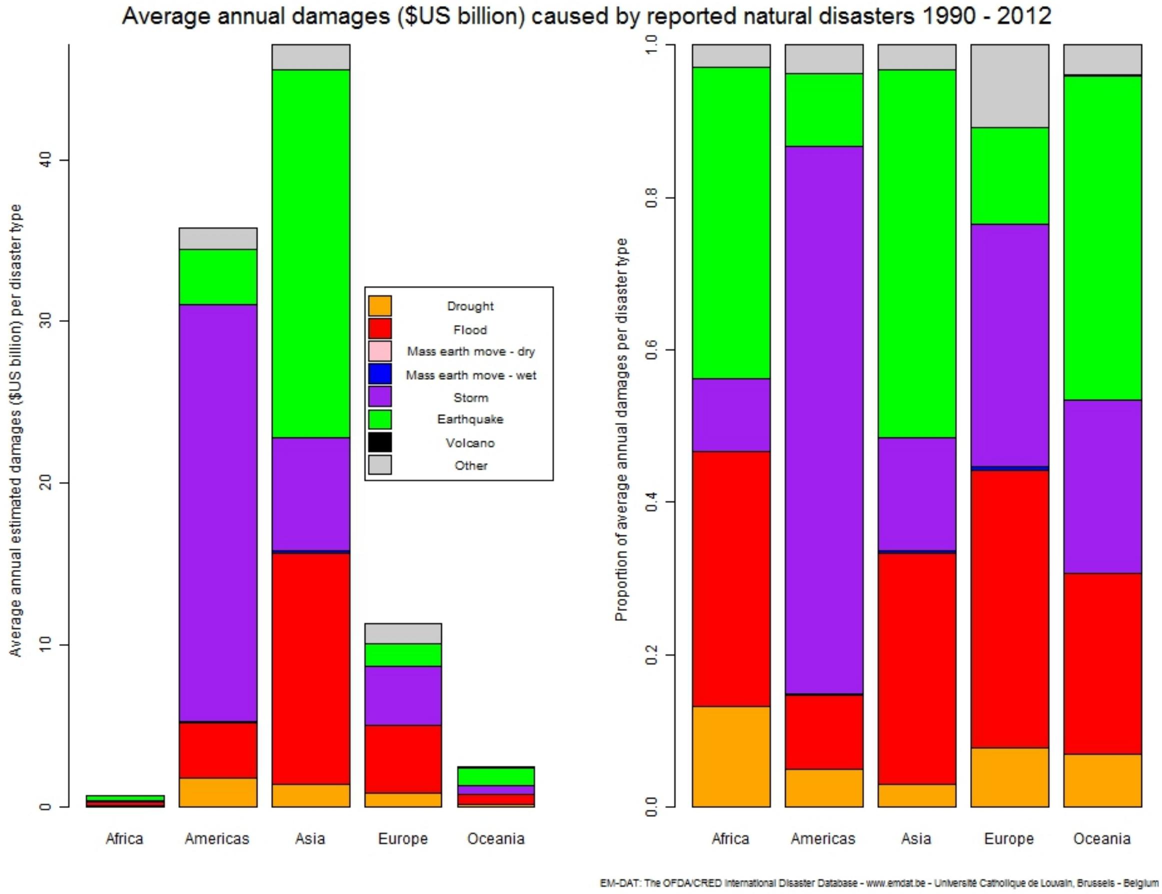
In the last years extreme precipitation events that translated into localized floods have been at the forefront of media and public attention also in Italy. Beyond the human, material and environmental consequences, localized floods are thought to have detrimental effects on the economic fabric of the affected areas, a concern that also motivates aid flows in the aftermath of the disaster. Considering this, the focus of this study is on one major flood that hit the Veneto region in autumn 2010 and it aims to assess the economic impact of such flood on firms' performance up to two years after the event.

Between October 31st and November 2nd 2010 Veneto has been hit by one of the most severe extreme weather events in the last 50 years according to the report published by the Regional Environmental Agency and the authorities of the Veneto Region (ARPAV). The event has been characterized by abundance and persistence of the rainfall rather than by intensity, according

[1] The EM-DAT database is maintained by the Centre for Research on the Epidemiology of Disasters, based at the Catholic University of Louvain in Belgium.

[2] The EEA defines the Economy First as *a scenario where a globalised and liberalised economy pushes the use of all available energy sources and an intensification of agriculture where profitable. The adoption of new technologies and water-saving consciousness are low and thus, water use increases. Only water ecosystems providing ecological goods and services for economies are preserved and improved* (EEA, 2012, p. 214).

Figure 1: Average annual damages



Source: EM-DAT: The OFDA/CRED International Disaster Database www.emdat.be - Université Catholique de Luvain, Brussels Belgium.

to the same report. In total an average of 173mm of rain fell during the period of observation (28/10/2010 - 11/11/2010) with peaks of more than 540mm in the Provinces of Belluno, Padova, Treviso and Vicenza. To give an idea of the magnitude of the extreme weather event Fig. 2 below shows the total amount of rainfall measured by each weather station in the region during the 15 days of observation, although severe precipitations have affected the region mainly for three days, from October 31^{st} to November 2^{nd} 2010. Fig. 3 shows the maximum intensity of daily precipitation[3] measured by the 193 weather stations compared to the average quantity usually falling on an average rainy day[4]. The graph clearly shows that in some areas of the region the amount of rain that fell on one day during the flood is more than twenty times the quantity that falls on an average rainy day. Both figures indicate the great variability of the quantity of rainfall in different areas of the region and it is evident that while some areas experienced extreme precipitations, others didn't. This feature is also shown in Fig. 4, which displays the distribution of the precipitations in the region according to the location of the 193 weather stations.

[3]Maximum daily precipitation measures the intensity of precipitation on a daily basis during the observed period. It is calculated as the total quantity of rainfall fallen on the day when it rained most.

[4]The quantity of precipitations on each of the flooding days, compared to the average quantity on an average rainy day, can be seen in the Appendix.

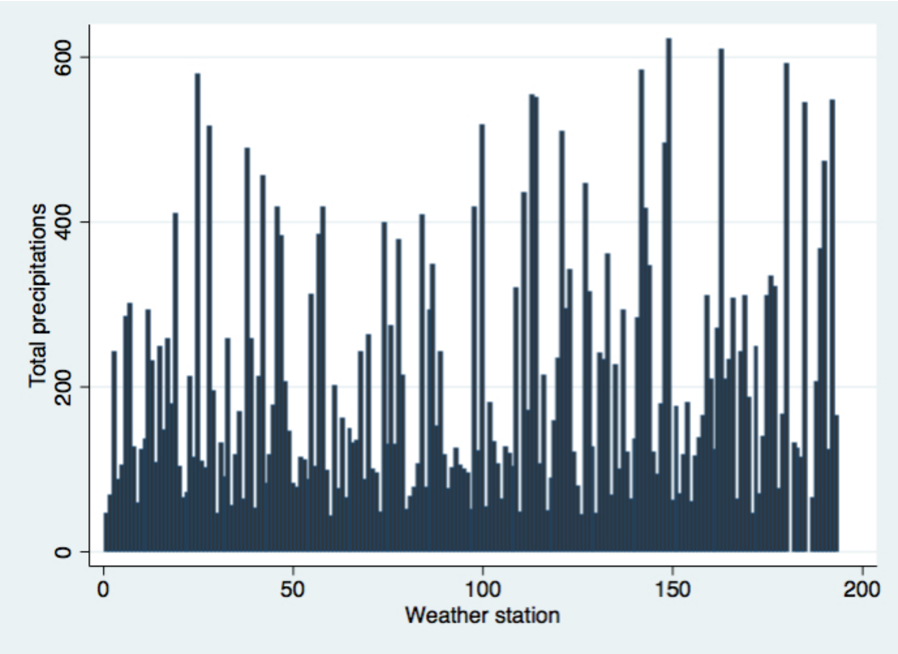


Figure 2: Total precipitations registered by each weather station.
The figure shows the quantity of precipitations (in mm) registered by 193 weather stations located in Veneto Region in the observed period (28/10/2010 - 11/11/2010). Each value is a sum over the period. Source: graph made using data from ARPAV.

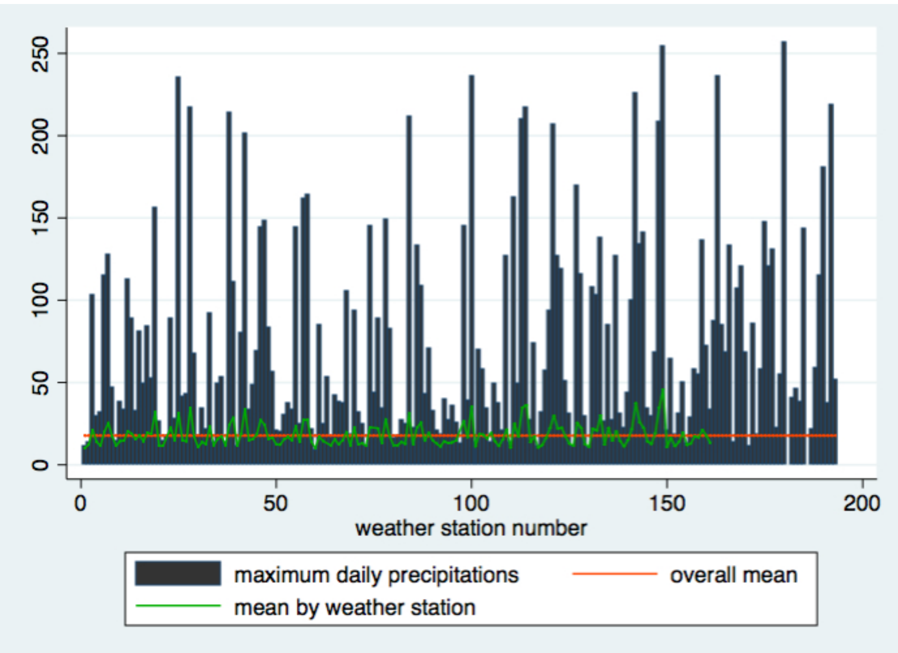


Figure 3: Maximum precipitations during the flood.
The figure shows the maximum precipitations (in mm) registered by each weather station in one day. The 'mean by weather station' (green line) represents the average quantity of rainfall fallen on a raining day in October and November during the observed period (2003-2012) excluding 2010. The value has been calculated by taking an average between October and November for each weather station. The data are available only for 163 stations. The 'overall mean' (red line) represents an average of the quantity of precipitations on a raining day in October and November calculated as an average among 163 weather stations during the observed period excluding 2010. The data are available only for 163 weather stations. The average value has been extended to the remaining 30 stations.
Source: graph made using data from ARPAV.

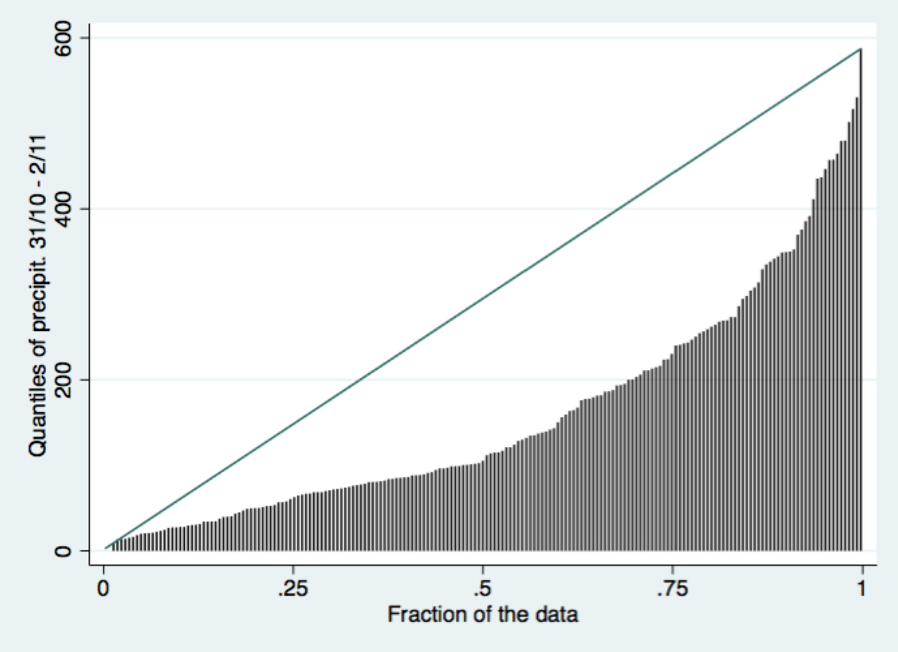


Figure 4: Distribution of precipitations during the flood.
The figure shows the distribution of precipitations in the Region according to the location of the 193 weather stations in Veneto Region. Only the proper flooding days (October 31^{st}, November 1^{st} and November 2^{nd}) are considered in this figure. Precipitations are measured in mm.
Source: graph made using data from ARPAV.

