Floods and firms: vulnerabilities and resilience to natural disasters in Europe*

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Abstract

Combining a rich database on natural hazards, granular flood risk maps and detailed information on firm geolocalisation, we study the dynamic impacts of floods on European manufacturing firms during the period 2007-2018. We find that water damages significantly and persistently worsen firm performance, and may endanger their survival. An average flood deteriorates total assets by about 2% in the year after the event, and up to 5% seven years out. The drop in sales and employment is comparable. We show how reallocation of economic activity within flooded regions can reconcile our results with the 'creative destruction' hypothesis proposed by the natural disaster literature.

Keywords: natural disasters, floods, climate risk, firm performance, panel local projections
JEL classification: D22, Q54, R11

1 Introduction

Natural disasters related to climate change have become more frequent and severe in recent decades. Among them, floods are the hazards most likely to intensify because of the long-term increase in temperature and the subsequent more extreme weather patterns. According to Blöschl et al. (2020), the

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past three decades were among the most flood-rich periods in Europe in the past five hundred years. Moreover, this time frame differs from other flood-rich periods in terms of its extent, air temperatures and flood seasonality. The increased frequency and severity of flooding episodes matches the projected upward trend in the associated economic losses. The European Environment Agency documents that flood-induced economic losses in the European Union (EU) already average over EUR 12 billion per year. Conservative, lower bound estimates show that exposing the EU economy to global warming of 3°C above pre-industrial levels would result in an annual monetary cost of at least EUR 170 billion, or 1.36% of the continent's GDP (European Environment Agency (2019)). Long-term projections from climate models (Feyen et al. (2020)) suggest that, in a scenario with inaction against a 3°C increase in temperature in 2100, almost half a million people in Europe would be exposed to river flooding each year, or nearly three times the number at present. Moreover, river flood losses would rise by a factor of six compared to current magnitudes, reaching nearly EUR 50 billion/year. Similarly, coastal flood losses would grow by two orders of magnitude and climb to EUR 250 billion/year in 2100, while 2.2 million people per year would be exposed to coastal inundation, up from the 100,000 people currently at risk.

While the long term aggregate effect of floods is widely assessed also in the context of climate models, little is known about their microeconomic impact over the short and medium term. This paper aims at filling this gap by studying the dynamic impacts of flood events on European manufacturing firms during the 2007-2018 period. We combine in a unique way a rich database on historical natural hazards, detailed information on firms' location as well as flood risk maps to geolocalise firms that are exposed to inundation in counties across 17 European countries. Importantly, our approach allows us to disentangle firms that were actually exposed to water damage from firms that were likely shielded from it within the same disaster county. Then, using a panel version of the local projections method developed by Jordà (2005), we examine how several measures of firm performance evolve over the short and medium term after a flood event.

We find that water damages have a significant and persistent adverse effect on firm performance. In the year after the event, an average flood deteriorates firms' assets by about 2% and their sales by about 3%, without clear signs of full recovery even after 8 years. While adjusting more sluggishly, employment follows a similar pattern, and contracts over the full horizon period. As a consequence of deteriorating firm performance and sluggish employment reaction, labour productivity also decreases during the first two years after the flood. Then, it starts to slowly recover and eventually reaches the counterfactual no-flood level after about 6 years. On the other hand, average wages in the impacted firms do not show clear sign of recovery even after 8 years.

We further characterize the baseline findings, and document significant heterogeneity in the impact of floods depending on the severity of the hazard as well as on economic and financial factors that affect firms' vulnerability. In particular, we find that major flooding episodes are far more disruptive than milder ones. Similarly, highly indebted firms fare particularly poorly in the aftermath of water hazards, arguably due to deteriorated credit conditions following the destruction of physical capital usually used to collateralize borrowing. On the other hand, more frequent floods do not significantly worsen firm performance, suggesting that adaptation strategies are successfully implemented in flood-prone areas. Finally, we find evidence that flooding may endanger firm survival, as firms exposed to water damage are on average less likely to continue regular operations.

While there is abundant literature on the aggregate economic impacts of natural disasters (see, e.g., Noy (2009); Skidmore and Toya (2002); Felbermayr and Gröschl (2014); Cavallo et al. (2013)), empirical studies taking a microeconomic perspective on the issue have emerged only recently, also thanks to the increased availability of sufficiently granular data. In their influential contribution, Leiter et al. (2009) consider the floods that hit France, Italy, Spain, and United Kingdom in 2000. They show that firms located in the affected regions (at NUTS2 geographic classification) increase their assets and employment in the two years following the event compared to firms in regions that have not experienced flooding. A number of contributions corroborate the view that natural disasters eventually have beneficial growth effects, also at the microeconomic level, in both developed and developing economies. For instance, Coelli and Manasse (2014) investigate the short-term impact of the 2010 flood in the Italian region of Veneto. Using a difference-in-differences setting, they document an increase in value added for firms affected by floods in the two years after the shock. Similarly, focusing on a major flood that hit Germany in 2013, Noth and Rehbein (2019) find that firms located in the disaster regions have significantly better economic and financial performance after the flooding. Such positive growth effects are interpreted as evidence that disasters provide opportunities to substitute outdated capital stock and to adopt new technologies. In this respect, they would act as a type of Schumpeterian creative destruction. The positive growth effect of upgrading technology and enhancing factor composition would be particularly marked in developing economies (Cuaresma et al. (2008); Noy and Vu (2010)). By contrast, more recent evidence suggests negative implications from being exposed to floods. For instance, using satellite images, Hossain (2020) finds a negative effect of floods on output, capital, and employment in Indian manufacturing, with important differential effects based on firms' productivity. Indaco et al. (2019) investigate the impact of hurricane Sandy on the New York area in 2012 using establishment-level data. The authors document a drop in employment and wages over the medium term, as well as relocation of some firms to less risky areas, suggesting that climate risk may affect also business location.

By and large, the findings of negative impacts seem to be derived mainly in the context of studies focusing on single major events that hit confined areas. By contrast, studies that consider several flood events and exploit variability in the cross section and over time suggest milder implications of flooding on economic outcomes, both at the aggregate and disaggregate levels. Arguably, adaptation and preparedness, particularly in the case of less severe events in flood-prone areas, play a crucial role in driving the results. Roth Tran and Wilson (2020) estimate that, unlike for other hazards such as hurricane and tornadoes, floods have a significant negative effect on US counties only in the year of the disaster, followed by a modest positive effect in the medium term. Similarly, in their study of large urban floods that occurred in 40 countries across the globe, Kocornik-Mina et al. (2020) find little evidence of permanent movement of economic activity away from stricken cities in response to flood episodes. Focusing on firms in the US, Jia et al. (2022) show that the actual impact of floods is vastly different from that of flood risk. Their fixed effects panel estimates suggest that actual floods in the period 1998-2018 had a negligible impact on firm entry and exit, as well as local employment and population. The mild negative GDP effect were again driven primarily by the current year's flood shock, and quickly faded away in the aftermath of the hazard. As opposed to actual flood events, they find that increasing flood risk has a large negative impact on firm entry, employment and output in the long run. All in all, the 'creative disasters' hypothesis is still very influential in the literature, and far from being explicitly and convincingly challenged when it comes to flooding.

The contribution of this paper to the literature is twofold. First, our results shed light on the microeconomic impact of flooding in the short and medium term. We do find strong evidence of disruptive and persistent effects of water damages on firm performance. Assets, employment, sales of firms that are directly affected do not recover even 8 years after the disaster. Moreover, our results point to 'destruction' in the more radical form of firms exiting the market in the aftermath of flooding. Overall, our analysis indicates that the negative effects of flooding on firm performance and behaviour may be more significant and persistent than generally thought. In this respect, our findings lend support to the recent evidence that suggests negative implications of natural hazards other than floods for firm operations. Extreme weather events, and more broadly climate risk, have been found to affect several specific margins of adjustment, such as firms' investment strategies (Lin et al. (2019); Li et al. (2020); Rao et al. (2021)), investors' sentiment and market valuation (Hong et al. (2019); Sautner et al. (2020)), credit conditions, (Faiella and Natoli (2019); Rehbein and Ongena (2020); Correa et al. (2020); Brown et al. (2021)), and the organization of production along the supply chain as well as product market outcomes (Cavallo et al. (2014); Todo et al. (2015); Barrot and Sauvagnat (2016); Boehm et al. (2019); Pankratz and Schiller (2019); Custodio et al. (2020); Carvalho et al. (2021)).

As a second contribution, we provide an important qualification to the 'creative destruction' narrative when it comes to flooding. We document a positive post-flood performance for firms in disaster regions that are likely not directly impacted by water damages because they are located further away from areas at risk of flooding. We take this evidence as suggestive of 'reallocation' of economic activity taking place from deluged firms towards firms shielded from direct water damage in disaster regions. Hence, our results tone down the creativity argument, in that we show that positive performance is to be attributed only to firms not directly impacted by the floods. By contrast, firms more likely exposed to flood events display negative performance over the medium term. Taken together, our findings point to a major pitfall in early studies that put forward the 'creative destruction' hypothesis for natural disasters on firm-level outcomes. Considering all firms in disaster regions as directly impacted like the early literature leads to severe underestimation of the negative impact of natural hazards at the microeconomic level. Importantly, when we consider aggregate variables, we do find evidence of positive evolution for comparable outcomes at regional level. However, the granular evidence that we provide suggests caution in interpreting these findings, as they hide important composition effects. The net effect from the reallocation of economic activity across impacted and non-impacted firms in the same region may result in positive aggregate dynamics, leading to conclusions on the impact of floods that cannot be extrapolated to the more granular level.

Our findings advice against relying only on aggregate analyses, and point to the need of modelling the short and medium term impacts of natural disasters also at the microeconomic level to adequately assess and fully characterize the impacts of climate change-related natural hazards in a comprehensive way. Complementing the long-term macroeconomic models commonly employed for the analysis of climate change with microeconomic evidence is of paramount importance also from a policy perspective, notably for the design and better targeting of climate adaptation policies.

The remainder of this paper proceeds as follows. First, Sections 2 and 3 present the data and describe the sample, respectively. Section 4 illustrates the econometric strategy, as well as the full set of results for the dynamic impact of floods on firm-level outcomes. Section 5 introduces the survival analysis. In Section 6 we discuss our findings in the light of the 'creative destruction' hypothesis for natural disasters. Finally, Section 7 concludes.

2 Data

In this section we illustrate the main data we use in the analysis.

Flood events. Information about flood events is collected from the Risk Data Hub (RDH) compiled by the Joint Research Centre (JRC) of the European Commission (Faiella et al. (2020)). The RDH is a GIS web platform of European wide risk data and methodologies for disaster risk assessment. Its historical section comprises a harmonized collection of multiple databases and metadata of past natural disasters in EU Member States. Collected information include the type of hazard (flood, earthquake, forest fire, landslide, tsunami, volcano), the year of the event, and, crucially for our identification strategy, the area affected by the hazard. Quantitative information on each disaster, such as the number of injured and dead people, and the economic losses associated to the event, is available for about half of the events recorded in our sample period.

