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

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Abstract

Exploiting a rich database on natural hazards and detailed information on firm geographical location, we investigate the dynamic impacts of flood events on European manufacturing firms during the 2007-2018 period. 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%, without clear signs of full recovery even after 8 years. While adjusting more sluggishly, employment follows a similar pattern, experiencing growth in negative territory for the same number of years at least. While the estimated order of magnitude may appear negligible, the frequency of water hazards suggest a significant compound effects from repeated floods with potentially disruptive economic and social consequences for regions that are hit repeatedly.

1 Introduction

Natural disasters, particularly those related to climate change, have become more frequent and severe in recent decades Agency (2019). Damages and economic losses associated to these hazards have also been on an upward trend. In the European Union (EU), such losses already average over 12 €billion per year. Conservative, lower bound estimates show that exposing today's EU economy to global warming of 3°C above pre-industrial levels would result in an annual loss of at least 170 €billion, or 1.36% of EU GDP.

Against this backdrop, 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.

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Blöschl et al. (2020) document that the past three decades were already among the most flood-rich periods in Europe in the past five hundred years, and that this period differs from other flood-rich periods in terms of its extent, air temperatures and flood seasonality. 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 50 €billion/year. By the same token, coastal flood losses would grow by two orders of magnitude and climb to 250 €billion/year in 2100, while 2.2 million people per year would be exposed to coastal inundation, compared to 100,000 at present.

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. The European Green Deal, while committing to climate neutrality by 2050, aims also to better prepare the EU to the unavoidable impacts of climate change through an ambitious adaptation action, in line with the Paris Agreement. Reinforcing adaptive capacity and minimising vulnerability to climate impacts requires a better understanding of how economic behaviour and activity might evolve following natural disasters. While there is abundant literature on the aggregate economic impacts of natural disasters, empirical studies with a microeconomic perspective have emerged only recently thanks to the availability of sufficiently granular data. Such microeconomic evidence is particularly relevant in order to better design and tailor policy intervention.

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 natural hazards and detailed information on firm geographical location to pin down companies that are directly affected by the floods hitting a specific region. 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%, without clear signs of full recovery even after 8 years. While adjusting more sluggishly, employment follows a similar pattern, experiencing growth in negative territory for the same number of years at least. While the estimated order of magnitude may seem negligible, the frequency of flood events suggest a significant compound effects from repeated floods with potentially disruptive economic and social consequences for regions that are hit repeatedly.

Our paper is related to the growing literature investigating the economic consequences of natural disasters using firm-level data. Leiter et al. (2009) consider the shock caused by the 2000 floods that hit France, Italy, Spain, and United Kingdom. Relying on the NUTS2 geographic classification, they find that assets and employment of firms located in the affected regions increase compared to firms located in untreated regions in the two years following the event. They document a heterogeneous effect across firms, with a stronger impact among those with high shares of intangible assets. Yet, after the flood, productivity decreases, particularly when the share of intangible assets is higher. Coelli and Manasse (2014) investigate the short-term impact of the 2010 flood in the Italian region of Veneto. Using a difference-in-difference setting, they document that firms affected by floods have a value added growth in the two years after the shock in the order of 6.9 percentage points, of which 2 percentage points are due to disaster aids.

In contrast to early studies that suggest 'creative destruction', more recent papers uncover negative and persistent effects of natural hazards and climate risks on firm performance and behaviour, including location choices, investment decisions and upward and downward business relationships. Hossain (2020) studies the impact of floods on manufacturing Indian firms using satellite images. She finds a negative effect on output, capital, and employment with some differential effect across firms based on productivity. She also documents a certain level of reallocation of employees to the informal sector. Severe impacts on employment are documented also in Indaco et al. (2019). They study 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 in the period 2013-2017, and a relocation of some firms to less risky areas suggesting that climate risk may affect business location.[1] In Hsu et al. (2018) natural disaster reduces operating profits of firms in affected areas in the range of 1-2 percentage points. Still, technology diversity – measured with the Herfindahl index of technology categories of patents – allows firms to absorb these shocks with less disruptive consequences. In Hsu et al. (2019) firms with high corporate social responsibility (CSR) ratings are the ones that, when affected by natural disasters, experience a less marked reduction in profitability.