A natural question that arises when looking at these figures is whether the flood had a negative impact on the economic activity of firms located in areas that were hit by the flood and if there is any significant difference between these companies and those that haven't been directly exposed to it. Like most of studies and due to data availability the analysis focuses on the short-term effects (up to two years after the event). However, contrary to the majority of studies in the literature on the impact of natural disasters, this analysis uses firm-level data of a panel of 2065 manufacturing companies during the period 2003-2012. Given the focus on a small area of the country, characterized by firms with similar characteristics and operating in a similar context, the natural approach to perform this analysis is a difference in differences (DID) methodology. Following Leiter, Oberhofer, and Raschky (2009) we also take into account different levels of exposure and vulnerability of capital stock including the assets composition in the estimation. Finally, recognizing that disaster and recovery aid could represent a confounding factor in our analysis, we explicitly control for the presence of financial aid in the aftermath of the flood and distinguish between firms that received aid flows and those that didn't.
The results indicate that firms affected by the flood experience faster value added growth two years after the natural disaster, with a growth rate that is 6.9% higher than the one of firms that haven't been directly hit by the flood. We also found a 2% additional growth effect that is attributable to the presence of aid flows.

The paper is organized as follows: Section 1 reviews the existing literature on the economic impact of natural disasters. Section 2 describes the data and the main variables. Section 3 discusses the empirical strategy (model and econometric approach). Section 4 presents the results. The last section concludes.

1 Literature review

The focus of this literature review is on the economic impacts of natural disasters (in particular weather-related disasters), although it should be noticed that the consequences of natural catastrophes go far beyond the economic losses. Indeed, natural disasters comprise profound human, social, environmental and political consequences whose analysis, however, is beyond the scope of this study.

Many scholars distinguish between direct and indirect impacts. The former refer to the physical destruction caused to property and human beings (National Research Council, 1999). This category includes: damages to homes and their contents, damages to firms' capital and lost production, damages to infrastructure, people killed or injured, environmental degradation and emergency response (Kousky, 2013). Indirect damages, that some authors prefer to define as higher-order impacts (Rose, 2004), result from the consequences of physical destruction (National Research Council, 1999). They include business interruption for those businesses that didn't sustain direct damages, multiplier effects from reductions in demand and supply, adoption of costly measures as well as mortality, injury and environmental degradation (Kousky, 2013).

In practice measuring indirect impacts is difficult. Higher-order losses cannot be readily verified as direct ones and modeling them requires sophisticated economic models. Furthermore their size varies considerably depending on the resiliency of the economy and the path of recovery. Finally caution is required since these effects can be manipulated for political purposes (e.g. inflating multipliers) (Rose, 2004). These challenges make the majority of scholars opt for another approach: instead of trying to estimate direct and indirect costs, they evaluate the impact of natural disasters on macroeconomic indicators, primarily GDP and GDP growth. Macroeconomic variables are often used as a proxy of both kinds of impacts, relying on the fact that direct and indirect impacts could be large enough to have macroeconomic consequences. There are only few studies in the literature that adopt a microeconomic approach and use disaggregated data.

Within the literature on the economic impacts of natural disasters it is also possible to distinguish between studies looking at the short- to medium-term, defined as one to five years post disaster, and studies adopting a long-run perspective, beyond five years, with the bulk of the empirical evidence focusing on the short-run.

1.1 Macroeconomic studies

Macroeconomic theory does not have a unique answer to whether and how natural disasters affect economic growth: depending on the theoretical framework, different conclusions can be reached. Neo-classical growth models predict that the (physical and/or human) capital destruction may boost short-term economic growth. Endogenous growth models, instead, lead to different and less clear-cut conclusions: AK growth models with constant returns do not predict any change in the growth rate after a negative capital shock; models based on increasing returns predict that the capital destruction leads to a lower growth rate and within the Schumpeterian creative destruction's framework, negative shocks due to natural calamities may provide opportunities to upgrade obsolete capital and adopt new technologies, thus leading to

higher growth. Therefore the question on whether disaster events have positive, negative or no consequences is an empirical one.
The majority of macroeconomic studies regresses a macroeconomic variable, primarily GDP and GDP growth, on measures of disaster occurrence and intensity, generally using damages and fatalities as proxies for disaster's magnitude. These studies usually consider the disaster measure as exogenous, an approach that could be undermined by some problems of reverse causation since the impact of a natural disaster could also depend on the economic conditions of a country. For instance, the levels of income and development can determine the magnitude of the impact of natural calamities. Furthermore, political factors could influence macroeconomic conditions as well as the effects of natural disasters and the quality of institutions might shape both economic performances and the consequences of natural calamities.
Most studies use data from the EM-DAT database maintained by CRED. This is primarily due to the fact that the dataset is publically available, but it also ensures consistency with respect to the data used and the definition of natural disaster among different studies.
Finally, some of these papers adopt a cross-country approach, while others focus on a single country.

1.1.1 Multi-country studies

The bulk of empirical macroeconomic studies adopt a short-run perspective, while only few papers focus explicitly on the long-run effects of natural disasters.

Short-run focus The first, recent attempt to describe the short-run macroeconomic dynamics following natural disasters is Albala-Bertrand (1993). Using a sample of 28 disasters in 26 countries between 1960 and 1979 this study estimates the impact of natural calamities on GDP, GDP growth and rate of inflation by means of a simple before-and-after analysis. The results indicate that disasters do not impact GDP and may have a slightly positive impact on GDP growth; no effect is found on the rate of inflation. The author concludes that natural disasters are a problem of development rather than for development.
In an unpublished study Caselli and Malhotra (2004) fail to reject the hypothesis that losses of labor and capital stock have no effect on short-term economic growth. Using a dataset of 172 countries for events between 1974 and 1996 they estimate an equation using the difference in the log of output as dependent variable and include several controls and country and year fixed effects. When they include a dummy variable for the occurrence of natural disasters they don't find any significant effect.
Rasmussen (2004), in a statistical comparison among the Eastern Caribbean Currency Unions countries (ECCU), identifies a median reduction of the real GDP growth of 2.2 percentage points in the year of the event.
Raddatz (2007) quantifies the impact of a broad set of external shocks (natural disasters, price fluctuations, the role of the international economy) on the output of 40 low-income countries over the period 1965-1997. The author uses a panel vector auto-regression approach and assumes the shocks, including disaster occurrence, are exogenous. He finds that climatic disasters result in a 2% decline in real GDP one year after the event. However, overall external shocks explain only a small fraction of output variance (11%) and climatic disasters are only the third

most important source of fluctuation, accounting for 14% of the overall shocks' contribution to GDP variability.
Starting from 2009 several multi-country studies were performed to try to shed light on the impact of natural disaster, but no clear-cut evidence has been found. Noy (2009) investigates the reduction of GDP growth rates for a large sample of natural disasters. Using data from the EM-DAT database and a panel of 109 countries observed over the period 1979-2003, the author regresses the GDP growth on disaster magnitude and a set of control variables commonly used in short-run growth literature. Noy uses three measures of disaster impact: number of people killed and affected divided by population size in the year prior to the disaster and direct costs divided by previous years GDP, both weighted by month of occurrence. While he finds no evidence of any correlation between disaster population variables and GDP growth, he obtains strong indication that the amount of property damage is a negative determinant of GDP growth. Distinguishing between levels of economic development he finds that a one standard deviation increase in the direct damages of a natural disaster in a developing country is expected to reduce output growth by 9%. On the contrary, the effect on developed countries (OECD) is statistically significant but, with an increase of less than 1%, its economic importance is marginal.
Raddatz (2009) quantifies the macroeconomic impacts of climatic and other disasters in developing countries, using a vector auto-regressive model and under the assumption that the occurrence of natural catastrophes is exogenous. The analysis shows that climatic disasters have a negative and statistically significant impact on real GDP per capita: a large climate related catastrophe is associated with a 0.6% decline in GDP per capita. Most of the cost occurs in the year of the disaster. Disaggregating by climatic disaster type, droughts are found to have the largest impact, with cumulative losses of 1% of GDP per capita. Windstorms and floods, instead, do not have any significant impact. It is also found that the level of economic development influences the impact of natural disasters, with low-income countries responding more strongly. The author extends the analysis to investigate the impact of foreign aid and level of countrys indebtedness and finds that none of them impacts the growth effect of natural disasters.
In a recent working paper Cuñado and Ferreira (2011) analyze the economic impact of floods on per capita GDP growth in 118 countries between 1985 and 2008. Unlike the majority of studies, their data are obtained from the Global Archive of Large Flood Events kept by the Dartmouth Flood Observatory instead of from the EM-DAT database. They use a vector auto-regression in the presence of endogenous variables and exogenous shocks and find that floods have a positive effect on GDP growth with a mean impact of 1.5 percentage points. This positive effect is not experienced in the year of the flood, but in the year after the event and peaks two years after it. Their results also indicate that this outcome is mainly driven by developing countries: when the sample is split and separate regressions are run for developed and developing countries, flood have a significant impact only on GDP growth of the latter group.
Hochrainer (2009) adopts an approach that differs from most studies in that it compares the actual GDP post-disaster with a counterfactual projection that mimics the evolution of the GDP in a without disaster scenario. The sample consists of 225 large natural disasters[5] between 1960

[5]The threshold to define a large event is arbitrarily defined and is set as a share (1%) of GDP.

and 2005 and is based on information from two databases: EM-DAT and NatCatSERVICE[6]. Using an autoregressive moving average model to forecast GDP into a hypothetical no-disaster future, Hochrainer finds that disasters are expected to entail negative follow-on consequences in the short- to medium-term, with a median reduction of 4 percentage points below baseline GDP five years after the event. The author also finds that capital stock losses are the most important predictor for the negative adverse macroeconomic consequences.
Using a synthetic control method and data from EM-DAT database, a recent working paper from the Inter-American Developing Bank finds that even extremely large disasters have no discernible impact on economic growth, both in the short and long run (Cavallo, Galiani, Noy, & Pantano, 2010).

Long-run focus In one of the first empirical analyses to evaluate the long-run effects of natural disasters, Skidmore and Toya (2002) find a positive relationship among disasters, capital accumulation, total factor productivity and economic growth. They use a cross-section of 89 countries coupled with data on natural disasters occurred between 1960 and 1990. Using an ordinary least squares procedure they regress GDP growth on measures of disasters and a set of controls typically considered important determinants of growth. Their results indicate that climatic calamities have significant and positive effects on growth. Then they investigate the determinants of this positive relationship and find that natural disasters have a negative, but not statistically significant impact on physical capital investment, while climate-extremes-variables are significant and positively correlated with human capital accumulation. The authors also find an increase in total factor productivity after climatic disasters, which they interpret as some evidence that disasters provide opportunities to update the capital stock and adopt new technologies (Schumpeterian creative destruction). Furthermore, total factor productivity appears to be the primary route through which disasters affect growth.
Crespo Cuaresma, Hlouskova, and Obersteiner (2008) directly explore the idea of some type of Schumpeter's creative destruction by assessing the relationship between foreign technology absorption and catastrophic events. Focusing on a sample of 49 developing countries, which are assumed to have more obsolete capital stock, they estimate both a cross-section and a panel regression and conclude that natural disasters negatively affect technology absorption. Only relatively rich countries benefit from capital upgrading and thus may experience higher long-run growth rates of GDP per capita after a disaster.

1.1.2 Single-country studies

In general single-country studies adopt the same methodology as cross-country studies, but have a smaller unit of analysis and sometimes focus only on one type of disaster. Usually they have a short-run focus.
Among single-country studies Noy and Vu (2010) examine the impact of natural disasters on annual output growth in Vietnam. They use a provincial panel dataset for Vietnam; data on natural disasters are taken from the EM-DAT dataset for the period 1953-2008. They employ a Blundell-Bond System General Method of Moments procedure and three different measures

[6]NatCatSERVICE is maintained by the insurance company Munichs Re and focuses on insured and material losses.

of disaster impact: number of people killed and affected and amount of direct damages[7]. The results indicate that more lethal calamities, in terms of fatalities and lives affected, are associated with lower annual output but the impact of material losses on output is positive, though not statistically significant. When the focus is on output growth the authors find that higher direct damages lead to higher annual output growth: for one percentage point increase in direct damage (% output) there is an increase of output growth by 0.03%. This suggests that the possible negative economic effects are short-lived. Results indicate that more costly disasters (in terms of destroyed capital) seem to boost the economy in the short-run, which the authors interpret as evidence of the creative destruction hypothesis.