We focus on floods, notably river floods, flash floods and coastal floods.[1] Moreover, we retain events for which the affected areas could be precisely identified at the NUTS3 level, according to the

[1]River floods originate mainly from the overflowing of rivers caused by heavy rains or upstream dams. Flash floods are caused by the sudden increase in the intensity of the rains and the influence of groundwater recharge and the release of water stored in dams or dikes, and characterized by water spreading at high speed and force. Coastal floods are generally caused by the action of the wind in the waves of the sea and the seismic movement under it, causing flooding on the coastal edges.

European classification of territorial units, which roughly corresponds to counties.[2] Furthermore, we drop countries with no or very few events recorded during the 2007-2018 period from our sample.[3] The final sample includes 17 European countries, accounting for about 86 per cent of the GDP of the EU27 aggregate and the United Kingdom.[4]

Firm-level data. Financial data and information on firm location are retrieved from Orbis, a database compiled by Moody's Bureau van Dijk. Orbis contains detailed information on firm balance sheets and income statements, collected from official business registers, annual reports, newswires, webpages, and commercial information providers, and harmonized into an internationally comparable format. The longitudinal dimension and representativeness of Orbis data vary from country to country, particularly for smaller firms, depending on which firms are required to file information with business registries. As the largest international firm database covering around 200 million private and publicly listed firms in more than 200 countries across the globe, Orbis is increasingly used in the academic literature (see, e.g., Cravino and Levchenko (2017); Aminadav and Papaioannou (2020)). We exploit the historical version of the database, which collects the different vintages of the database annual releases. We restrict our sample to manufacturing firms observed during the 2007-2018 period. For each individual firm, we consider financial information,[5] the sector of activity (NACE Revision 2 codes),[6] and the address.

Flood hazard maps. Flood hazard maps provide spatial information about a number of variables (e.g. flood extent, water depth and flow velocity) that are crucial to quantify flood impacts and therefore to evaluate flood risk and to develop flood risk management strategy. We use the flood risk maps produced by the JRC (see Dottori et al. (2022)). They depict flood-prone areas in Europe and the Mediterranean basin for different return periods, ranging from 10 to 500 years. Based on the expected flood flow rate over the relevant return period, say 10-year, the flood water level can be mapped as an area of inundation. The resulting hazard map is referred to as the 1-in-10-year floodplain.[7] The maps have been developed and further improved using hydrological and hydrodynamic models, driven by the climatological data of the European and Global Flood Awareness Systems (EFAS and GloFAS). All maps are in raster format (GEOTIF) with a grid resolution of 100 meters. Operationally, to make the raster format tractable, we convert it by polygonization using the 8-connectedness method and

[2]NUTS aggregates are generally based on existing national administrative subdivisions. For example, districts in Germany and provinces in Spain correspond to NUTS3 regions. Throughout the paper we refer to NUTS3 entities as counties.

[3]These countries are: Cyprus, Denmark, Estonia, Finland, Latvia, Lithuania, Luxembourg, Malta, Netherlands, and Sweden. Moreover, we also exclude Greece from the estimation sample, since geolocalised postal codes – which are also used to calculate the distance of the firm from the nearest flood risk area; see more on this in Section 4.2 – are not available for this country.

[4]Source: Eurostat. The data refers to 2019.

[5]In practice, in the case of firms belonging to groups we consider only the unconsolidated financial statements.

[6]NACE Rev. 2 is the revised classification of the official industry classification used in the European Union adopted at the end of 2006.

[7]At the time of writing the paper, only river flood hazard maps, developed according to the methodology in Dottori et al. (2022), are publicly available for download. Similar maps for coastal floods are available from the JRC upon request.

a 300m buffer (equivalent to a distance of 3 pixels on the map). By overlaying firm geographic coordinates with the polygonized relevant flood hazard maps and combined with information on flood events, we are able to pinpoint firms likely impacted by past floods (see Section 4.2).

3 Recent floods in Europe

In the past three decades Europe experienced one of the most flood-rich periods over the past 500 years (Blöschl et al. (2020)). Not only have floods become more frequent and bigger in extent since the early 1990s, but the more recent flood events stand out in terms of timing and for the relationship between flood occurrence and air temperatures. While previous flood-rich periods were associated with relatively lower average air temperatures (by about 0.2 – 0.3 °C), increased air temperatures due to global warming (by about 1.4 °C than in the previous inter-flood period) are one of the main drivers of the current flood-rich period.

Figure 1 shows the geographical distribution of flood events in Europe between 2007 and 2018, with darker blue colours indicating a higher frequency of flood events in the NUTS3 counties.[8] Floods are particularly frequent in the Mediterranean basin area, where enhanced evaporation and convective activity have been increasing the frequency of autumn floods during the past few decades (Barriendos and Rordigo (2006); Barrera-Escoda and Llasat (2015)). In the Atlantic region, in particular in the UK and in Ireland, the seasonal shift of winter storms has resulted in more frequent winter floods. The seasonality of the floods has also become more pronounced in Central Europe, where earlier snowmelt and fewer ice-jam floods have shifted the dominant flood season towards the summer (Xoplaki et al. (2004); Berghuijs et al. (2019)). In this area, floods are typically associated with prolonged heavy precipitation hitting large areas, and sometimes aggravated by higher than usual soil moisture due to relatively cold winter or spring. One of the most important flood events in our sample, the flood of June 2013 in Central Europe affecting the Danube and Elbe catchments, is an example of such phenomenon (Blöschl et al. (2013)).

Table 1 reports the frequency of flood events in our sample. Overall, about 78 per cent of the NUTS3 counties in the selected countries have been hit at least once by a flood during the 2007-2018 period (see the last column of Table 1). Out of the 1,026 affected counties, 681 have been deluged more than once. In some counties, in particular in the United Kingdom, Spain, and Romania, floods are so frequent that they represent the norm rather than the exception. Conversely, Germany, Poland and Croatia experienced relatively fewer flood events. In these countries, between 33% and 43% of the counties have been spared flooding during the period considered. This is, however, at least

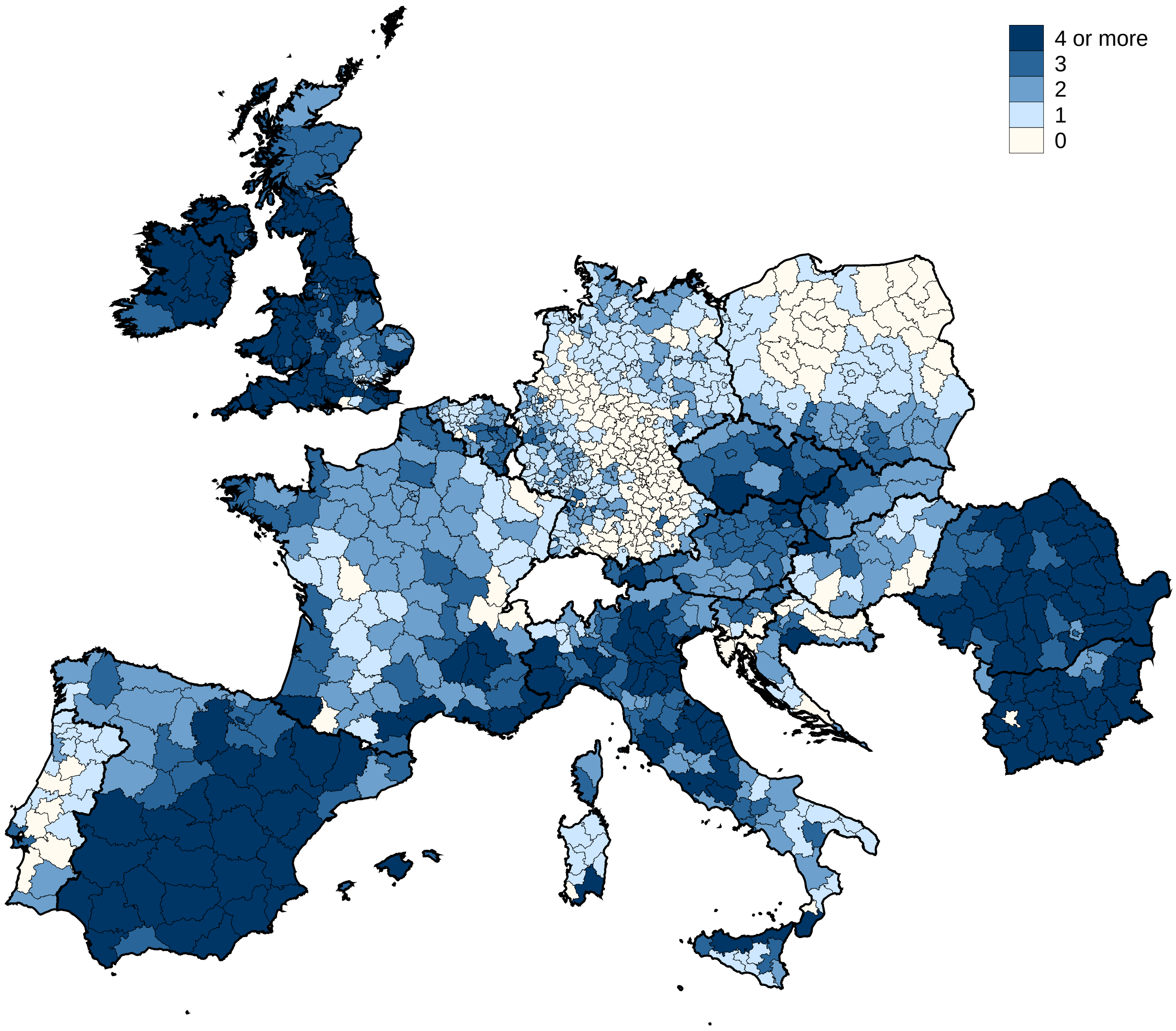
[8]Table A.1 in Appendix A displays the breakdown of the total number of flood events in our sample, by country and year.

partly related to the higher spatial granularity of the areas defined at the NUTS3 level, especially for Germany and Croatia.[9]

To gauge the timing of flood events, Table 2 displays the average number of years between flood events in counties affected by multiple floods during our sample period. On average, the temporal distance between flood events in NUTS3 counties affected by multiple hazards is about three years. Expectedly, the average number of years between events is decreasing with the number of events in a given county. Repeated floods in the same areas present a challenge for isolating the dynamic impact of one particular flood. In this respect, the 345 counties flooded only once during the 2007-2018 period provide an important piece of information for the econometric identification of firms' dynamic responses to floods. In the remaining impacted counties, firm performance after a specific flood may be contaminated also by the persistent impact of past floods. Thus, it is crucial to take into account previous flood events in any attempt to assess the dynamic impact of floods (see Section 4 for the technical details).

[9]For example, the average size of a rural district (Landkreise) in Germany is 1,422 km^2, and that of an urban district (kreisfreien Städte) is 150 km^2. For comparison, an average province in Spain has an area of 9,729 km^2.

Figure 1: Flood map (2007-2018)



Notes: The figure depicts the map of historical flood events occurred during the 2007-2018 period by NUTS3 areas. Canary Islands, Overseas France, the Azores and Madeira are not shown.

Table 1: Frequency of flood events between 2007 and 2018

	1	2	3	4	5	6	7	8	9	Total	%
AT	0	11	21	1	2	0	0	0	0	35	100
BE	16	14	9	2	0	0	0	0	0	41	93
BG	0	3	2	8	11	3	0	0	0	27	96
CZ	0	5	5	3	1	0	0	0	0	14	100
DE	166	73	10	0	0	1	0	0	0	250	66
ES	8	10	13	9	7	4	4	1	1	57	97
FR	19	43	19	6	3	0	0	0	0	90	89
HR	4	6	1	0	1	0	0	0	0	12	57
HU	6	9	1	1	0	0	0	0	0	17	85
IE	0	0	1	2	3	2	0	0	0	8	100
IT	24	22	25	27	9	0	0	0	0	107	97
PL	22	17	4	1	0	0	0	0	0	44	61
PT	14	3	1	0	0	0	0	0	0	18	72
RO	0	1	10	11	9	5	4	1	1	42	100
SI	1	4	4	0	0	0	0	0	0	9	75
SK	0	4	3	1	0	0	0	0	0	8	100
UK	30	23	33	21	20	19	18	4	1	169	98
All	345	266	171	107	68	34	26	6	3	1,026	78

Notes: The table reports the number of counties by frequency of floods. The column "Total" displays the total number of counties affected by a flood at least once between 2007 and 2018. The last column shows the percentage of the counties in a given country with at least one flood event recorded in our sample.

Table 2: Average number of years between events

	2	3	4	5	6	7	8	9	All
AT	4.1	3.1	3.3	2.8					3.2
BE	5.7	4.8	3.3						4.9
BG	6.0	4.2	3.3	2.7	2.2				3.0
CZ	3.6	2.4	2.6	2.8					2.7
DE	4.3	3.2			1.8				3.9
ES	3.5	4.2	3.0	2.5	2.0	1.8	1.6	1.4	2.7
FR	3.0	3.5	1.9	2.2					2.9
HR	2.5	2.0		2.0					2.2
HU	3.2	2.0	2.3						2.9
IE		5.0	3.2	2.3	2.0				2.6
IT	3.3	2.8	2.4	2.1					2.5
PL	1.4	3.0	3.0						2.0
PT	5.0	5.0							5.0
RO	2.0	3.5	2.7	2.5	2.0	1.8	1.3	1.4	2.4
SI	5.0	4.5							4.7
SK	4.5	5.2	3.7						4.6
UK	4.9	3.1	2.5	2.4	2.0	1.7	1.5	1.2	2.3
All	3.9	3.4	2.5	2.4	2.0	1.8	1.5	1.3	2.8

Notes: The table presents the average number of years between flood events in counties affected by multiple floods during the 2007-2018 period.

4 The dynamic impact of floods

4.1 The econometric model

To assess the dynamic impact of a flood on firms, we rely on three variants of the same econometric model. In our first model, we use local projections (LP) to investigate firms' dynamic responses to flood events in a panel framework. The general LP method is documented in Jordà (2005). In a panel framework, the impulse response function (IRF) is estimated sequentially for each horizon

$h = 0, ..., H$ using the following equation:

$$y_{i,t+h} - y_{i,t-1} = \beta_h D_{it} + \sum_{\tau=0,\tau\neq t}^{h} \theta_\tau D_{i\tau} + \gamma_h X_{i,k<t-1} + \delta_{csh} + \varepsilon_{i,t+h} \tag{1}$$

where $y_{i,t+h} - y_{i,t-1}$ is the cumulative change in the outcome variable of firm i (measured in logs) between time $t-1$, the period before the disaster, and $t+h$. The key variable of interest is D_{it}, a treatment dummy equal to one if firm i is impacted by a flood in time t, and zero otherwise. In addition, $\sum_{\tau=0,\tau\neq t}^{h} \theta_\tau D_{i\tau}$ is a set of dummies controlling for all other floods that occurred before the current event and between the current disaster and the horizon of interest h. These dummies ensure that the estimated impact of a disaster at time t is not contaminated by either lingering effects of past disasters or effects of other disasters that occur between the current disaster and horizon h. The term δ_{csh} represents county- and industry-specific (NUTS3$\times$NACE2) fixed effects, that absorb the effects of local economic shocks that may confound the effect of the natural disasters.

Finally, the vector $X_{i,k<t-1}$ controls for predetermined firm characteristics. More specifically, the vector X includes the second and the third lag of the firm's total assets, the number of employees, tangible assets as a share of total assets, intangible assets as a share of total assets, and leverage. We also include firm's age. To control for the cyclical position of the economy, we also include the country's output gap (deviations of the country's log annual real GDP from its HP-filtered trend with a scaling factor $\lambda = 100$).

The sequence of the estimated parameters $\hat{\beta}_h$ at horizons $h = 0, ..., H$ represents the IRF of the representative firm to an average flood, i.e. the average path of the outcome variable of the impacted firms relative to the other firms unaffected by the flood, that are taken as the counterfactual. Assuming that the error-terms $\varepsilon_{i,t+h}$ are independent and identically normally distributed, the $H+1$ equations can be estimated separately for each horizon using simple ordinary least squares (OLS). Roth Tran and Wilson (2020) use a similar LP method to study the local impact of natural disasters in the U.S. on a broad range of outcome variables at county level.

Our second and third models combine the LP methodology with a quasi-experimental estimation approach. The identification strategy involves two stages. First, a binary probit model is estimated to determine the probability that the firm i is impacted by a flood in time t based on observed predetermined characteristics:

$$\Pr\left(D_{it} = 1 | X_{i,k<t-1}\right) = \Phi\left(\alpha X_{i,k<t-1}\right) \tag{2}$$

where $\Pr$ denotes probability, $X_{i,k<t-1}$ is the same set of controls as previously defined, and Φ is the Cumulative Distribution Function (CDF) of the standard normal distribution. The probabilities of being assigned to the treated group conditional on observed characteristics (i.e. the propensity scores) are then predicted using the estimated eq. 2.

In the second stage, we estimate the LP model in eq. 1 by weighting the observations with the inverse of the propensity scores obtained from the first stage. The weights used for treated firms is given by $1/\hat{\mathrm{Pr}}$, whereas non-treated firms receive a weight equal to $1/(1-\hat{\mathrm{Pr}})$. This inverse propensity score weighting (IPW) scheme mitigates confounding by placing more weights on observations that were difficult to predict, thereby improving on the covariate balance between the treated and the control groups (Rosenbaum and Rubin (1985)).

The conventional IPW method does not require adjusting for the same set of covariates in a second stage regression. To control for previous flood events ($\sum_{\tau=0,\tau\neq t}^{h} \theta_\tau D_{i\tau}$) and the fixed effects (δ_{csh}), we estimate the second stage outcome regressions as in eq. 1, but without including $X_{i,k<t-1}$ as additional covariates. We refer to this model as the augmented inverse propensity weighted (AIPW) estimator.

In our third model, the controls $X_{i,k<t-1}$ are included both in the first stage probit and the second stage LP equations. Since the same covariates are taken into account via two channels, the literature refers to this method as "doubly robust". The main advantage of this approach is that it provides consistent estimates if either the first stage model for the propensity score or the outcome regression model (or both) are correctly specified (Glynn and Quinn (2010)). We refer to our third model as the doubly robust AIPW estimator. With a different objective, Jordà et al. (2016) use a similar method (IWP combined with LP in a doubly robust way) to compare the path of the economy in normal recessions and during financial crisis.

4.2 Which firms are exposed to floods?

Firms impacted by a flood are not directly observed. As discussed in Section 2, the flood events are recorded in our database at the level of NUTS3 territorial units. Nonetheless, the whole NUTS3 area is unlikely to be affected whenever a flood occurs in the county. Hence, in the occurrence of a flood, within the same county there will be firms directly exposed to water damage and firms not affected by it. To pinpoint the two groups, we overlay the information on firm geographical location from Orbis and the flood hazard maps of the JRC (see Section 2).

Table 3 tabulates the geographic information that we use to geolocalise firms. Orbis reports the exact coordinates (latitude and longitude) for about 55% of firms (see the second row of Table 3). For the remaining firms, we use postal codes. In particular, we merge firms' postal codes in Orbis with the GeoNames database on geographic coordinates of all postal codes in the relevant countries.[10] An additional 40% of firms are thus geolocalised relying on the full postal code (maximum number of digits for a given country; third row of Table 3). In about 2 per cent of the cases, the postal codes recorded in Orbis cannot be perfectly matched with the postal codes in the GeoNames database.

[10]The GeoNames database is downloaded from http://download.geonames.org.

In these cases, we either take the postal code in the numerical vicinity available in the GeoNames database (the nearest neighbour postal code), or – in countries with alphanumeric postal codes, i.e. UK and Ireland – we identified firms' location using 3-digit outward postal codes (fourth and fifth rows of Table 3).[11] Finally, we exclude from the estimation sample about 4% of the firms for which the geographical location cannot be identified (first and last rows of Table 3).

Table 3: Geocode

	Nb. of obs.	%
Missing geographic info	341,504	3.71
Firm geolocalised	5,048,660	54.89
Postal code geolocalised	3,613,278	39.29
Nearest neighbour postal code	166,926	1.81
3-digit postal codes for the UK and IE	26,365	0.29
Not geolocalised	474	0.01

Notes: The table tabulates the geographic information reported in Orbis used for geolocalising firms.

We define as treated firms those that are located in a 1-in-10-year flood risk area. Overall, roughly 7% of all firms turns out as being in the treated group according to this classification.[12] The control group is defined using a similarly conservative approach. We consider as unaffected by flood events all the firms that are located at least 10km away from the flood risk areas defined in the 1-in-500-year maps.[13] At a distance of 10km and above, firms are unlikely to be damaged by the flood, even if we take into account the uncertainty of our calculated distance measure.[14]

One concern with the use of forward-looking hazard maps that rely on modelled inputs is measurement error.[15] To address this issue, we adopt an alternative method to disentangle affected and unaffected firms for each flood event.

[11]For Ireland, only 3-digit outward postal codes (Eircodes) are available in the GeoNames database for copyright reasons. On average, 3-digit postal codes correspond to an area of 3.7km $\times$ 2.9km.

[12]The value is comparable, despite some differences, with what reported by Benincasa et al. (2022) using survey data. Specifically, according to the 2019 Enterprise Survey, at the question "Over the last three years, did this establishment experience monetary losses due to extreme weather events (such as storms, floods, droughts, or landslides)?" roughly 9.3 percent of surveyed firms responded affirmatively.