Hammes and Vu (2010) undertake a similar analysis. They investigate the consequences of natural catastrophes on annual output and output growth over the period 1995 to 2007 in China. Their results indicate that both fatalities and the amount of direct damages reduce output: a 1% increase in the ratio of people killed to population is associated with a fall in output of 47 billion Yuan and a 1% rise in direct damages decreases output by 3.27 million Yuan. The number of people affected has no significant impact. With respect to output growth, the authors find that the impact of direct damages' amount is positive and significant, leading to a fall of output growth of 0.235%. Nevertheless, the number of people killed or affected has no statistically significant effect on growth.

Focusing on a developed country Strobl (2010) estimates the impact of hurricanes on county growth rates in the United States between 1970 and 2005. He assumes a standard neoclassical growth model, where a hurricane strike is considered as a negative shock to the capital stock and he develops a hurricane destruction index based on a monetary loss equation, wind speed and local exposure characteristics to employ as a proxy of disaster's severity. Based on county fixed effects and a spatial autoregressive error term, the econometric estimate indicates that a county's annual growth rate falls on average of 0.45 percentage points after a hurricane of average intensity. The author also shows that about 28% of the negative growth effects are due to relatively rich people moving away from affected counties. A hurricane destruction of one standard deviation above the average reduces the growth rate by 0.93 percentage points. These results are quite large given that the county growth rate is around 1.68%. The impact is found to disappear after one year.

In a recent Bank of Italy working paper Barone and Mocetti (2014) examine the impact of two earthquakes that occurred in Italy in 1976 and 1980, focusing on both the long- and short-term. Using a synthetic control method, the authors compare the GDP per capita after the earthquake in each stricken area (Friuli Venezia Giulia and Irpinia) to the one of a synthetic control group of Regions. In the short-term the results indicate no significant effects of the earthquake in both areas. However, this is shown to mainly depend on the financial aid in the aftermath of the disaster. Estimation of the yearly GDP growth in the absence of financial aid indicates that the growth would have been lower in both areas (between 0.5 and 0.9 percentage points in Friuli and between 1.3 and 2.2 percentage points in Irpinia). Also GDP per capita would have been lower. In the long-term the authors find that the two earthquakes had opposite effects: positive in Friuli and negative in Irpinia. In Friuli, 20 years after the event, the GDP per capita growth was 23% higher than in the control group, while in Irpinia GDP

[7]All these disaster measures are normalized and weighted for month of occurrence as in Noy (2009).

growth dropped by 12%. The authors also find that this outcome is mainly due to differences in institutional quality between the two affected areas.

1.2 Sector-specific studies

There is a group of recent papers that recognize the necessity of a disaggregation among economic sectors and disaster types in order to assess the economic impacts of natural calamities, claiming that this can also be a way to reconcile apparently contradictory findings in the current empirical literature. More precisely, different natural disasters affect different sectors of the economy through different channels and thus their effects are likely to differ according to the type of disaster and across sectors, countries as well as level of development.

In a World Bank working paper Loayza, Olaberra, Rigolini, and Christiaensen (2009) estimate the effects of different natural disasters (droughts, floods, storms and earthquakes) separately by economic sector (agriculture, industry and services) and take into account levels of economic development. They use a sample of 94 developed and developing countries over the period 1961-2005. The data on natural disaster are obtained from the EM-DAT dataset. Their results indicate that severe disasters never increase growth, but events of lesser magnitude can have positive effects in some sectors. Another finding is that growth in developing countries is more sensitive to natural disaster, more sectors are affected and the magnitude of such impacts is larger, both when positive and negative impacts are found. Disaggregation by disaster type shows that different calamities affect economic sectors differently: drought and storms have a negative impact on agriculture, whereas floods have the opposite effect. There is no significant effect on the industrial sector and only floods have a positive and significant impact on services. When the analysis is restricted to developing countries, all economic sectors are affected. The authors estimate that a typical drought in developing countries reduces agricultural and industrial annual growth rate by 1 percentage point, producing a 0.6 percentage points decline of GDP growth. A typical flood increases growth in all sectors by 0.8-0.9 percentage points, leading to an increase of GDP growth of 1 percentage point.

A more recent but similar analysis by Fomby, Ikeda, and Loayza (2013) obtains many of the findings of Loayza et al. (2009). The paper estimates the mean response of GDP per capita growth and its main components, agricultural and non agricultural per capita value-added growth, to four types of natural disasters: droughts, floods, earthquakes and storms. The sample consists of 84 countries observed over the period 1960 to 2007. Data on natural disasters are obtained as usual from the EM-DAT dataset and are used to develop a measure of disaster intensity based on the percentage of people killed and affected. As in Loayza et al. (2009) the effect of each calamity is estimated separately, also distinguishing between levels of economic development. Climatic disasters have the largest and most significant effects. In developing countries droughts negatively affect GDP growth, resulting in a cumulative response of 2 percentage points. This impact is stronger when only the agricultural sector is considered. In the sample of advanced economies the negative response only applies to agricultural growth. In contrast to droughts, floods tend to have positive impacts. In developing countries both GDP growth and agricultural and non-agricultural value-added growth experience a positive response. In developed countries floods significantly affect only agricultural growth, generating a cumulative positive response of 2 percentage points. The authors also find that the timing of the response varies with both the type of disaster and the sector of economic activity. However, a general pattern can be identified, with the response of non-agricultural sector occurring after a climatic disaster has affected agricultural growth. Finally, the study confirms that only disasters of moderate intensity can be beneficial and that the effects, both positive and negative, are stronger on developing countries.

Cuñado and Ferreira (2011), discussed above, also estimate the impact of natural disasters distinguishing between agriculture and non-agricultural output growth and providing separated estimates for developed and developing countries. Their findings indicate a positive impact of floods on all the subcomponents of GDP for the entire sample of countries. When developing countries are analyzed separately, the authors find a positive and significant increase in both agricultural and non-agricultural output growth. The cumulative mean impact of a flood shock is 2.2 and 3 percentage points on agriculture and non-agriculture growth respectively. For the sample of advanced economies, floods have a significant and positive impact only on the agricultural sector, which experiences a mean cumulative increase of output growth of 1.2 percentage points.

1.3 Microeconomic studies

There are only few studies in the literature that adopt a microeconomic approach. The methodology used in these studies is a difference in difference strategy, in which similar units of analysis are compared after a natural calamity has occurred and differences arising in the aftermath of the event are attributed to the effect of the natural disasters on the treated units.

In a recent working paper Anttila-Hughes and Hsiang (2011) measure the post-disaster economic and health effect of typhoons on Filipino households[8]. This paper makes use of disaggregated data, combining province-level data on storm incidence with household survey data. Using a difference-in-difference approach that exploits random variation in each location's typhoon incidence and including province and year fixed effects, the authors find that typhoons reduce average income (net of transfers) the year after they strike. The average short-run effect, considering the average annual typhoon exposure, is to depress income by 6.7%. The authors also find that income losses translate one-for-one into a reduction of household expenditures, with the average household cutting its spending by 7.1%. Furthermore this reduction affects mainly human capital investment and much less pure consumption goods.

Leiter et al. (2009) focus on firms' performance instead. The authors examine the impact of floods on capital accumulation, employment and productivity for a sample of European manufacturing firms up to two years after the event. They use firm level data, which allow them to take the firms asset structure and their degree of vulnerability into account. Using a difference in difference approach they find that companies located in regions affected by a major flood in 2000 experience on average higher growth of total assets and employment than firms in unaffected regions. On the contrary the effect on productivity is negative. They also find that the assets' structure influences the response to the flood. The positive effect on input factors prevails for companies with larger shares of intangible assets, whereas the negative effect on productivity is decreasing in the share of intangible assets.

[8]Here we report only economic effects.

The empirical literature on the impact of natural disasters is vast. Nevertheless, it remains unclear about their effects: some studies do not report any significant effect, others indicate negative impacts and some find positive effects. The review also showed that the majority of studies adopt a macroeconomic approach, while only few papers use disaggregated data.
This research paper contributes to the literature in that it tries to estimate the effects of a major flood that occurred in the region of Veneto in 2010 using a microeconomic approach. In particular it looks at the impact of the natural disaster on firms value added growth using firm level data coupled with data on quantity and intensity of precipitations. Through a difference in differences methodology this study compares similar firms in the same region that differ only because of their random exposure to the flood, attributing to the inundation possible differences in performance in the aftermath of the event.

2 Data and descriptive statistics

In order to investigate the response of Veneto region firms to the 2010 flood, we use data on firms' performance coupled with data on the extreme weather event.
Data on the natural disasters are obtained from the Centre of Research on the Epidemiology of Disasters (CRED) in Brussels and from the Agenzia Regionale per la Prevenzione e Protezione ambientale del Veneto (ARPAV), the regional Environmental Agency.
Much of the literature on natural disasters relies on the publically accessible Emergency Events Database (EM-DAT) maintained by the Centre for Research on the Epidemiology of Disasters (CRED)[9]. EM-DAT is an international database and it includes events that fit at least one of the following criteria: 10 or more fatalities, 100 or more people affected, declaration of a state of emergency or a call for international assistance. This database has been used to investigate the natural disasters that occurred in Italy in the decade for which data on firms are available (2003-2012) and to be consistent with the definition of disaster commonly used in the literature. Several floods affected the country during the observed time period; Veneto has been chosen because it allows to analyze firms' response for at least two years after the flood and because detailed data are available for this disaster event.
High quality information about the 2010 flood is provided by ARPAV. The Regional Environmental Agency released detailed data on the amount and the intensity of the rainfall measured by 193 weather stations positioned in the regional territory in the period from 28/10/2010 to 11/11/2010. In addition to this, the database maintained by ARPAV contains information about the geographical location (latitude and longitude) of each weather station and historical data on average monthly precipitations. The richness and the precision of the meteorological data are crucial to distinguish between flooded and non-flooded areas.
Data on firms are provided by the AIDA database. The database is distributed by the Bureau Van Dijk and covers 1 million companies in Italy. It contains detailed accounts, company financials with up to 10 years of history, trade description (industry classification), contact information, geographic location (latitude and longitude) and information about companies'

[9]Other databases with an international coverage of natural disasters are the NatCatSERVICE and the Sigma, maintained by the insurance companies Munich Re and Swiss Re. Since EM-DAT is publicly accessible most analyses use data from the EM-DAT database.

organizational structure. From this database we selected data on performance for the manufacturing firms located in Veneto. The dataset obtained for the empirical analysis is a panel of 2084 companies observed over a period of 10 years, from 2003 to 2012.
The AIDA and ARPAV databases are merged using the information about the geographic location of firms and weather stations. More precisely, using latitude and longitude, each firm in the sample is matched to the nearest weather station among the 193 positioned in the region[10]. The average and the median distance between each firm in the sample and the matched weather station are 4.17km and 2.16km respectively, while the minimum and the maximum distance are 0.13km and 12.60km. This allows to determine the quantity of precipitation received by each firm during the observed period (28/10/2010 - 11/11/2010) with a high degree of precision. Furthermore, this information is crucial to define the treatment and the control group, using a more objective criterion than the amount of reported losses or government reimbursements.

2.1 Precipitations

Table 1 reports mean, median, standard deviation, minimum and maximum precipitations for each of the 15 observed days, for the cumulative and for the maximum daily intensity. The

Table 1: Precipitations

	Mean	Median	SD	Min	Max
precipitations 28/10	.9820513	0	12.21945	0	257
precipitations 29/10	.1620513	0	1.608493	0	32
precipitations 30/10	.1592821	0	1.423357	0	18.2
precipitations 31/10	48.45005	36.6	34.59999	0	218.9
precipitations 1/11	52.91585	41.7	36.36454	0	236.4
precipitations 2/11	31.53528	28	16.59654	0	90.4
precipitations 3/11	.3746154	.2	.8062778	0	8.6
precipitations 4/11	.1043077	0	.1281831	0	.6
precipitations 5/11	.148718	.2	.1518685	0	.8
precipitations 6/11	.1292308	0	.3249769	0	2
precipitations 7/11	7.166257	6.2	4.908876	0	38.2
precipitations 8/11	9.364359	9.4	3.415285	0	25.4
precipitations 9/11	11.43385	11.6	4.018876	0	25
precipitations 10/11	9.769128	8.6	5.795597	0	36.2
precipitations 11/11	.0133333	0	.0499016	0	.2
precipit (flood days)	132.9012	100.4	82.55859	0	479.4
total precipitations 28/10-11/11	172.7084	136	93.79491	0	591
maximum daily precipitations	56.27046	43.3	37.81218	0	257

Notes: Precipitations are measured in mm. Precipit. (flood days) indicates the total quantity of rain fallen during the three flooding days (October 31^{st} - November 2^{nd}). Maximum daily precipitation measures the intensity of precipitation on a daily basis. It is calculated as the total quantity of rainfall fallen on the day when it rained most.

table shows that the extreme precipitations have been concentrated during three days, from October 31^{st} to November 2^{nd}. The increase in the quantity of rainfall during these days is enough to lead to a considerable rise in the mean and median precipitations. The increase in