[13]Geodesic distances (i.e. the shortest path between two points along the surface of the Earth) are calculated using the formula developed by Vincenty (1975).

[14]A map with the location of affected firms is presented in Figure B.1 in Appendix B.

[15]Dottori et al. (2022) provide a detailed validation exercise using official hazard maps for a limited number of countries, namely Hungary, Italy, Norway, Spain and the UK. They find that the modelled maps can identify on average two-thirds of reference flood extent, with different accuracy performance over the return periods. For instance, for return periods equal to or above 500 years, the maps can correctly identify more than half of flooded areas. See in Figure C.1 Appendix C for a graphical example.

Specifically, we adopt an agnostic, purely data-driven approach and assume that the likelihood of being directly exposed to a flood depends only on the distance between the firm geographical location and the nearest river, lake or coastline. Then, we pinpoint the affected firms by recursively estimating eq. 1 for different values of the distance below which an average flood is likely to cause damage. In this case, roughly 5% of all firms are considered treated, whereas the control group comprises firms that are located at least 700 metres away from the closest river, lake or coastline. We describe the methodology in detail in Appendix E. This alternative categorisation of the treated and untreated groups yields very similar results and confirms all the conclusions presented in the paper.[16]

4.3 Baseline results

We present the results from estimating eq. 1 for (the log of) five different outcome variables: total assets; sales; the number of employees; labour productivity, calculated as output per employee; and wages, measured as the aggregate firm payroll over the number of employees. Figures 2 and 3 show the estimated IRFs using the panel LP (graphs on the left-hand side), the AIPW (in the middle) and the doubly robust AIPW models (on the right-hand side).[17] The X-axes correspond to the number of years ($h \geq 0$) after the flood events. The blue lines indicate the IRFs obtained as the series of coefficients $\hat{\beta}_h$, which capture the impact of the flood on the outcome variables y in each of the h years after the event, and the light blue areas are the corresponding 95% confidence intervals.

Water damages have a significant and persistent adverse effect on firm performance. In the year after the event, an average flood deteriorates firms' total assets by about 2% (panels (a)-(c) in Figure 3). The drop reaches about 3% three years out, and peaks at more than 5% seven years out. In the eighth year, total assets display a gradual recovery but remain below the no-disaster counterfactual, by around 2%. All the impacts are statistically significant throughout the horizon period under consideration. The results from the three models are very similar, suggesting that specification errors in the unweighted panel LP specification are negligible.

We show the results for firm sales in panels (d)-(f) of Figure 2. Not surprisingly, sales deteriorate rather swiftly in the aftermath of a flood, reflecting the immediate disruption to firm operations triggered by the hazard. The fall in sales is already around 3% in the year after the disaster, and hovers around 5-6% with respect to the counterfactual with no floods as of three years and up to seven years out. Again, while there are signs of recovery as of eight years after the hazard, at the end of the relevant horizon sales are still 3-4% lower than what they would have been in the absence of the flood.

[16]These robustness checks are not presented in the paper for reasons of brevity, but are available from the authors upon request.

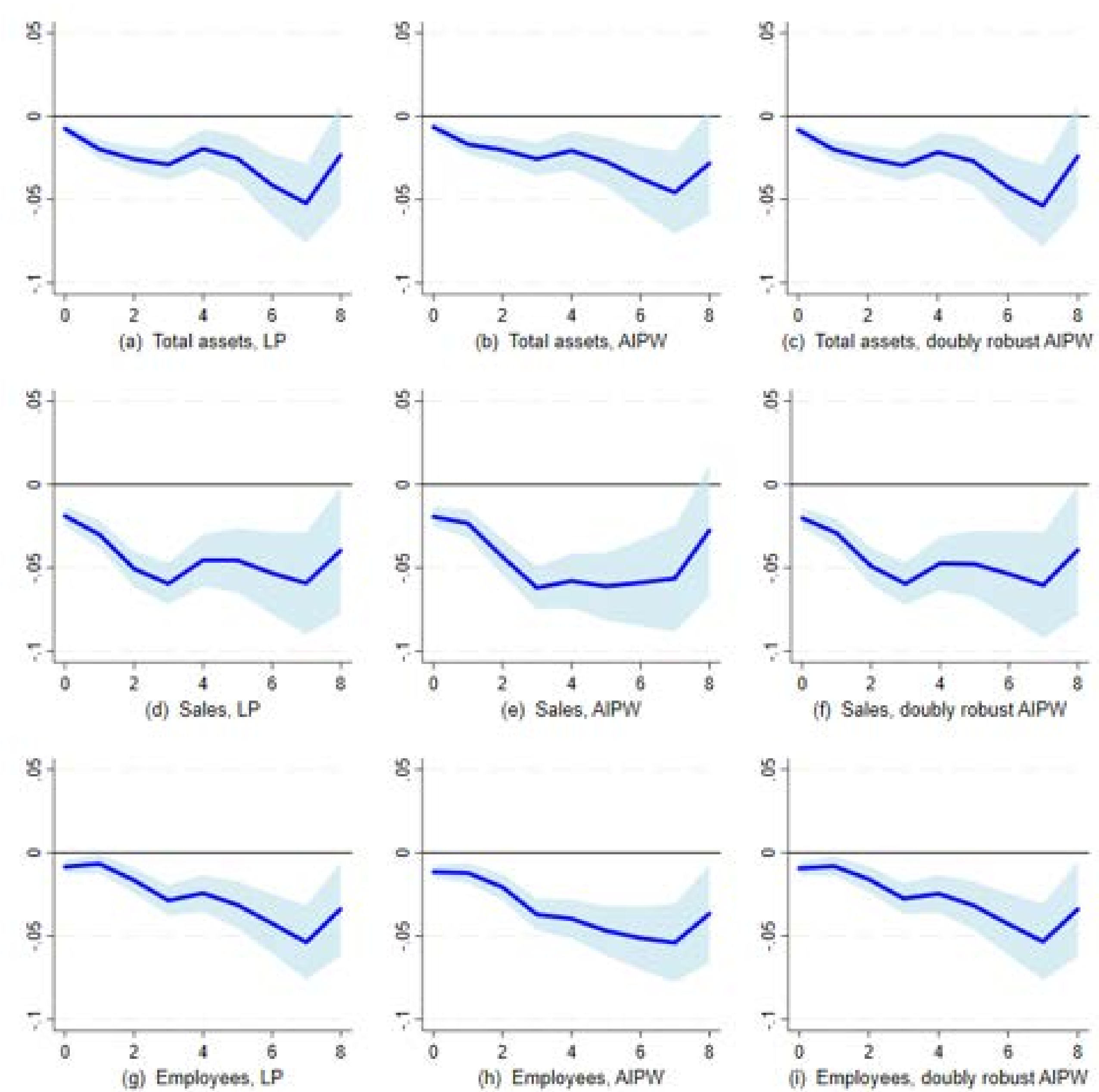
[17]The balance table on predetermined variables in the unweighted LP model, as well as the reweighted AIPW and doubly robust AIPW models are presented in Appendix D.

The number of employees reacts more slowly to flood damages (panels (g)-(i)). Employment declines by roughly 1% in the year following the event, and it starts to gradually deteriorate afterwards. The magnitude of the shock seven years after the flood is comparable to that recorded for total assets and sales. Likewise, a mild rebound is evident seven years out, when the negative impact on employment is in the range of 3%, from 5% in the previous year. Importantly, all estimated impacts are statistically significant.

Several factors can possibly explain the more sluggish adjustment in employment. For example, legal impediments to dismissal, severance pay, or the activity of the trade unions may all prevent firms to adjust employment in response to shocks. Moreover, employers may find it optimal to choose other margins of adjustment (such as through hour worked, wages, or simply by reducing work intensity and accepting profitability loss) if they perceive the shock as temporary. In this case, firms may choose to hoard labour in order to avoid future hiring costs (advertising, screening, processing and training new employees) and any sunk costs associated with human capital investments in employees. If the persistence of the shock is not known in advance, firms may still respond sluggishly to shocks, as the positive option value to waiting decreases the propensity to adjust quickly and induces them to gather more information on the exact nature of the shock. Finally, labour hoarding can also be encouraged by state intervention, such as subsidised working time reductions or other forms of compensation for workers' income losses, which reduce the costs of labour hoarding for firms. See Hamermesh and Pfann (1996) for a comprehensive survey on the implications of adjustment costs on factor demand.

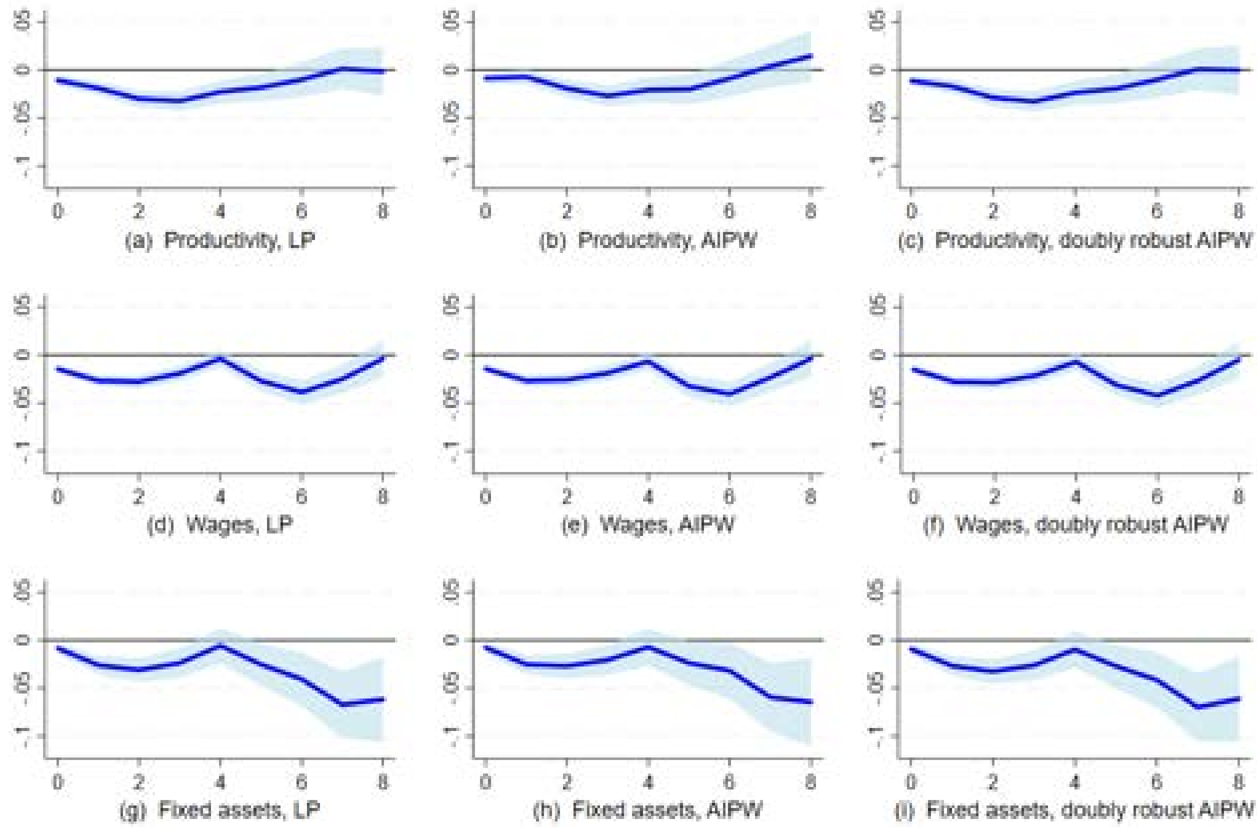
To fully characterize firms' margins of adjustment related to the labour factor, Figure 3 plots the IRFs for productivity, calculated as output per worker, and average wages, obtained as firms' total payroll divided by the number of employees. As a consequence of the worsened productive conditions and the sluggish reaction of employment, labour productivity also deteriorates (panels (a)-(c) in Figure 3). Productivity shows sign of recovery around three years after the flood, as the number of employees starts to decrease. As of five years out the impacts of the flood are not statistically different from zero across all three LP specifications, and the counterfactual level of labour productivity without the natural hazard is eventually reached about six years out. The evolution of average wages displays a rather marked double dip pattern, and is estimated with high precision. Even eight years out average wages at the impacted firms are still below their counterfactual level with no floods.

Figure 2: Impact of an average flood on firm total assets, sales, and the number of employees



Notes: the figure displays the impulse response functions (IRFs) derived from the local projections (LP, graphs to the left), the augmented inverse propensity weighted estimations (AIPW, in the middle) and the doubly robust AIPW estimations (to the right) for total assets (in log, first line), sales (in log, second line), and the number of employees (in log, third line). The X-axes correspond to the number of years after the flood events (h*). The blue lines indicate the estimated impacts of the flood on the outcome variable* h *years after the event (*$\hat{\beta}_h$*), and the light blue areas are the corresponding 95% confidence intervals.*

Figure 3: Impact of an average flood on firms' productivity and wages



Notes: the figure displays the impulse response functions (IRFs) derived from the local projections (LP, graphs to the left), the augmented inverse propensity weighted estimations (AIPW, in the middle) and the doubly robust AIPW estimations (to the right) for the firm's labour productivity (in log, first line) and average wages (in log, second line). The X-axes correspond to the number of years after the flood events (h). The blue lines indicate the estimated impacts of the flood on the outcome variable h years after the event ($\hat{\beta}_h$), and the the light blue areas are the corresponding 95% confidence intervals.

4.4 Heterogeneity

The baseline results in the previous section characterize the average dynamic impact of a flood on several measures of firm performance. However, the actual impact of flood episodes is likely to differ from the average treatment effect in a number of dimensions. In this section we shed light on different sources of heterogeneity, both in terms of specific features of the natural hazards, and in relation to firm characteristics.

The heterogeneous IRFs are estimated by replacing the treatment indicator dummy D_{it} in eq. 1 by two interactive variables, $d \times D_{it}$ and $(1-d) \times D_{it}$, where the dummy d defines the subsample under consideration. Similarly, the set of dummies controlling for all other floods ($\sum_{\tau=0,\tau\neq t}^{h} \theta_\tau D_{i\tau}$ in eq. 1) are also interacted with the dummies d and $(1-d)$.

The baseline results in the previous section reveal no significant differences between the benchmark LP model and its alternative versions that make use of quasi-experimental estimation (see Figures 2 and 3). Hence, in the heterogeneity analysis, we focus on the IRFs of firms' assets obtained from the benchmark LP model. We are reassured that the benchmark model does not suffer from serious misspecification.

4.4.1 Severity and frequency of flood events

First, we consider heterogeneity in terms of disaster severity and frequency of flood episodes. Specifically, we let the IRFs vary for the firms exposed to the alternative types of floods defined accordingly.

Typically, severity is evaluated based on the monetary damages that are caused by the disaster (see, e.g., Roth Tran and Wilson (2020)). This approach has shortcomings, however. As pointed out by Botzen et al. (2019) there are variable thresholds for including events in disaster databases. Moreover, damages therein are recorded as (uncorrected) monetary estimates from local authorities, which may be inflated shortly after a disaster. Further, the quality of disaster intensity measures and reporting may vary across jurisdictions. To overcome these data issues, more recent approaches characterize natural disasters based on primary geophysical or meteorological variables, (Felbermayr and Gröschl (2014); Hsiang and Jina (2014)). We take this alternative route. Specifically, to discriminate among flood events of different degrees of severity, we rely on the categorization provided by Blöschl et al. (2020). Using historical documentary evidence, the authors derive a numerical intensity index that reflects flood magnitude rather than flood damage. As such, the indicator is not subject to the endogeneity bias of ex-post measures based on economic losses. Three categories of flood magnitude are identified: notable (class 1), great (class 2) and extraordinary (class 3). We consider floods in class 2 and class 3 as severe events.

Panel (a) of Figure 4 displays the IRFs for the two subsets of firms: those exposed to severe floods (red line) and those exposed to milder flood episodes (blue line), alongside the corresponding 95% confidence intervals.[18] As expected, large-scale floods turn out to have more disruptive consequences than less severe flood episodes. Compared to unexposed ones, firms hit by a major disaster experience a deterioration of total assets by around 4% already one year after the event. By contrast, over the same time span, the asset damage for firms exposed to less severe flooding is in the range of 1%. In the following years, the IRFs display a marked convergence. Although the point estimates start to diverge again five years out, the associated standard errors are large and the two IRFs are no longer statistically different from each other.

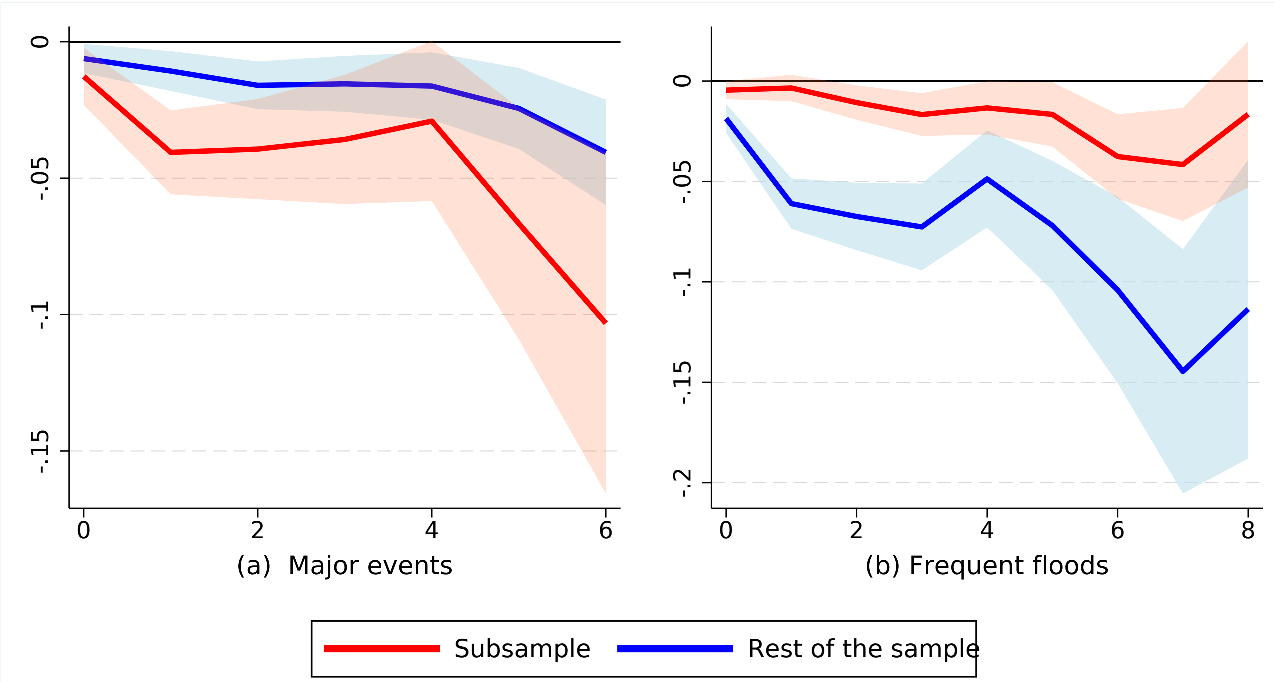
[18]Data on the severity of the floods in Blöschl et al. (2020) are available only until 2016, our estimation sample for this exercise is thus reduced. For the same reason, the IRFs are estimated only up to 6 years after the event.

Next, we look at the frequency of flood episodes as a potential source of heterogeneity in the impact of these hazards. As discussed in Section 3, two regions out of three in our sample experienced more than one flood episode between 2007 and 2018. On average, firms were flooded three times during this period. Hence, we consider firms hit by at least three floods as those exposed to frequent episodes, while we treat those experiencing one or two floods as the alternative subsample. Panel (b) in Figure 4 shows the dynamic impact estimated on the two alternative subsamples. For firms that are repeatedly deluged (red IRFs), the reduction in total assets is significantly milder than that experienced by the firms (blue IRFs) that are flooded less frequently. Assets of firms located in flood-prone areas deteriorate only gradually, by less than 1% one year out, and up to 7% seven years out. Subsequently, there are signs of recovery to the no-flood counterfactual, when the estimated impact of the looses its statistical significance. Firms that are exposed to less frequent water hazards experience more pronounced losses in total assets, which range from more than 6% the year after the flood episode to 14% seven years out. While there are sign of mild recovery in the eighth year, assets remain well below the counterfactual level without floods. The negative impact of the hazards are strongly significant throughout the time horizon under consideration. These apparently counter-intuitive findings are in line with the evidence for US counties documented in Roth Tran and Wilson (2020). We conjecture that our results are indicative of successful adaptation strategies. Arguably, hazards occurring in flood-prone areas are largely anticipated. Hence, firms at risk are likely to internalize the costs associated with flooding by taking adaptation measures, such as taking up insurance or implementing better building standards.[19] However, the lack of sufficiently granular data does not allow to explicitly test for these hypotheses.[20]

[19]We explored the possibility that more frequent floods are generally milder, and found that this is not the case. Hence, we are reassured that the results are not driven by the severity of the flood episodes.

[20]We made an attempt to use proprietary data on insured losses to assess the role of insurance in mitigating the impact of frequent floods. However, the fact that this data is available at the country level, and the limited number of events covered, significantly reduced the size of the (sub)sample(s) and actual within-country variability.