[10]For 16 companies in the sample the data on latitude and longitude are not available. In this case the match is not possible and these observation are dropped.

the variability of rainfall during the flooding days can also be noticed, suggesting that only some areas have been hit by the flood.
Table 2 reports summary statistics for the total precipitations and maximum daily intensity in each province. As shown in the table, Belluno, Vicenza, Treviso and Padova are the provinces

Table 2: Precipitations by Province

	Mean	Median	SD	Min	Max
Belluno					
total precipitations 28/10-11/11	27.44778	0	89.48925	0	591
maximum daily precipitations	11.09037	0	36.52741	0	257
Padova					
total precipitations 28/10-11/11	11.31248	0	38.29337	0	543.4
maximum daily precipitations	2.971836	0	10.29553	0	143.6
Rovigo					
total precipitations 28/10-11/11	4.963375	0	14.92984	0	63.2
maximum daily precipitations	1.209054	0	3.737368	0	22.4
Treviso					
total precipitations 28/10-11/11	19.41069	0	65.17197	0	543.4
maximum daily precipitations	7.133831	0	24.68617	0	164.2
Venezia					
total precipitations 28/10-11/11	8.859114	0	27.66879	0	124
maximum daily precipitations	2.202785	0	6.876166	0	33.6
Verona					
total precipitations 28/10-11/11	11.11059	0	35.87179	0	340.8
maximum daily precipitations	3.142821	0	10.45234	0	119.2
Vicenza					
total precipitations 28/10-11/11	23.1024	0	75.31425	0	554
maximum daily precipitations	7.525674	0	25.15913	0	236.4
Total					
total precipitations 28/10-11/11	16.81384	0	58.9694	0	591
maximum daily precipitations	5.478153	0	20.43013	0	257

Notes: Precipitations are measured in mm. Maximum daily precipitation measures the intensity of precipitation on a daily basis. It is calculated as the total quantity of rainfall fallen on the day when it rained most.

where it rained most. However, the large standard deviations in these provinces indicate that extreme precipitations didn't strike homogeneously, suggesting that only some areas have been severely affected.
The large variability of precipitations both between and within provinces in the region suggests that there is scope for an analysis of the floods effects in the affected areas and indicates a difference in difference methodology as the most natural approach.

2.2 Firms

Table 3 shows the number of manufacturing firms located in each province of Veneto. Vicenza and Treviso have the highest concentration of firms, with 54.3% of the regional firms located in these two provinces.
Table 4 displays the number of firms located in flooded and non-flooded areas. Slightly more

Table 3: Number of firms by province

Province	Number of firms	Percent
Belluno	519.00	2.59
Padova	3437.00	17.16
Rovigo	486.00	2.43
Treviso	5090.00	25.41
Venezia	1580.00	7.89
Verona	3134.00	15.65
Vicenza	5784.00	28.88
Total	20030.00	100.00

than 25% of firms in the region operate in areas that have been exposed to the flood, according to the criterion used to distinguish between flooded and non-flooded areas[11].

Table 4: Number of firms in flooded and non-flooded areas

Treatment	Number of firms	Percent
No-Flood	14933.00	74.55
Flood	5097.00	25.45
Total	20030.00	100.00

Table 5 reports the number of affected and non-affected firms within each province. Vicenza and Treviso are the areas where the highest number of companies has been exposed to the event; here the flood has directly hit 3500 and 1135 companies respectively, corresponding to 60.51% and 22.3% of the provinces' firms. Moreover, as Table 3 shows, with 28.9% and 25.4% respectively, these provinces have the highest concentration of manufacturing firms. On the contrary, in the Belluno province the flood has affected the majority of firms, with 73.6% of firms located in flooded areas, but only 2.6% of the regional firms are in this province.
Table 6 shows the number of observations in the sample before and after the flood.

Table 5: Number of firms in flooded and non-flooded areas by province

Province	No-Flood No. of firms	Flood No. of firms	Total No. of firms	No-Flood Percent	Flood Percent	Total Percent
Belluno	137.00	382.00	519.00	26.40	73.60	100.00
Padova	3397.00	40.00	3437.00	98.84	1.16	100.00
Rovigo	486.00	0.00	486.00	100.00	0.00	100.00
Treviso	3955.00	1135.00	5090.00	77.70	22.30	100.00
Venezia	1580.00	0.00	1580.00	100.00	0.00	100.00
Verona	3094.00	40.00	3134.00	98.72	1.28	100.00
Vicenza	2284.00	3500.00	5784.00	39.49	60.51	100.00
Total	14933.00	5097.00	20030.00	74.55	25.45	100.00

Table 7 displays the number of observations in the treatment and in the control group before and after the natural disaster.

[11] See empirical strategy.

Table 6: Number of observations before and after the flood

Pre/Post-Flood	Number of obsr	Percent
Pre-Flood	16103.0	80.4
Post-Flood	3927.0	19.6
Total	20030.0	100.0

Notes: the pre-flood period comprises the years from 2003 to 2010. The post-flood period refers to 2011 and 2012.

Table 7: Number of observations before and after the flood by treatment

Treatment/Period	Number of obs	Percent
0/0	12001.00	59.92
0/1	2932.00	14.64
1/0	4102.00	20.48
1/1	995.00	4.97
Total	20030.00	100.00

Notes: for the variable Treatment/Period the first number refers to the treatment or control group, the second one to the time period before or after the flood: 0/0 denotes an observation belonging to the control group before the flood; 0/1 indicates to an observation in the same group after the event; 1/0 is an observation belonging to the treatment group before the flood; 1/1 refers to an observation in the same group after the flood.

2.3 Main variables

Table 8 reports mean, median, standard deviation, minimum and maximum of the main variables, distinguishing between the groups of affected and non-affected firms and between the period before and after the disaster event.

Considering the pre-flood period, firms located in the non-flooded areas are on average slightly larger both in terms of total assets[12] and in terms of employees. However, the median firms in the two groups are more similar to each other with respect to both variables.

Looking more specifically at the productive assets, Table 8 shows that before the event the sum of tangible[13] and intangible[14] assets (Assets) is on average slightly larger for the control group, although this small difference disappears considering the median assets. In terms of tangible fixed asset the average firm operating in a non-flooded area is slightly larger. On the contrary intangible assets are on average higher for affected firms. However, in both cases the difference is negligible when looking at a company with median characteristics. The share of intangible assets, calculated as the ratio between intangible fixed assets and the sum of tangible and intangible fixed assets, is similar in both groups, both in average and median terms.

Summary statistics of value added indicate that companies in areas hit by the flood are slightly more productive on average, although the difference shrinks when the median productivity is considered. In terms of value added per employee firms in non-flooded areas have better performances on average but the difference is very small. The median values are slightly larger for

[12]Total assets are given by total receivables due to shareholders, total fixed assets (total tangible fixed assets, total intangible fixed assets and total financial fixed assets), total current assets (total inventories, total receivables, total financial assets and total liquid funds) and total accrued income and prepaid expenses.

[13]Tangible fixed assets comprise: land and buildings; plant and machinery; industrial and commercial equipment; other assets; addition in progress and advances and depreciation provision.

[14]Intangible fixed assets comprise: start-up and expansion costs; research and development expenses; industrial patents and intellectual property rights; concessions, licenses, trademarks and similar rights; goodwill; additions in progress and advances; others and amortization provisions.

non-affected companies.

Inspection of maximum values of total assets, assets and value added also shows that there are

Table 8: Summary statistics of the main variables

Value Added

	Observations	Mean	Median	SD	Min	Max
0/0	12001	4748.667	2147.323	14776.67	.001	1013700
0/1	2932	4773.553	2113.94	11633.3	.001	215513.1
1/0	4102	4297.594	1980.458	9168.966	.9842107	164020.1
1/1	995	4288.486	1883.663	9125.132	.001	138720.8

Value Added per employee

	Observations	Mean	Median	SD	Min	Max
0/0	12001	56.6238	49.27266	32.95921	.0005	318.8578
0/1	2932	54.963	48.59666	32.18068	.0000175	311.1376
1/0	4102	56.03332	45.90213	36.95243	.3457883	315.6109
1/1	995	54.59068	47.11374	33.40911	.001	255.1976

Total Assets

	Observations	Mean	Median	SD	Min	Max
0/0	12001	18976.82	7863.719	51776.86	1.042528	2882645
0/1	2932	21205.91	8733.313	51853.36	20.74036	718554.6
1/0	4102	16991.23	7748.512	40459.45	4.17011	773372.5
1/1	995	19020.05	8395.337	49638.1	9.750721	838585.1

Assets

	Observations	Mean	Median	SD	Min	Max
0/0	12001	4697.55	1496.821	13120.88	0	236026.2
0/1	2932	5364.527	1902.008	13414.12	0	287949.4
1/0	4102	4473.274	1478.418	13189.07	0	290376.3
1/1	995	4999.918	1903.163	13449.95	0	262336.7

Tangible fixed Assets

	Observations	Mean	Median	SD	Min	Max
0/0	12001	4056.557	1308.548	10976.28	0	233782.6
0/1	2932	4725.935	1642.332	10870.6	0	177505
1/0	4102	3604.147	1297.493	6669.398	0	117540.1
1/1	995	4272.846	1744.896	7936.434	0	108890.5

Intangible fixed Assets

	Observations	Mean	Median	SD	Min	Max
0/0	12001	640.9938	46.83421	5460.209	0	207259.7
0/1	2932	638.5918	46.89125	6064.582	0	245500.1
1/0	4102	869.1263	46.95687	9352.768	0	269653
1/1	995	727.0718	44.18599	6874.282	0	153446.2

Employees

	Observations	Mean	Median	SD	Min	Max
0/0	12001	78.85668	43	192.1752	1	6299
0/1	2932	79.80014	42	201.0776	1	6162
1/0	4102	70.55583	41	103.158	1	2044
1/1	995	68.95678	41	98.8198	1	853

Share of Intangible Assets

	Observations	Mean	Median	SD	Min	Max
0/0	11979	.1217324	.0346667	.1913689	0	1
0/1	2921	.1204735	.0277778	.1992515	0	1
1/0	4087	.1178565	.0327869	.188799	0	1
1/1	985	.1077548	.0238298	.1861278	0	1

Notes: Value added, value added per employee, total assets, assets, tangible fixed assets and intangible fixed assets are measured in thousands of Euro. Total assets are given by total receivables due to shareholders, total fixed assets (total tangible fixed assets, total intangible fixed assets and total financial fixed assets), total current assets (total inventories, total receivables, total financial assets and total liquid funds) and total accrued income and prepaid expenses. The variable Assets is the sum of tangible and intangible fixed assets. The share on intangible assets (SIA) is the ratio between total intangible fixed assets and Assets. Treatment/Period is defined as follows: the first number refers to the treatment or control group, the second one to the time period before or after the flood. 0/0 denotes an observation belonging to the control group before the flood; 0/1 indicates to an observation in the same group after the event; 1/0 is an observation belonging to the treatment group before the flood; 1/1 refers to an observation in the same group after the flood.

some very large companies in the sample, especially in the group of non-affected firms.

The summary statistics discussed above show that treated and non-treated firms have similar assets and performance characteristics in the period before the event and thus the flood treatment can be considered as randomly assigned to companies.

Comparing the pre-and-post-flood period, Table 8 shows that value added and value added per employee are on average lower after the flood, both for affected and non-affected firms. The same is true when median values are considered. The average firm reduced its number of employees in the post-flood period in both groups of companies. In median terms, instead, the number of employees decreases only for non-treated companies while it stays constant for affected firms. A very slight decrease can also be noticed in the share of intangible assets in both groups. Unlike the former variables, total assets, assets and tangible fixed assets show a different pattern when comparing pre-and-post-flood period: for both groups of companies and both in average and median terms, total assets are higher after the flood than before. Intangible assets, instead, are lower after the flood, both for the treated and the control group.