Figure 4: Heterogeneity by severity of floods and number of floods in the county



Notes: the figure displays the impulse responses derived from the local projections (LP) for the firm's total assets. Graph (a) presents the estimated impulse responses for major events (red line) and milder flood episodes (blue line). Graph (b) shows the estimated impulse responses for frequent floods (3 or more in our sample; red line) and less frequent flood episodes (blue line). The light red and blue areas are the associated 95% confidence intervals.

4.4.2 Firm heterogeneity

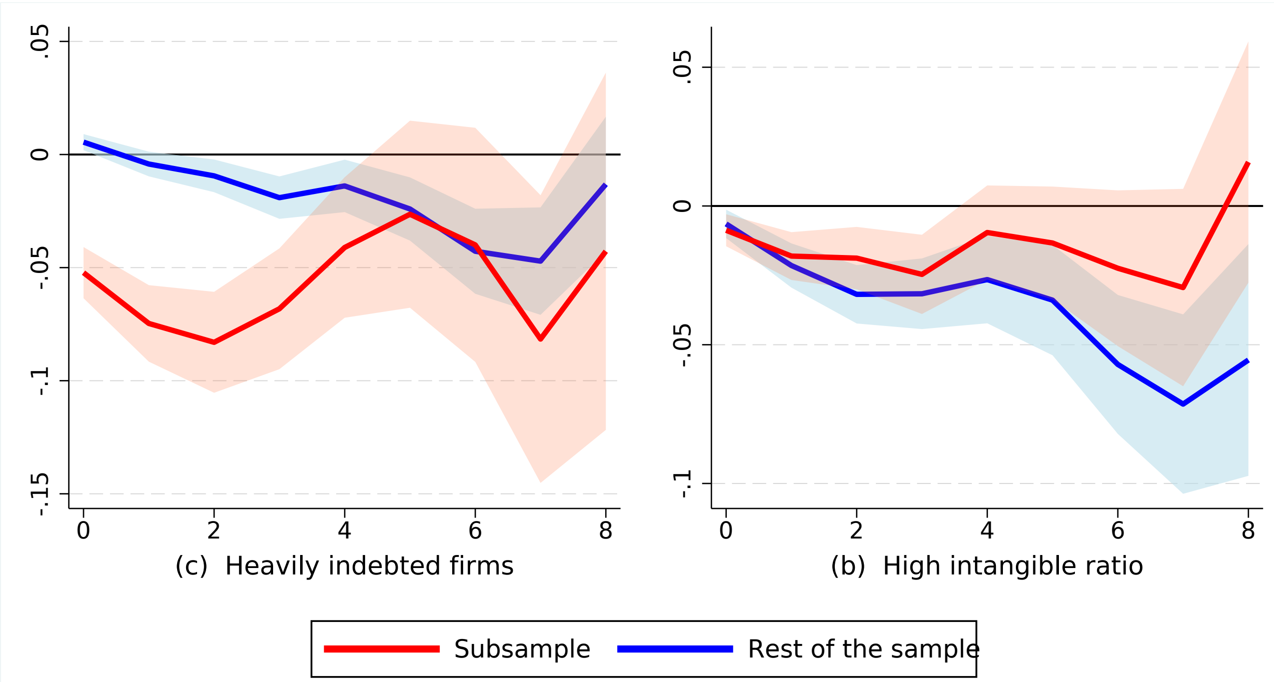
Next, we zoom in on firm heterogeneity as a second important factor in the response to natural disasters. In particular, we examine aspects that likely affect firms' vulnerability to the physical damage and to the loss of fixed tangible capital that are normally associated with the occurrence of water hazards. Importantly, these features impact firm performance not only via the real channel, through the direct damage to production capacity, but also indirectly via the financial channel. The immediate disruption in their operations may impair firms' ability to service and repay their debt, with potential feedback effects onto production and, ultimately, the ability to weather the hazard. This effect may be further exacerbated by the negative water damage effects on the value and availability of physical assets pledged as collateral in bank loans (see, e.g., Koetter et al. (2020); Nguyen et al. (2022); Ouazad and Kahn (2022)). The resulting increase in information asymmetry in credit markets as well as lenders' concerns for climate change after a disaster (Correa et al. (2020)) may worsen access to finance and amplify firm fragility (Ginglinger and Moreau (2019)).

Against this backdrop, we consider firm capital structure, and focus specifically on indebtedness. Thus, we examine separately the dynamic impacts of floods for firms characterized by different levels of leverage. In particular, we classify as highly leveraged the firms with a debt-to-assets ratio in the top quartile of the sample distribution. The remaining firms are those that we consider non-highly leveraged. As discussed above, we expect the latter to be less at risk from flood damage. The respective IRFs are depicted in panel (a) of Figure 5. In line with expectations, more indebted firms appear much more vulnerable to flood damage than less leveraged firms, at least in the short term. Their assets deteriorate by 5% upon impact, and by more than 8% two years out. In magnitude, this is roughly eight-fold the damage suffered by less indebted firms. As of five years after the disaster, highly indebted firms seem to temporarily rebound from the sharp initial drop in assets, although the effect is not estimated with precision, as the large confidence bands indicate. By contrast, less leveraged firms experience a progressive significant deterioration of assets by up to 5% seven years after the flood episode. Also in this case, the impact of the water hazard becomes insignificant eight years out.

The second dimension of heterogeneity that we investigate is firms' reliance on intangible assets in their operations. Generally, intangible capital is associated to higher growth (see, e.g., Corrado et al. (2013); Niebel et al. (2017)). In the context of natural hazards, Leiter et al. (2009) argue that not only intangibles are less vulnerable to physical risk, but, when resulting from R&D and similar activities, such as software, patents or licenses, they may act as a multiplier that enhances post-hazard operating performance. In fact, they document that, on average, a larger share of intangible assets is associated with higher firm growth and productivity in the aftermath of a flood.

In a similar vein, we use the intangible ratio - that is the ratio between intangible and total assets - to split the sample of firms. As the distribution of intangible assets at the firm level is highly skewed, we consider the intangible ratio at the sector level. Hence, firms belonging to a sector with an intangible ratio above (below) the mean sample value are considered as potentially less (more) vulnerable to flood damage. Panel (b) in Figure 5 shows the resulting IRFs. As expect, firms in high-intangible sectors (red line) seem to recover faster from a flood episode than those relying more heavily on tangible capital (blue line). The latter experience a steady deterioration of assets, from 2% the year after the flood to 7% seven years out. The impacts are statistically significant throughout the time horizon under considerations. However, as is apparent, the overlapping confidence intervals do not allow us to draw strong conclusions on the fact that the two groups of firms are actually on statistically different recovery paths after being hit by water damage. Arguably, over time other factors may affect firms' recovery from natural disasters, such as technology diversification (Hsu et al. (2018)).

Figure 5: Heterogeneity by firm characteristics



Notes: the figure displays the impulse responses derived from the local projections (LP) for the firm's total assets. Graph (a) presents the estimated impulse responses for heavily indebted firms (debt-to-assets ratio in the top quartile of the sample distribution; red line) and non-highly leveraged firms (blue line). Graph (b) shows the estimated impulse responses for firms belonging to a sector with an intangible ratio above the mean sample value (red line) and the rest of the firms (blue line). The light red and blue areas are the associated 95% confidence intervals.

5 Survival analysis

Our estimates of the dynamic impacts of flooding suggest that water hazards affect negatively and persistently firm performance. Assets and employment of firms exposed to an average flood in our sample decrease by the 3% on average over the time horizon under consideration, sales are 4.5% lower than they would have been in the no-disaster counterfactual scenario. Moreover, in the previous section we have documented that the negative impacts are unevenly spread across firms, and crucially depend on the frequency and the severity of the flood episodes. Importantly, these results capture the intensive margin of firm adjustment to flooding. In other words, they characterize outcomes of firms that are still in the market after the disaster. When leading to significant deterioration of firm balance sheets, water damage may also affect firm survival, however.[21] In this section, we shed light on post-disaster adjustment at the extensive margin by estimating a model of firm survival.

[21] In principle, firm exit could also take the form of relocation away from inundated areas into areas shielded from water damage. Indaco et al. (2019) find evidence of some relocation following the 2012 hurricane that hit the New York area. By contrast, Kocornik-Mina et al. (2020) document little permanent movement of economic activity away from flooded cities in the US. The nature of our data does not allow us to consider this alternative margin of adjustment for firms.

5.1 The model

To complement the analysis carried out on surviving firms, we investigate the effects of flood events on firms' exit probabilities using an extended Cox model. The aim is to estimate firm survival since 2004, the first year in our sample. We therefore exclude from this analysis firms born after 2004 based on information on their age and the year of the observation. Firms that already existed in 2004, but entered the sample at a later year are considered as left-censored observations.

We define firm exit as a dummy variable which takes the value of one whenever the firm's recorded status is "Bankruptcy", "Dissolved" or "In liquidation" in the following year, and zero otherwise. Firms exiting the sample without any information on the company's dissolution are treated as right-censored observations.

Building on the Cox proportional hazards approach (Cox (1972)), our empirical model assumes that the hazard denoting the probability of firm i exiting the market ($h_i(t)$) at time t depends on a baseline hazard function $h_0(t)$, a distributed lag function of the the treatment dummy indicating that the firm i is impacted by a flood in a given year ($\sum_{\tau=0}^{h} \phi_\tau D_{i,t-\tau}$), and a set of lagged time-dependent covariates $Z_{i,t-k}$:

$$h_i(t|Z_i) = h_0(t) \times \exp(\sum_{\tau=0}^{h} \phi_\tau D_{i,t-\tau} + \mu Z_{i,t-k} + \delta_s + \delta_{c'}), h_0(t) > 0 \tag{3}$$

In our survival model, t refers to the analysis time with $t = 0$ for the year 2004. The baseline $h_0(t)$ depends only on time t and, thus, can take any form, while covariates enter the model linearly. The covariates are time-varying, thus the proportional hazards assumption of the baseline Cox model does not hold. Therefore, we estimate the extended version of the Cox model (a.k.a. non-proportional hazards model; see Kleinbaum and Klein (2011)).

The main parameters of interest, denoted by ϕ_τ, are the effects of current or past flood events on firms' survival probabilities. The vector $Z_{i,t-k}$ includes a set of additional covariates that are likely to affect the firm's survival probability: the return on assets (ROA) as an indicator of profitability; a dummy variable that equals one when a negative ROA is recorded, and zero otherwise; leverage; cash flow (relative to total assets); the intangible ratio, measured as intangible assets over total assets; tangible ratio; total assets, as a measure of firm size; and the firm's age. We also control for industry (NACE2-level; δ_s) and region (NUTS2-level; $\delta_{c'}$) fixed effects to capture exit waves of firms due to sectoral patterns and local shocks. Standard errors are clustered at year level.

5.2 Results

Table 4 displays the main results from the extended Cox model in eq. 3. The parameters are presented in the form of hazard ratios. A statistically significant hazard ratio indicates how the probability of a firm exiting the market is multiplied when a specific determinant changes by one unit. A coefficient higher than one indicates that the variable is a risk factor increasing the probability of firm exit. Conversely, if an estimate is below one, such determinant is considered as a preventive factor inhibiting a firm's exit from the market.

The first simple benchmark model, presented in the first column of Table 4, estimates the impact of an average flood up to 3 years after the event without any pre-determined additional control ($Z_{i,t-k}$). Results show that the average flood immediately increases the hazard rate by a factor of 1.074. The highest probability of failure occurs one year after the event, with an increase in the hazard rate by 9.2%. Conditional on surviving the first two years after the flood, past disasters do not seem to have significant effect on the survival of the firm.

The next two models in the second and third columns of the table include the full list of pre-determined controls $Z_{i,t-k}$. In the second model, only the contemporaneous and one-year lagged flood indicators are included. Accordingly, the model includes the second lag of the additional pre-determined control variable ($Z_{i,t-2}$).[22] The third model incorporates a second-order distributed lag polynomial of the treatment dummy D_{it} and the third lag of the additional controls ($Z_{i,t-3}$). Results from the models augmented with additional controls confirm that floods have a negative impact on firms' survival probability up to two years after the event. The exit probability is the highest in the year following the flood event. When additional explanatory variables are included in the model, the contemporaneous effect of the flood remains significant at the 10% level.

The estimated hazard ratios for the remaining variables are in line with the previous literature. Our estimates indicate that higher and (most importantly) positive ROA, lower leverage, higher cash flow on total assets ratio, higher share of tangible and lower share of intangible assets, as well as greater size and longer existence increase the firm's survival probability.

The last model in the last column of Table 4 assesses the heterogeneity of the impact of flooding on firms' survival probability. In this specification, the lagged treatment dummy D_{it-1} is interacted with the same set of indicators as in Subsection 4.4. In particular, consistent with the analysis in Subsection 4.4, we consider an indicator of major floods; a dummy indicating the firm's exposure to frequent floods; a dummy of heavily indebted firms; and an indicator of firms belonging to a sector with an intangible ratio above the sample mean.

[22] Using the second lags ensures that the control variables are not affected by the flood in $t-1$. Indeed, the flood at $t-1$ arguably affects the firm's performance at $t-1$ (e.g. ROA decreases), which would make it impossible to disentangle the direct impact of the flood from its indirect impact via the firm's deteriorating profitability.

In accordance with the conclusions drawn from the LP models on surviving firms (Subsection 4.4.1), firms that are more frequently deluged seem to be better adapted to face the challenges of extreme weather conditions. Our results show that firms that experience repeated floods have a significantly higher chance of survival following a flooding episode than those which are deluged only once or twice during the same period. This highlights again that firms can indeed take adaptation measures to reduce their vulnerability to the adverse impacts of floods.

On the other hand, contrary to expectations, major floods result in a lower hazard and therefore a longer survival time than less severe events. One possible reason for this puzzling result is that major floods are likely followed by assistance and financial support from governments and public authorities, including in the form of temporary tax relief measures, but also from the general public as they attract broad interest and attention and media coverage, while localised floods might be mostly unnoticed.[23] The peculiarity of a major flood event may also help firms to renegotiate their debt obligations. These supports might help the deluged firm to survive, despite the difficult economic conditions and the firm's deteriorating balance sheets.

Regarding firm characteristics, the survival of highly leveraged firms is severely compromised after being exposed to flooding. The estimated hazard ratio is almost 90% higher for firms with a debt-to-assets ratio in the top quartile of the sample distribution than for less indebted firms. On the other hand, we do not find significant effect of the firm share of intangible assets in total assets on firms' survival potential after a flood.

[23]For instance, in the wake of the disastrous German flooding in summer 2021, the federal government and the Länder set up a recovery fund €30 billion to help the affected households, the damaged businesses and other bodies with reconstruction efforts. The funds were directed also to repair and reconstruction of government-owned infrastructure. Moreover, the immediate assistance package included a waiver of rescue expenses and local tax relief measures. At the same time, solidarity initiatives were set up, which raised contributions from the business and private sector (see, e.g.,Vodafone donates 1,000,000 euros for flood victims).

Table 4: Survival analysis

	W/o controls	DL(1) controls (t-2)	DL(2) controls (t-3)	Heterogeneity
Flood (t)	1.074**	1.035	1.063*	
	(0.027)	(0.029)	(0.032)	
Flood (t-1)	1.092***	1.122***	1.128***	1.880***
	(0.027)	(0.033)	(0.034)	(0.105)
Flood (t-2)	1.019		0.975	
	(0.027)		(0.033)	
Flood (t-3)	1.049			
	(0.030)			
Major flood (t-1)				0.602***
				(0.045)
Food × Frequent floods (t-1)				0.241***
				(0.016)
Food × heavily indebted firms (t-1)				1.874***
				(0.105)
Food × High intangible ratio (t-1)				0.930
				(0.053)
ROA < 0		2.270***	2.047***	2.251***
		(0.034)	(0.033)	(0.034)
ROA		0.944**	0.997	0.952*
		(0.019)	(0.024)	(0.019)
Leverage		1.022***	1.025***	1.022***
		(0.003)	(0.004)	(0.003)
Cash / Total assets		0.512***	0.510***	0.541***
		(0.022)	(0.024)	(0.024)
Intangible ratio		1.530***	1.534***	1.576***
		(0.099)	(0.107)	(0.105)
Tangible ratio		0.467***	0.471***	0.471***
		(0.016)	(0.017)	(0.016)
Total assets		0.855***	0.859***	0.862***
		(0.004)	(0.004)	(0.004)
Age		0.996***	0.996***	0.996***
		(0.001)	(0.001)	(0.001)

*Notes: The table presents the results from various specifications of the extended Cox model. All models include industry (NACE2) and location (NUTS2) fixed effects. *** Significant at 1%; ** significant at 5%; * significant at 10%.*

6 Unravelling the ‘creative destruction’ result

The analysis in the previous sections support the notion that flood events are significantly disruptive for the affected firms. At the extensive margin, flooded firms in general display a higher probability of default in the aftermath of the hazard. At the intensive margins, floods significantly deteriorate the performance of surviving firms. While clearly in accordance with common wisdom, this is at odds with the economic literature that points to natural disasters sparking ‘creative destruction’, both at the microeconomic and at the aggregate level. Creative destruction at a granular level arises essentially because damaged fixed assets are replaced with newer, more productive vintages of capital (Leiter et al. (2009); Noth and Rehbein (2019)). Other margins of adjustment, such as public policies, direct aid, migration, would come into play and determine a positive performance at the aggregate level (see, e.g., Roth Tran and Wilson (2020)). In this section, we discuss our findings in the light of the creative destruction hypothesis, and show how these apparently contrasting results can be reconciled.

6.1 Composition effects and reallocation

When looking at the effect of floods - and natural disasters in general - on firms, the notion of affected entities is crucial. In fact, the creative destruction result at the microeconomic level seems to hinge upon a looser definition of affected firms (Leiter et al. (2009); Noth and Rehbein (2019)). Specifically, all the firms in a flooded region are considered equally impacted by the hazard. At the same time, also recent studies that are able to pinpoint more precisely firm location uncover rather negative impacts of flood events on GDP, although only in the short run, while corporate performance, including entry and exit, seems to be only mildly affected by water damage (Hossain (2020); Jia et al. (2022)).

If the physical impact of floods is contained and localised, we expect the performance of firms in the same region to evolve differently in the aftermath of an hazard. Specifically, firms that are directly exposed to inundation and experience destruction of their physical capital and production facilities in all likelihood suffer more from flooding events than firms that are located further away from the stricken areas, and thus shielded from actual water damage. As physical damage compounds the effect of general disruptions in local product and labour markets, the loss in economic activity will be more marked and persistent for directly exposed firms. Hence, arguably, in the recovery phase, we would expect some reallocation of economic activity across firms depending on their actual exposure to the water hazard.

To formally prove this point, we operationalise the contention above by estimating the heterogeneous effects of floods on firms that are directly impacted and on those that are not impacted by floods occurring in the same county, according to the categorisation introduced in Section 4.2. As before, we consider the firms that are located within a 1-in-10-year flood risk map as the impacted firms, while all the firms in the same county that are located at least 10km away from the flood risk areas defined in the 1-in-500-year maps are those deemed unaffected by the flood event. With this classification at hand, we estimate the IRFs for the two subsamples of firms. Differently to the LP model in eq. 1, we include region-industry (NUTS2×NACE2) fixed effects that account for unobservables heterogenity across regions-industries.[24]

The estimated IRFs, alongside the 95% confidence bands, are plotted in panel (a) of Figure 6 . In line with the baseline results, the blue IRFs indicate a negative dynamic response of total assets for firms that are directly exposed to floods. The loss in total assets gradually reaches 2% in the third year from the hazard. Slightly positive asset growth, although not statistically significant, is recorded only eight years out. By contrast, firms that are in the flooded county but not directly exposed to water damage display a positive performance in the aftermath of the hazard (red IRFs). In particular, the estimated asset growth ranges from around 0.5% in the short run (1-2 years after the flood) to 3% eight years out.

In the spirit of the early 'creative destruction' literature, when a flood occurs in a specific county, we consider all firms in that county as potentially exposed to the hazard. The red IRFs in panel (b) of Figure 6 plots the dynamic response of total assets when all the firms in the affected counties are considered hit by the flood event. As is apparent, the effect of flooding is projected as much milder than in the baseline case, with a maximum contraction of around 1% six years out, followed by a rapid recovery in the subsequent two years. Moreover, the confidence bands indicate that the impact is mostly not statistically different from zero. If we would consider all firms in a flooded county as directly affected by the hazard, we would thus significantly underestimate the negative impact of flooding on firm performance, both in magnitude and in its degree of persistence.