To further investigate the average differences between affected and non-affected firms before and after the occurrence of the flood, a mean difference test has been performed for the main

Table 9: Mean difference test for the main variables in the pre- and post-flood periods

Mean difference test (pre-flood)

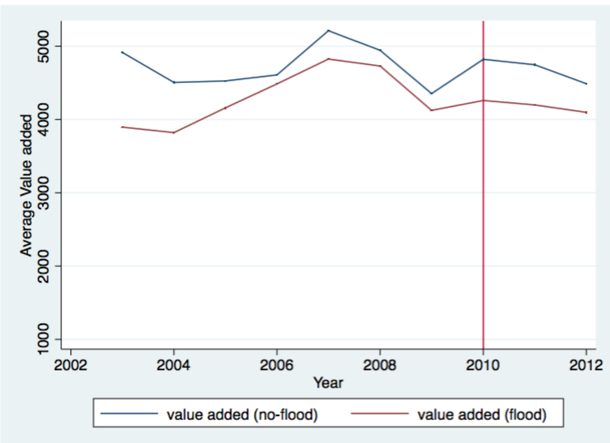
	mean diff	two-sided p	one-sided pl	one-sided pu	mean control	mean treat
VA	222.9553	.5485833	.7257083	.2742917	4676.169	4453.213
VAempl	-.7137525	.5949733	.2974867	.7025133	55.22527	55.93902
TA	1679.618	.3076885	.8461558	.1538442	20082.02	18402.41
Assets	154.0296	.7681441	.6159279	.3840721	5421.03	5267.001
TtangFA	396.5686	.2167994	.8916003	.1083997	4777.235	4380.666
TintFA	-242.539	.4393105	.2196553	.7803447	643.7955	886.3345
SIA	.0008743	.9017071	.5491464	.4508536	.1155676	.1146933
employees	8.908197	.0613505	.9693247	.0306753	80.37559	71.46739

Mean difference test (post-flood)

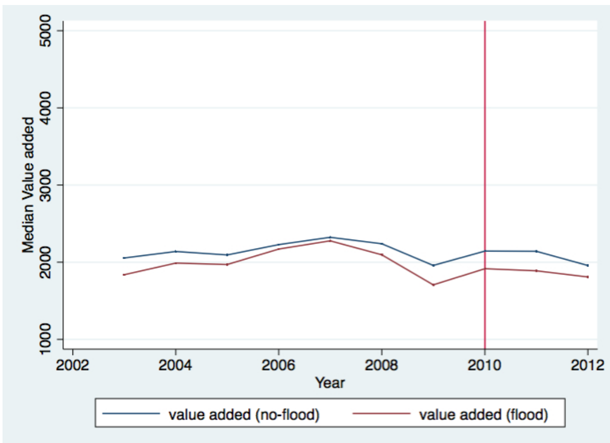
	mean diff	two-sided p	one-sided pl	one-sided pu	mean control	mean treat
VA	485.0674	.1783971	.9108015	.0891985	4773.553	4288.486
VAempl	.3723243	.75921	.620395	.379605	54.963	54.59068
TA	2185.862	.2355402	.8822299	.1177701	21205.91	19020.05
Assets	364.6094	.4597822	.7701089	.2298911	5364.527	4999.918
TtangFA	453.0893	.1593728	.9203136	.0796864	4725.935	4272.846
TintFA	-88.47994	.7180696	.3590348	.6409652	638.5918	727.0718
SIA	.0127186	.0687175	.9656412	.0343588	.1204735	.1077548
employees	10.84335	.0256883	.9871559	.0128441	79.80014	68.95678

Notes: Value added (VA), value added per employee (VAempl), total assets (TA), assets (Assets), tangible fixed assets (TtangFA) and intangible fixed assets (TintFA) are measured in thousands of Euro. Total assets are given by total receivables due to shareholders, total fixed assets (total tangible fixed assets, total intangible fixed assets and total financial fixed assets), total current assets (total inventories, total receivables, total financial assets and total liquid funds) and total accrued income and prepaid expenses. The variable Assets is the sum of tangible and intangible fixed assets. The share on intangible assets (SIA) is the ratio between total intangible fixed assets and Assets. From left to right, column titles denote mean difference, two-sided p value, lower one-sided p value, upper one-sided p value, mean in control and mean in treatment group. In this table two years are considered for both the pre-flood and the post-flood periods: the pre-flood period comprises the years 2008 and 2009; the post-flood period includes 2011 and 2012. The year in which the flood occurred, 2010, has not been considered, due to the fact that the flood struck at the beginning of November and the its effects are observed from 2011 onwards.

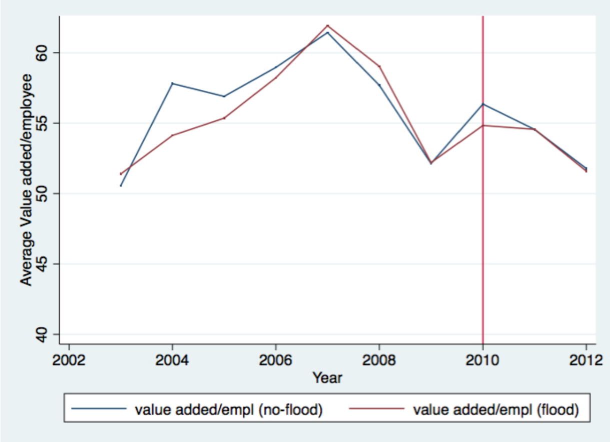
Figure 5: Time trends of the main variables



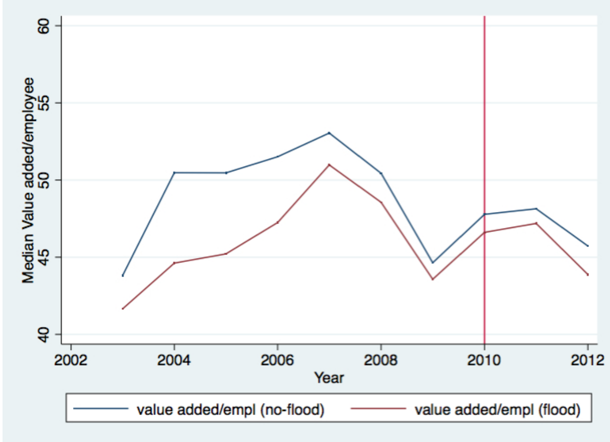
(a) Average value added



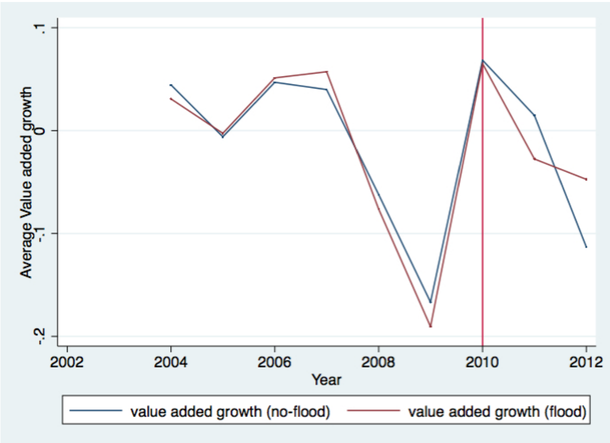
(b) Median value added



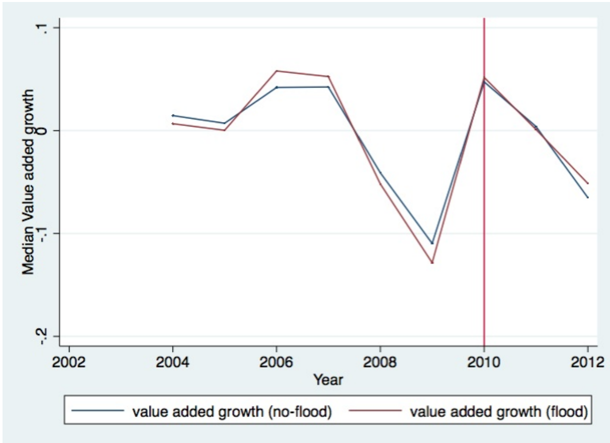
(c) Average value added per employee



(d) Median value added per employee

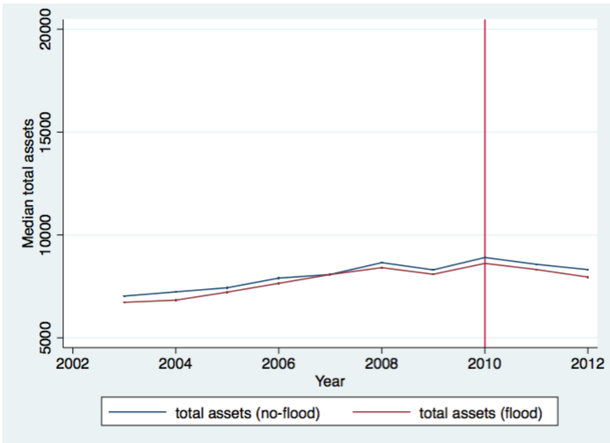


(e) Average value added growth

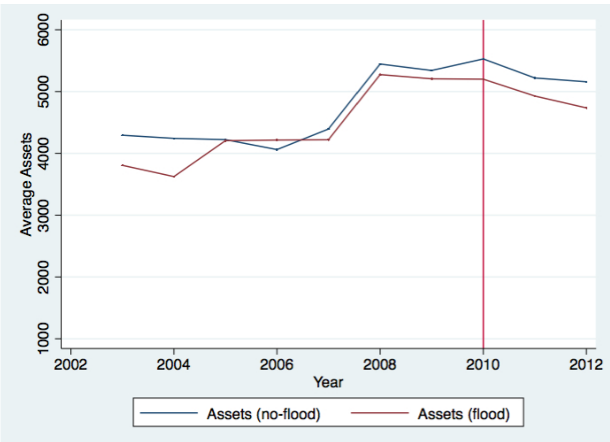


(f) Median value added growth

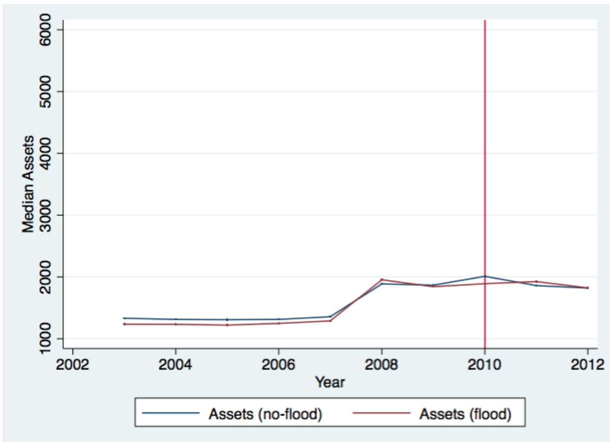
(g) Average total assets



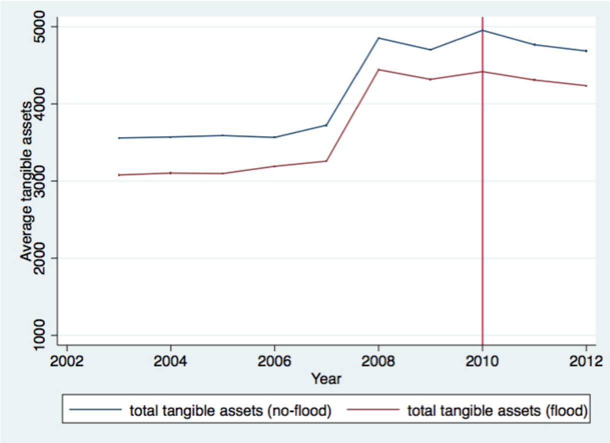
(h) Median total assets



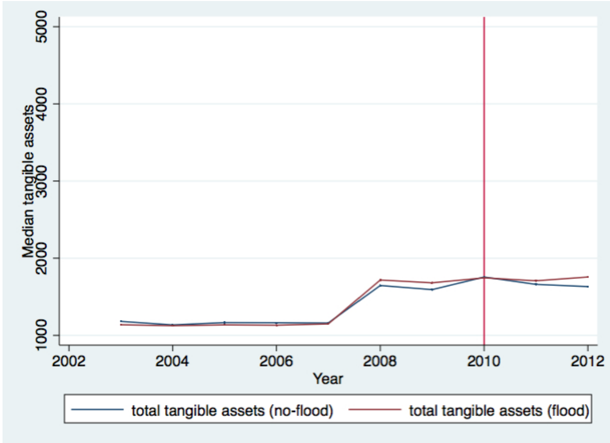
(i) Average assets



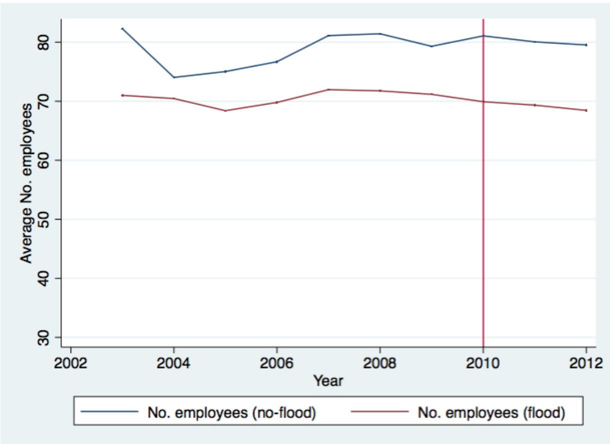
(j) Median assets



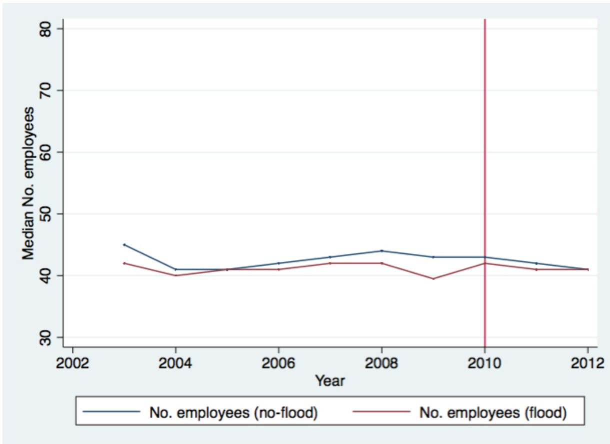
(k) Average tangible fixed assets



(l) Median tangible fixed assets



(m) Average number of employees



(n) Median number of employees

Notes: Value added, value added per employee, total assets, assets and tangible assets are measured in thousands of Euro. The variable Assets is the sum of total tangible and intangible fixed assets.

variables. In order to have a balanced comparison, the same number of years has been considered for the pre- and post-period[15]. Results are reported in Table 9. Before the flood no significant differences can be identified between firms exposed to the flood and the control group of companies in the region. The only exception is the number of employees, for which there is a 6% significant difference between the mean values in the two groups of firms. This difference remains, with a stronger significance, in the post-flood period. After the flood, value added is on average lower for firms located in affected areas; this difference is significant at a 9% significance level. The tangible assets are also lower on average for the treated group (at 8% significance level). Significant differences in the aftermath of the flood can also be identified in the share of intangible assets, with affected firms having on average a lower share.

The mean difference test confirms that before the occurrence of the flood, firms located in flooded and non-flooded areas had similar characteristics, so that the treatment can be considered as randomly assigned to companies. After the flood has occurred some statistically significant differences can be noticed, which gives reasons to perform a more formal analysis on the impact of the flood in the region.

The graphs in Figure 5 provide a graphical representation of differences between the treatment

[15]The pre-flood period comprises the years 2008 and 2009; the post-flood period includes 2011 and 2012. The year in which the flood occurred, 2010, has not been considered, due to the fact that the flood struck at the beginning of November and the its effects are observed from 2011 onwards.

and the control group of firms, showing the evolution of input factors and value added for the treated and the control group in the sample period 2003-2012. For each variable both the average and the median values are plotted[16]. The graphical trend analysis shows that the variables considered have similar patterns in the pre-flood period and thus there are no apparent reasons to suspect that some firms have worse or better performances in the aftermath of the event for causes different from the randomness of the flood. This is a further confirmation that firms have been randomly assigned to the flood treatment.

3 Empirical strategy

3.1 Estimation procedure

In the empirical analysis we compare the value added growth of companies exposed to the 2010 flood to the one of a control group of unaffected firms up two years after the event. We distinguish between affected and non-affected companies on the basis of their location in flooded and non-flooded areas. The criterion to decide whether an area has been hit by the flood or not is the quantity of rainfall[17].

The distribution of the precipitation during the observed period and during the three flooding days suggests a cutoff point at around 70% of the distribution when the entire period is considered and at around 75% of the distribution when the analysis is restricted to the proper flooding days (see Fig. 9 and Fig. 4). A firm is considered as affected by the flood if it is located in an area belonging to the highest 30% of the entire period distribution or to the top 25% of the fooding days distribution. According to the distribution the threshold values corresponding to the 70^{th} and 75^{th} percentile are 208.4mm of rainfall fallen during the observed period and 181.6mm fallen during the three flooding days. These threshold values correspond to a quantity of rain which is more than eleven times the amount that falls on an average rainy day[18], at least one and a half times the median value of the precipitations' distribution for the entire observed period and at least twice the median quantity fallen during the three flooding days in the region.

The impact of the 2010 flood on firms' performance is estimated following a difference in differences (DID) approach. Firms located in flooded areas represent the treatment group, companies operating in areas where extreme precipitations didn't strike constitute the control group. The trend analysis of the main variables and the mean difference tests discussed above confirm that there are no reasons to suspect that differences in firms' performance after the natural disas-

[16]As Table 8 shows there are some very big firms in the sample, therefore it is important to consider both average and median characteristics.

[17]We recognize that the quantity of rainfall alone is not the most accurate measure to determine if an area is flooded or not. Indeed, beyond intense and/or long lasting precipitations other factors, such as snow/ice melt, the water levels in the rivers and the soil status and characteristics, are also important (Field et al., 2012, p. 175). However, we think that a physical measure of precipitations is a more objective criterion than the use of damage reports. As Yang (2008) and Rose (2004) point out, the prospect of aid may create incentives to inflate losses causing the estimation of the outcome of interest to be biased. Therefore, taking into account our data availability, we preferred to use the quantity of rainfall as the best available criterion to distinguish between flooded and non-flooded areas.

[18]10 times when only the three flooding days are considered.

ter can be attributed to causes different from the flood. Therefore a difference in differences methodology can be implemented to estimate the impact of the flood on value added growth.
The empirical estimation is based on the model below, in which value added growth is regressed on a constant, on capital (ΔlAssets) and labor inputs (Δlemployees) growth[19], on the first difference of the share of intangible assets (ΔSIA), on the DID (DID) dummy, on time dummies (year08, year09, year10, year11 and year12), on the interaction of the DID dummy with the input factors, with the share of intangible assets and with the time dummies of interest.

$$\begin{aligned}\Delta lVA_{ijkt} = {} & \beta_0 + \beta_1 \Delta lAssets_{ijkt} + \beta_2 \Delta lemployees_{ijkt} + \beta_3 \Delta SIA_{ijkt} + \beta_4 year08 + \beta_5 year09 \\ & + \beta_6 year10 + \beta_7 year11 + \beta_8 year12 + \beta_9 DID_{jt}2011 + \beta_{10} DID_{jt}2012 \\ & + \beta_{11} DID_{jt}2011 \Delta lAssets_{ijkt} + \beta_{12} DID_{jt}2012 \Delta lAssets_{ijkt} + \beta_{13} DID_{jt}2011 \Delta lempl_{ijkt} \\ & + \beta_{14} DID_{jt}2012 \Delta lempl_{ijkt} + \beta_{15} DID_{jt}2011 \Delta SIA_{ijkt} + \beta_{16} DID_{jt}2012 \Delta SIA_{ijkt} + e_{ijkt}\end{aligned} \quad (1)$$

The subscripts denote a firm i, located in in area j, operating in industry k[20] at time t.
The share of intangible assets accounts for the production technology of the firms in the sample. As Crespo Cuaresma et al. (2008) first noticed, the magnitude of the impact of a natural disaster does not only depend on the intensity of the disaster per se, but also on the level of technology. Following Leiter et al. (2009), we also introduced an interaction term between the DID dummy and the first difference of the share of intangible assets (SIA); this allows to control for different degrees of vulnerability. The idea is that tangible assets are potentially more exposed to physical destruction than intangible assets and thus firms can respond differently to the flood depending on their asset structure. The interaction term allows to assess this possibility.
The time dummies are added to the model to control for general macroeconomic conditions in the country and business cycle trends, such as the financial and economic crisis after 2008, that might influence the estimation results. Starting from 2011, the year after the flood has occurred, the time dummies are interacted with the DID to analyze the effect of the flood separately for each year. Indeed, while the generic DID dummy would estimate the overall impact, the interaction of the treatment binary variable with the time dummies allows to identify the flood's effects one year and two years after the flood and see when a potential recovery starts.
The DID dummy is also interacted with the capital and labor variables to check the possibility of a different contribution of the input factors to value added growth due to the flood. This is done separately for each year after the flood.
In the estimation of the model we use cluster-robust standard errors[21] to take into account a possible within-cluster correlation that would invalidate the hypothesis testing. The reason is that we suspect a correlation among firms located in the same *comune* (municipality), which is due to the role played by financial aid after the flood. Indeed, after the declaration of a state of

[19]Value added, assets and number of employees are in logarithmic terms, therefore their first difference represents their growth rate.

[20]Industry classification provided by the Aida database is either the Ateco 2007 or the Nace Rev. 2.

[21]Cluster-robust standard errors have been suggested by White (1984), Liang and Zeger (1986) and Arellano (1987) and are implemented in Stata using the cluster option. For a more detailed discussion on the clustering problem, see Bertrand, Duflo, and Mullainathan (2004), Cameron, Gelbach, and Miller (2008), Cameron and Miller (2010) and Barrios, Diamond, Imbens, and Kolesr (2012).

emergency in the Veneto region, two commissarial orders[22] established the municipalities eligible for aid for the emergency, reconstruction and recovery phase and determined the transfers to be allocated to each municipality, whose amount was established *ad hoc*[23] and varies among municipalities. This means that there is reason to suspect a correlation among firms belonging to the same municipality and suggests the *comune* as the most appropriate clustering level. The use of cluster-robust standard errors is the most used solution to account for group dependence: it is possible to calculate a variance-covariance matrix that controls both for heteroskedasticy and within-cluster correlation, and to perform correct hypothesis testing provided that the number of clusters is large. In our sample there are 403 municipalities, which allows us to use cluster-robust standard errors as a valid method to control for within group correlation.

3.2 Variables

All the monetary variables have been deflated using a GDP deflator and expressed with respect to 2005 prices as the base year. The GDP deflator has been obtained from the World Bank database.

The DID estimator is represented by the interaction between a treatment and a time dummy. The treatment dummy equals one if a firm is located in an area where more than 208.4mm of rain fell during the observed period or more than 181.6mm[24] fell during the flooding days; it equals zero otherwise. The time dummy takes value one for the years 2011 and 2012 (post-flood period) and zero for the previous years (pre-flood period). Since the flood event occurred at the beginning of November and the graphical trend analysis of value added suggests that 2010 has been a productive year (Fig. 5), it is likely that the biggest impact of the flood occurred in 2011 rather than in 2010. Therefore we only consider 2011 and 2012 as the after-flood period but not 2010, the year in which the flood occurred.

The variables value added, assets, number of employees, tangible and intangible assets are transformed in logarithms before including them in the regression function. This operation requires some caution. Inspection of the data shows that Aida dataset contains some observations with negative value added, but this information doesn't seem to be very reliable, or informative, therefore we preferred to drop such observations. After this operation 441 observations are dropped. Furthermore there is a tiny group of observations (10) with zero value added. We augment each value of the remaining observations by one Euro before taking the log of value added. The resulting sample consists of 2065 firms.

Another clarification is required for the number of employees. According to the Aida database's definition, the number of employees refers to the number of workers employed, whereas when only the entrepreneur is present, a value of zero is reported. In order not to lose precious information when taking the log of employees, we add one to each value corresponding to the number of employees.

Finally, inspection of the data highlights the presence of some outliers when we look at the value added per employee. These extreme values do not seem to be the result of reporting er-

[22] Ordinanza Commissariale n.9 (17/12/2010) and Ordinanza Commissariale n.3 (21/01/2011).

[23] The amount of financial aid to be allocated to each municipality is based on municipalities', firms' and private citizens' damage reporting in the immediate aftermath of the flood.

[24] These are the threshold values corresponding to the highest 30% and 25% of the distribution of precipitations during the observed period and during the flooding days respectively.

rors in the dataset, but rather they appear to be due to misreporting of some companies in the sample. More specifically, for a small number of extremely large firms the reported number of employees is zero (one after our transformation), and this makes the value added per employee to skyrocket for these companies. This is true for every year and in particular in 2009. Outliers could distort our estimation results, therefore observations from the top 1% of the value added per employee's distribution are dropped. This operation eliminates 203 observations from the sample. A graphical check confirms that this adjustment is enough to eliminate outliers due to suspected misreporting.
The final sample consists of a panel of 2065 firms observed between 2003 and 2012.