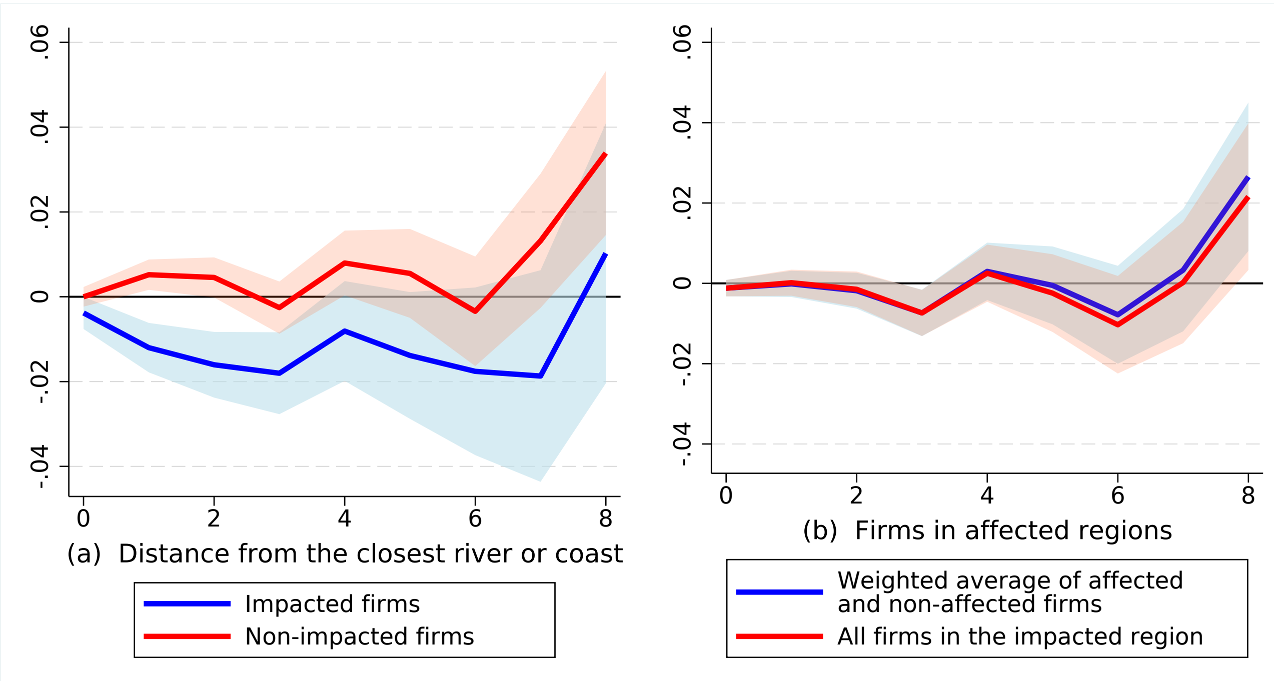
As an alternative way of presenting the results, the blue line in the right hand side panel of Figure 6 displays the weighted average of the two IRFs associated with directly impacted firms and non-impacted firms in the same county presented separately in the left-hand side panel. The IRF almost perfectly overlaps with the one obtained when all the firms in the flooded county are considered affected to the flooding episode, as do the corresponding confidence bands (shaded areas).

Taken together, these findings point to a composition effect driving the 'creative destruction' result when it comes to the impact of natural disasters. In particular, when the impacts of floods are localised and relatively contained, firms directly exposed to water damage experience 'destruction', that is, bear the most disruptive consequences of floods. By contrast, the 'creativity' attributed to flood events in the short and medium term has likely to be ascribed to the firms that, shielded from the direct impact of water damage, can arguably continue and expand their operations in the aftermath of the hazard.

[24]By including NUTS2×NACE2 fixed effects in the model, we implicitly take firms located in non-flooded counties in the same NUTS2 region (and industry) as the control group.

In a way, these firms benefit from reallocation of economic activity within the same local area, with significant growth effect up to the medium term.

Figure 6: Firms in flooded counties



Notes: the figure displays the impulse responses derived from the local projections (LP) for the firm's total assets. Graph (a) presents the estimated impulse responses for firms directly impacted by the flood (blue line) and those in the same county that are not directly exposed to water damage (red line). Graph (b) shows the estimated impulse responses when all firms in a specific county where flood occurred are considered as potentially exposed to the hazard (red line); and the weighted average of the two impulse responses from the left-hand side graph, associated with directly impacted firms and non-impacted firms in the same county (blue line). The light red and blue areas are the associated 95% confidence intervals.

6.2 County-level outcomes

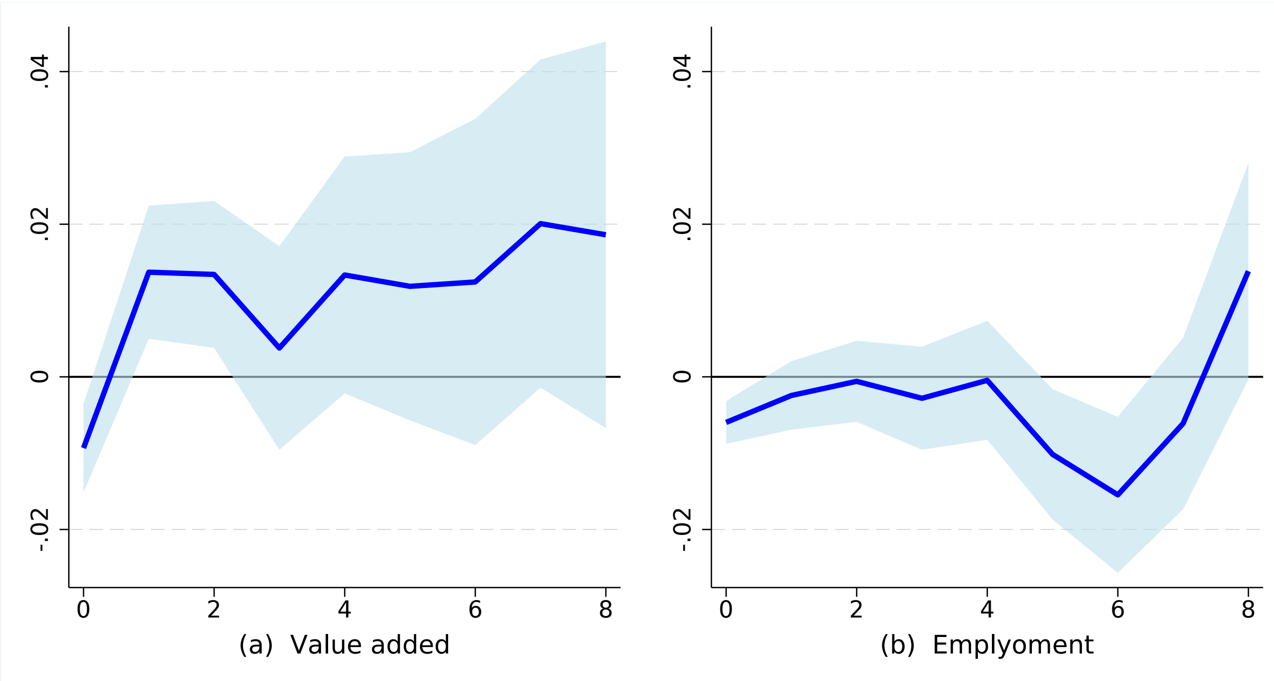
The findings in the previous section highlight the importance of going granular when analysing the impact of natural disasters. Even at the microeconomic level, an imprecise definition of entities actually exposed to flood episodes will likely result in misleading conclusions on the actual disruption brought about by the hazards, hiding important reallocation and composition effects.

In this section, we make a step further and examine how the microeconomic impacts uncovered at the firm level translate when it comes to aggregate outcomes. To this purpose, following Roth Tran and Wilson (2020), we estimate a simplified version of our baseline LP model on panel data at NUTS3 level. Accordingly, the subscripts i in eq. 1 change to subscripts c, denoting the various NUTS3 counties. We focus on two outcome variables, namely gross value added and employment for the industry sector excluding construction (for consistency with the firm-level model estimated on manufacturing firms). The vector $X_{c,k<t-1}$ includes the second and third lags of these variables and we also include country fixed effects.

Figure 7 shows the corresponding IRFs. After a drop upon impact, industrial gross value added shows immediate signs of recovery that last over the medium term, although their statistical significance is not persistent (panel a). Growth above 1% is recorded in the first year after the flood already. Panel (b) in Figure 7 shows the average evolution of employment in the industry sector in flooded regions. Excluding a dip six years out, water damages do not seem to significantly affect employment levels.

These results are in sharp contrast with what we have documented in the analysis at firm level. Clearly, many factors other than adjustments in the corporate sector come into play that are likely to drive aggregate outcomes, such as government transfers to impacted regions, developments on the housing market, or population dynamics (see, e.g., Roth Tran and Wilson (2020)). While uncovering these channels is clearly beyond the scope of this paper, the aggregate outcomes that we document once again are suggestive of the importance of considering adjustment at the microeconomic level in evaluating the consequences of natural disasters.

Figure 7: Industry value added and employment at the regional level



Notes: the figure displays the impulse responses derived from a simplified version of the baseline local projection model (LP) on regional panel data at NUTS3 level. The left-hand side graph presents the impulse response for the regional gross value added for the industry sector excluding construction, and the right-hand side graph shows the results for regional employment in the same sectors. The X-axes correspond to the number of years after the flood events (h). The blue lines indicate the estimated impacts of the flood on the outcome variable h years after the event ($\hat{\beta}_h$), and the the light blue areas are the corresponding 95% confidence intervals.

7 Conclusion

Floods are among the climate-related hazards most likely to intensify because of the long-term increase in temperature and the subsequent more extreme weather patterns. As the frequency and severity of flood events, and the associated economic, social, and environmental costs, are expected to increase further in the decades ahead due to global climate change, understanding their impact is of paramount importance, particularly for the design of policies and private schemes aimed to increase the resilience of the affected economic agents and local communities. Reinforcing adaptive capacity and minimising vulnerability to climate impacts requires a better understanding of how economic behaviour and activity might evolve following natural disasters.

In this paper we investigate the dynamic impacts of flood events on European manufacturing firms during the 2007-2018 period. We exploit a rich database on historical natural hazards, combined with granular flood risk maps and detailed information on firm geolocalisation to examine the performance of firms that are directly affected by the floods hitting a specific area. We find that water damages have a significant and persistent adverse effect on firm-level outcomes. In the year after the event, an average flood deteriorates firms' assets by about 2% and their sales by about 3%, without clear signs of full recovery even after 8 years. While adjusting more sluggishly, employment follows a similar pattern, experiencing a contraction for the same number of years at least. The drop in firms' activity and the sluggish reaction of employment result in deteriorating labour productivity during the first two years after the flood. The productivity then starts to slowly recover before reaching its pre-flood level after about 6 years. On the other hand, average wages in the impacted firms remain subdued for at least 8 years.

Major flooding episodes are far more disruptive than milder ones. Moreover, highly indebted firms fare particularly poorly in the aftermath of flooding, arguably due to deteriorated credit conditions following the destruction of physical capital that can be pledged as collateral for bank credit. On the other hand, more frequent floods do not significantly worsen firm performance. We consider the latter results as suggestive of successful adaptation strategies being adopted in flood-prone areas. Finally, we find evidence that flooding may endanger firm survival, as firms exposed to water damages are on average less likely to remain operative.

Overall, our findings suggest that floods have disruptive consequences for firm performance. We reconcile this conclusion with the evidence on 'creative destruction' often advanced in the literature on the impact of natural disasters by documenting diverging dynamics and significant reallocation of economic activity between firms actually exposed to water damage and unaffected firms in flooded regions. Similarly, these important composition effects remain inevitably hidden when we consider the positive evolution of regional aggregates. Our analysis points to the need to consider adjustment at the microeconomic level in evaluating the consequences of natural disasters.

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