4 Results

The first column of Table 10 reports the estimated impact of the 2010 flood on firms' value added growth, according to the empirical model presented above (1). The results show that the flood has a positive and significant impact on value added growth. This effect is not experienced in the immediate aftermath of the event, but two years afterwards, whereas one year after the flood the tendency is negative although not statistically significant. In 2012 firms hit by the flood grow faster than unaffected companies: the estimation shows that these companies experience a value added growth that is 6.9% higher than the one of the control group. This also indicates that negative effects of the flood, if there are any, are short-lived and already in the second year after the flood there is a recovery for the firms located in flooded areas.
The asset structure has a significant impact on the value added growth of firms exposed to the flood. The estimation indicates that a positive change in the share of intangible assets is associated with a lower value added growth, but this result is overturned in the case of affected firms. In 2011, the year after the flood, a positive change in the share of intangible assets is expected to increase value added growth of treated companies. In 2012 the tendency is still positive but not statistically significant.
The first and more direct explanation for the faster value added growth of affected firms can be found within a neoclassical growth theory framework: to the extent that the flood damaged or destroyed the capital stock of hit firms, the new capital adoption in the recovery phase leads to a higher growth. These results can also be interpreted according to models based on Schumpeterian creative destruction, in which the negative shock due to the flood might have provided opportunities to update the capital stock and adopt new technologies for those firms that suffered direct damages, thus leading to higher growth. This is in line with some macroeconomic results in the literature that find a positive impact of natural disaster on GDP growth (Skidmore & Toya, 2002; Crespo Cuaresma et al., 2008; Noy & Vu, 2010).
The faster value added growth experienced by the treated firms also raises a question related to the role of the financial aid received by companies that reported material and economic losses due to the flood. Indeed, these transfers could attenuate the economic losses suffered by firms located in flooded areas and help the recovery. In other words, if a firms receives financial aid, the capital upgrade and new technology adoption could be partially or completely paid

Table 10: Estimates of flood effect on value added growth

	(1)		(2)		(3)	
VARIABLES	VA growth	se	VA growth	se	VA growth	se
DlAssets	0.131***	(0.0279)	0.129***	(0.0288)	0.128***	(0.0288)
Dlempl	0.376***	(0.0382)	0.387***	(0.0395)	0.388***	(0.0401)
DSIA	-0.149**	(0.0726)	-0.165**	(0.0753)	-0.169**	(0.0769)
G1_2011					-0.0578	(0.0364)
G1_2012					0.0546**	(0.0276)
G2_2011					0.00843	(0.0221)
G2_2012					-0.00429	(0.0220)
G3_2011					-0.0278	(0.0341)
G3_2012					0.0752**	(0.0377)
G1_2011_DSIA					1.139***	(0.379)
G1_2012_DSIA					0.308	(0.302)
G2_2011_DSIA					0.188	(0.431)
G2_2012_DSIA					0.438**	(0.190)
G3_2011_DSIA					0.421	(0.537)
G3_2012_DSIA					0.422	(0.685)
DID2011	-0.0341	(0.0270)	-0.0392	(0.0276)		
DID2012	0.0691**	(0.0277)	0.0689**	(0.0270)		
DID2_2011			0.0135	(0.0204)		
DID2_2012			0.00124	(0.0199)		
DID2011_DSIA	0.941**	(0.370)	0.971**	(0.391)		
DID2012_DSIA	0.399	(0.420)	0.228	(0.417)		
DID2_2011_DSIA			0.0532	(0.400)		
DID2_2012_DSIA			0.394**	(0.179)		
Constant	0.0378***	(0.00259)	0.0379***	(0.00261)	0.0380***	(0.00261)
Observations	17,724		17,724		17,724	
Number of firms	2,059		2,059		2,059	
Adjusted R-squared	0.120		0.121		0.121	

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

Notes: the three estimated models also contain year-time dummies and interaction variables between treatment dummy (DID for model 1, DID and DID2 for model 2, G1, G2 G3 for mode 3), year-time dummies and the input variables (DlAssets and Dlempl). In model 3, G1 denotes firms that experienced extreme precipitations but didn't receive aids; G2 indicates firms that haven't been hit by extreme precipitations but received financial aid; G3 are firms hit by extreme precipitations that received financial aid after the flood; G4 is the reference group and denotes firms that haven't been hit by extreme precipitation and didn't receive aid flows. In each model cluster-robust standard errors are used; the cluster unit is *comune*.

with the aid received, so that the firm could be better off after the disaster and have better performance. An interesting question is therefore what would have been the pattern of the value added growth of affected firms after the disaster in the absence of aid flows.

An indication comes from a recent paper from the Bank of Italy (Barone & Mocetti, 2014), which adopts a macroeconomic approach to analyze the economic impacts of two earthquakes that occurred in Italy in 1976 and 1980. The authors show that in the absence of financial aid the GDP growth is estimated to be between 0.5% and 0.9% lower five years after the Friuli's earthquake and between 1.3% and 2.2% lower after the quake in Irpinia. However, the question of the contribution of financial aid to the recovery after a natural disaster needs further investigation.

4.1 The role of financial aid

In order to get an insight into the role of aid flows for the recovery of Veneto's firms, we exploit the information provided by the two commissarial orders[25] with which the Italian government and the local authorities established the municipalities eligible for aid and allocated financial aids for the emergency and recovery phases based on the damage reporting of municipalities, private firms and private citizens immediately after the flood.
To investigate this possibility we augmented the model (column 2 of Table 10) with a binary variable (DID2) indicating whether a firm received financial aid after the flood or not[26]. Two types of treatment are therefore considered: whether a firm is located in an area hit by extreme precipitations or not (according to the threshold values corresponding to the 70^{th} and 75^{th} percentile of the precipitations' distribution during the observed period and the three flooding days) and whether a firm is located in an area that received financial aid after the flood or not. Although it hasn't been possible to identify the exact amount of aid flows that each company obtained, the two commissarial orders provide the complete list of municipalities that received financial transfers in the aftermath of the disaster[27], part of which were devoted to the recovery of firms exposed to the flood. This information has been used to identify the companies that benefited from financial aid and a dummy variable has been added to the model to account for the aid effect. DID2 takes value one for all the companies located in municipalities that received aid, it is zero otherwise.
Table 11 displays the number and the percentage of firms in the treatment and in the control group that received financial aid and those that didn't. As the table shows, two thirds of the firms exposed to extreme precipitations also received financial aid after the flood, a factor that could explain the non significance of DID2 in the second regression model, since the effect of the aid is also captured by the DID dummy for two thirds of the firms in the sample. The DID dummy denoting firms exposed to extreme precipitations remains significant and its magnitude doesn't change. Also, the assets structure maintains a positive and significant role in this second model specification, both for firms affected by extreme precipitations and for firms that received financial aid, although the effect is experienced in 2011 for the former group and in 2012 for the latter one.
A likelihood ratio test confirms that controlling for aid flows yields to a significant improvement in the estimated model.
In model 2 the dummy variables DID and DID2 identify two groups with overlapping observations. As it can be noticed in Table 11, among firms hit by extreme precipitations, about two-thirds (67.75%) received financial aid in the aftermath of the disaster, but the rest (32.25%) didn't. In order to better explore the aid contribution to the faster growth of the firms exposed

[25] Ordinanza Commissariale n.9 (17/12/2010) and Ordinanza Commissariale n.3 (21/01/2011).

[26] The model also contains the interaction terms between the DID2 dummy, the year binary variables and the input factors.

[27] The complete list of municipalities (comuni) declared eligible of financial aid after the flood is listed in the commissarial orders with which the Italian government and the local authorities established the aid floods for the hit areas. These are the Ordinanza Commissariale n.9 (17/12/2010) and Ordinanza Commissariale n.3 (21/01/2011).

Table 11: Number of observations by treatment group

extreme/no extreme precipitations	no aids	aids	Total
	No.	No.	No.
no extreme precipitations	8134.00	6799.00	14933.00
extreme precipitations	1644.00	3453.00	5097.00
Total	9778.00	10252.00	20030.00
	%	%	%
no extreme precipitations	54.47	45.53	100.00
extreme precipitations	32.25	67.75	100.00
Total	48.82	51.18	100.00
	%	%	%
no extreme precipitations	40.61	33.94	74.55
extreme precipitations	8.21	17.24	25.45
Total	48.82	51.18	100.00

Notes: the table shows the number of observation in each treatment group. Two types of treatment are considered: whether a firms is located in an area hit by extreme precipitations or not (according to the threshold values corresponding to the 70^{th} and 75^{th} percentile of the precipitations distribution during the observed period and the three flooding days) and whether a firm is located in an area that received financial aid after the flood that hit the Veneto region in autumn 2010 or not. The two treatments identify four groups: firms that haven't been hit by extreme precipitation and didn't receive aid flows (bottom right cell); firms that haven't been hit by extreme precipitations but received financial aid (bottom left cell); firms that experienced extreme precipitations but didn't receive aids and firms hit by extreme precipitations that received financial aid after the flood. The first part of the table displays the number of observation in each of the four groups. The second part reports the percentage of firms that received financial aid and that didn't for the first treatment classification (extreme precipitations). The third part reports the percentage of observations in each group.

to the flood, we used the information provided by the above-mentioned commissarial orders to create four mutually exclusive and exhaustive groups of firms. The two types of treatment, that is whether a firm is located in an area hit by extreme precipitations or not and whether a firm benefited from financial aid after the flood or not, identify four groups: firms that experienced extreme precipitations but didn't receive aids (denoted as G1); firms that haven't been hit by extreme precipitations but received financial aid (G2); firms hit by extreme precipitations that received financial aid after the flood (G3) and firms that haven't been hit by extreme precipitation and didn't receive aid flows (G4). The number and the percentage of firms in each of the four groups are displayed in Table 11.

These groups are used to estimate a new model in which the distinction between the two treatments is made explicit, allowing to asses the effective role of aid for the recovery of affected companies and its possible additional effect.

Column 3 of Table 10 reports the estimated impact of the 2010 flood on firms' value added growth according to the new model[28]. The result shows that the flood had a positive and significant impact on value added growth of both firms that received financial aid and companies that didn't. Consistently with the results of model 1 and 2, the positive effect is experienced in 2012, two years after the flood struck, whereas in 2011 the tendency is negative, with a more negative effect for firms that didn't receive any aid, but not statistically significant.

In order to assess the role of financial aid to the recovery of hit firms, a comparison between G3_2012 and G1_2012 is instructive. The difference between these two estimated coefficients, indeed, represents the additional effect of the aid. In 2012 firms that have been exposed to the flood and received aid flows grow at a rate that is 7.5% higher than the one of the reference

[28]As in the original model and in model 2, each treatment dummy is interacted with the time dummy (for 2011 and 2012) and with the input factor dummies, separately for each year after the flood.

group of firms[29], while firms hit by the flood that didn't benefit from the financial aid grow at a 5.5% higher that the reference group. This result indicates that, even without financial aid, firms are still able to recover and grow faster than unaffected companies, but that there is a 2% additional effect on growth that is due to the aid. However, we fail to reject the hypothesis that the estimated coefficient of the dummy denoting hit companies that benefited from aid flows (G3_2012) and the one of those that didn't (G1_2012) are statistically different.
Finally, receiving free financial aid without having been exposed to the flood doesn't have any significant impact on the value added growth of this group of companies (G2). Both in 2011 and in 2012 the estimated coefficient of G2 is found to be not significant, nor important in magnitude.
This analysis showed that the role of aid flows in the aftermath of natural disasters is an important factor to consider. Future research should include financial aid in the estimation of the economic impact of natural disasters, although acquiring information about national and international aid flows is often difficult. More research needs to be done in order to improve our knowledge of the true usefulness of emergency and recovery aid.

Conclusion

In this empirical analysis we estimated the impact of a major flood that hit the region of Veneto in 2010 on firms' performance up to two years after the event. Using information about geographical locations based on latitude and longitude, we matched each company in the region to the nearest weather station and distinguished between affected and non-affected firms on the basis of the quantity of precipitations received by each firm in the sample. Using firm level data and a difference in differences approach we compared the value added growth of the treatment group to the one of a control group of firms that haven't been hit by the flood. Our results indicate that the flood had a positive impact on the treated firms, whose value added growth was 6.9% higher two years after the flood struck. The estimation also shows that the positive impact was not experienced in the immediate aftermath of the disaster, but two years after the event.
We also found that the assets structure had a positive impact on the value added growth of firms exposed to the flood: a positive change in the share of intangible assets increased value added growth of treated companies.
We further investigated the role of aid transfers after the flood for the faster growth of firms exposed to extreme precipitations. Using the information provided by the commissarial orders with which the Italian government established the municipalities eligible for emergency and recovery aid, we identified the firms that benefited from financial flows and constructed four mutually exclusive and exhaustive groups, which allowed us to distinguish between firms that received financial aid and those that didn't, both in the treatment and in the control group. Using again a difference in difference procedure, our results indicate that, among firms exposed to the flood, both the ones that benefited from financial aid and the ones that didn't grow faster

[29] In the estimated model, the reference group is group 4, indicating those companies that neither experienced extreme precipitations nor received financial aid.

than the reference group of firms that neither have been exposed to the flood, nor received financial aid. We also found that there is a 2% additional growth effect that is attributable to the contribution of aid in the recovery phase.

This analysis showed that possible negative effects of the flood were short-lived and already two years after the event the companies exposed to the flood experienced a recovery. Furthermore, the financial aid after the natural disaster contributed to this outcome, with an additional growth effect experienced by firms that benefited from aid flows.
In this analysis we explicitly addressed the role of aid flows in the recovery phase after a natural disaster and answered the question of what would have been the pattern of the value added growth of affected firms after the disaster in the absence of aid flows in our study case. However, the role of national and international aid flows in the aftermath of natural catastrophes has been rarely addressed so far and it is in need of further investigation.

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Appendix

Robustness checks

The results of model 3 are robust to a change in the number of years considered, to the exclusion of 2010, the year of the flood, and to the estimation of the same model using OLS instead of fixed effects procedure.
The estimated coefficient of the dummy denoting firms exposed to the flood that received financial aid (G3_2012) ranges between 7.3% and 9% in 2012. For companies affected by the flood that didn't benefit from financial aid, the estimated coefficient in 2012 (G1_2012) ranges between 5.5% and 6.9%.

Table 12: Estimates of flood effect on value added growth - Robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	VA growth	se	VA growth	se	VA growth	se
DlAssets	0.0534**	(0.0223)	0.0565***	(0.0194)	0.117***	(0.0272)
Dlempl	0.347***	(0.0551)	0.351***	(0.0663)	0.451***	(0.0407)
DShare	-0.168	(0.120)	-0.0351	(0.0676)	-0.116*	(0.0667)
G1_2011	-0.0558	(0.0392)	-0.0398	(0.0379)	-0.0575	(0.0353)
G1_2012	0.0548**	(0.0273)	0.0694**	(0.0305)	0.0596**	(0.0261)
G2_2011	0.0269	(0.0253)	0.0302	(0.0261)	0.0117	(0.0199)
G2_2012	0.0145	(0.0242)	0.0145	(0.0279)	0.00511	(0.0221)
G3_2011	-0.0183	(0.0376)	-0.00975	(0.0356)	-0.0266	(0.0324)
G3_2012	0.0863**	(0.0395)	0.0908**	(0.0409)	0.0735**	(0.0366)
G1_2011_DShare	1.097**	(0.456)	0.886*	(0.466)	1.115***	(0.356)
G1_2012_DShare	0.286	(0.302)	0.153	(0.310)	0.203	(0.238)
G2_2011_DShare	0.230	(0.495)	-0.0500	(0.420)	0.0414	(0.387)
G2_2012_DShare	0.441**	(0.221)	0.417**	(0.205)	0.333**	(0.163)
G3_2011_DShare	0.517	(0.607)	0.328	(0.657)	0.524	(0.482)
G3_2012_DShare	0.684	(0.740)	0.592	(0.737)	0.341	(0.625)
Constant	-0.0635***	(0.00894)	-0.0637***	(0.00759)	0.0117***	(0.00368)
Observations	9,674		7,770		17,724	
Number of firms	2,026		2,025			
Adjusted R-squared	0.093		0.085		0.134	

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

Notes: model 1 uses fixed effects for the period 2008-2012; model 2 uses fixed effects for the period 2008-2012, excluding 2010; model three uses OLS for the entire period considered (2003-2012). The three estimated models also contain year-time dummies and interaction variables between treatment dummy (G1, G2 G3), year-time dummies and the input variables (DlAssets and Dlempl). In the three models, G1 denotes firms that experienced extreme precipitations but didn't receive aids; G2 indicates firms that haven't been hit by extreme precipitations but received financial aid; G3 are firms hit by extreme precipitations that received financial aid after the flood; G4 is the reference group and denotes firms that haven't been hit by extreme precipitation and didn't receive aid flows.
In each model cluster-robust standard errors are used; the cluster unit is *comune*.

The flood

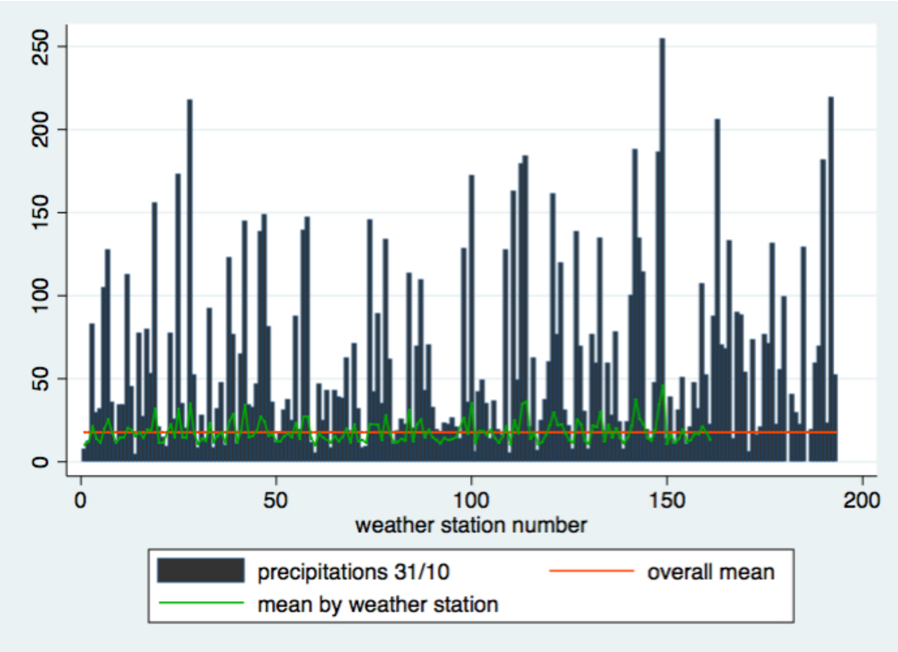

Figure 6: Precipitations during the first flooding day.

The figure shows the quantity of precipitation (in mm) registered by each weather station in the first flooding day. The 'mean by weather station' (green line) represents the average quantity of rainfall fallen on a raining day in October and November during the observed period (2003-2012) excluding 2010. The value has been calculated by taking an average between October and November for each weather station. The data are available only for 163 stations. The 'overall mean' (red line) represents an average of the quantity of precipitations on a raining day in October and November calculated as an average among 163 weather stations during the observed period excluding 2010. The data are available only for 163 weather stations. The average value has been extended to the remaining 30 stations.
Source: graph made using data from ARPAV.

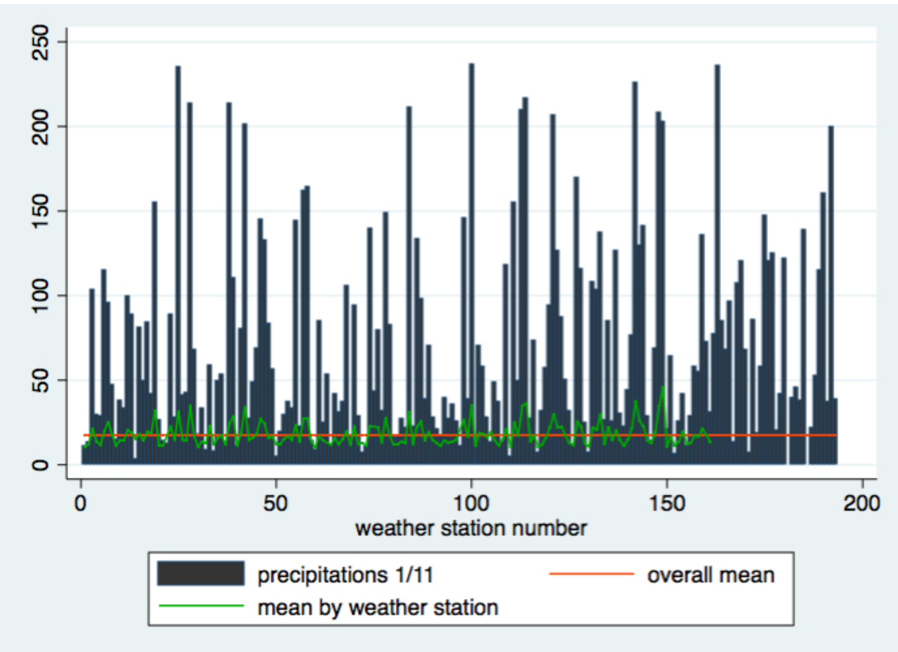

Figure 7: Precipitations during the second flooding day.

The figure shows the quantity of precipitation (in mm) registered by each weather station in the second flooding day. The 'mean by weather station' (green line) represents the average quantity of rainfall fallen on a raining day in October and November during the observed period (2003-2012) excluding 2010. The value has been calculated by taking an average between October and November for each weather station. The data are available only for 163 stations. The 'overall mean' (red line) represents an average of the quantity of precipitations on a raining day in October and November calculated as an average among 163 weather stations during the observed period excluding 2010. The data are available only for 163 weather stations. The average value has been extended to the remaining 30 stations.
Source: graph made using data from ARPAV.

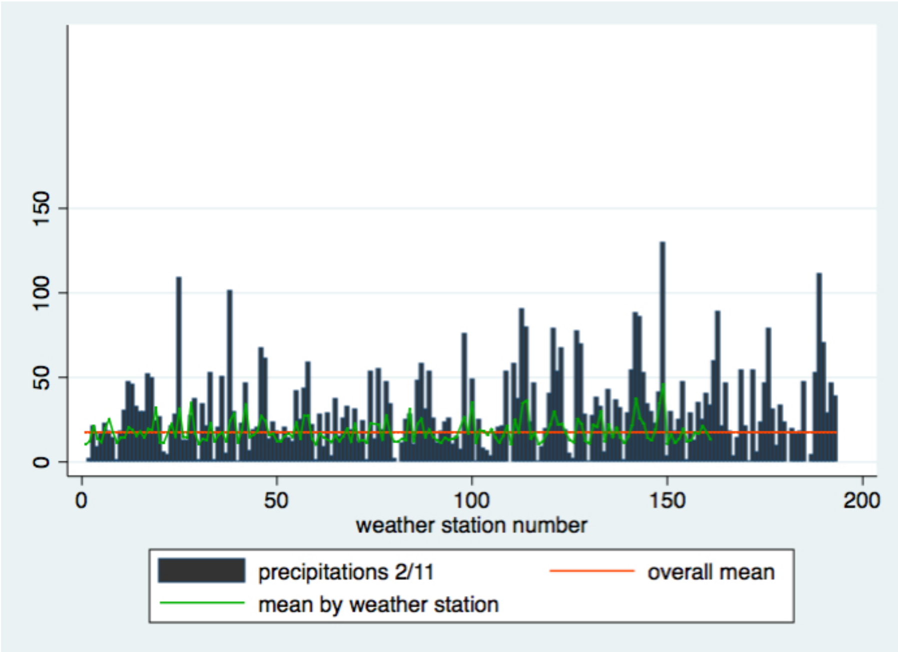

Figure 8: Precipitations during the third flooding day.
The figure shows the quantity of precipitation (in mm) registered by each weather station in the last flooding day. The 'mean by weather station' (green line) represents the average quantity of rainfall fallen on a raining day in October and November during the observed period (2003-2012) excluding 2010. The value has been calculated by taking an average between October and November for each weather station. The data are available only for 163 stations. The 'overall mean' (red line) represents an average of the quantity of precipitations on a raining day in October and November calculated as an average among 163 weather stations during the observed period excluding 2010. The data are available only for 163 weather stations. The average value has been extended to the remaining 30 stations.
Source: graph made using data from ARPAV.

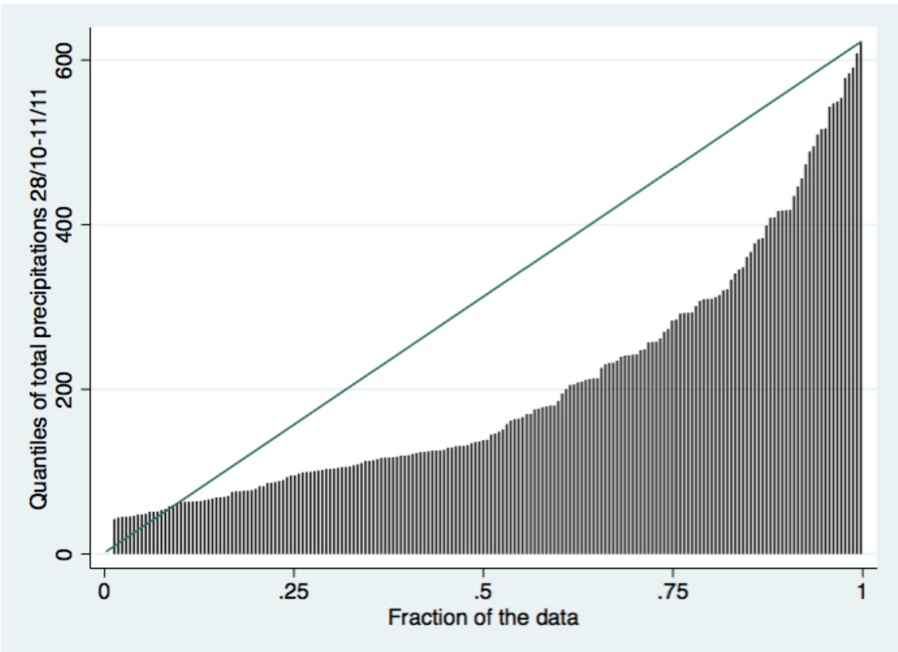

Figure 9: Distribution of precipitations.
The figure shows the distribution of precipitations in the Region according to the location of the 193 weather stations in Veneto Region. The entire observation period (October 28^{th} – November 11^{th}) is considered in this figure.
Source: graph made using data from ARPAV.

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