Extreme weather events, which are becoming more frequent because of climate change, have consequences also for firms' investment choices into particular assets. Focusing on the electricity producing industry, Lin et al. (2019) show that utilities invest more in flexible power plants in those regions where extreme weather conditions cause more volatile and hotter temperatures. The effect seems to be driven by long-term changes in climate rather than abnormally high temperatures that occur over a short period. By the same token, using Indian monsoon data, Rao et al. (2021) show that rain-sensitive firms adjust their investment strategies to generate value based on the extreme rainfall conditions. In other words, they tend to significantly increase their investments following excess rainfall periods, while reducing investment following deficit rainfall periods. Li et al. (2020) document that, in response to higher unexpected climate risk, public firms significantly increase their investment but experience lower employment growth the following year. Moreover, there is evidence that climate related risks decrease firms' market valuations (Hong et al. (2019); Sautner et al. (2020)) and increase borrowing costs (Faiella and Natoli (2019); Rehbein and Ongena (2020); Correa et al. (2020)). Brown et al. (2021) find that banks charge higher interest rates, accompanied by stricter loan provisions, to

[1]These findings are related to the literature investigating how climate change impacts on real estate prices (see, e.g., Baldauf et al. (2020); Murfin and Spiegel (2020)).

firms drawing on their credit lines in response to the cash flow shocks from unexpectedly severe winter weather and snowfalls.

The availability of detailed customer-supplier data for some countries has enabled the analysis of the disruptions that natural disasters cause to production networks. Evidence from the 2011 earthquake in Japan highlights spillover effects in the supply chain (Todo et al. (2015); Carvalho et al. (2021)) that propagated across countries via multinational firms (Boehm et al. (2019)).[2] Idiosyncratic shocks from major natural disasters that affect suppliers are found to impose substantial output losses on customers, especially when the produced inputs are specific. These output losses translate into significant market value losses, and spill over to other suppliers (Barrot and Sauvagnat (2016)).

Climate change risks not only reduces the operating performance of suppliers and customers, but may also lead to termination of supply chain relationships (Pankratz and Schiller (2019)). Similarly, exploiting production networks, Custodio et al. (2020) find that increases in local temperature lead to a reduction in supplier sales. This effect, which is more pronounced among suppliers in manufacturing and heat-sensitive industries, can be attributed mainly to a contraction of labour supply and productivity due to workers' absence or harder working conditions from weather shocks.[3] This finding is in line with previous evidence suggesting that climate change leads to a reduction in labour supply and productivity (Graff Zivin and Neidell (2014); Chen et al. (2019)).

A related strand of literature considers the impact of natural disasters on the economy at aggregate level, with mixed conclusions. While most of the evidence point to a negative aggregate impact of natural disasters in the short-run (Raddatz (2007); Noy (2009)), there are some exceptions (Cunado and Ferreira (2014); Cavallo et al. (2014)). Cunado and Ferreira (2014) document a positive impact on GDP already two years after the flood events, while Cavallo et al. (2013) find that there is no statistically significant impact on GDP. As for the long-run impacts, against the mixed predictions of macroeconomic growth models, the empirical evidence points to a positive effect of natural disasters (Skidmore and Toya (2002); Cuaresma et al. (2008)). Positive impacts on income per capita at the county level are uncovered by Tran and Wilson (2020) starting from eight years after the disaster, however with some variability across disaster severity, types of disaster, pre-disaster level of income, and the frequency with which individual areas have previously been hit. Overall, heterogeneity across the areas that are considered in the different studies might be an important determinant of the lack of consensus on whether natural disasters have positive or negative economic impacts. Indeed, institutional and other domestic factors (i.e. political factors) seem to affect both the severity of the macroeconomic effect and the subsequent recovery (Cavallo et al. (2013); Felbermayr and Gröschl (2014)).[4] An emerging strand of the literature highlights the role of natural disasters as a source of

[2]Some papers document an impact of earthquake also on pricing behaviours Cavallo et al. (2014); Heinen et al. (2019).

[3]Differently, Addoum et al. (2020) conducting an analysis at establishment-level find no effect for extreme temperatures on sales, productivity and profitability.

[4]Also higher temperatures are negatively related on GDP growth and trade, however with heterogeneous effect across countries (Dell et al. (2008); Jones and Olken (2010)).

risk for public finance and financial stability. Klomp (2014) show that natural catastrophes threaten the solvency of commercial banks. Böhm (2020) study climate risk in a sample of emerging countries and find detrimental effects on sovereign creditworthiness. Vulnerabilities to climate risks are associated to an increase in public spending, which reduces public debt sustainability (Klomp (2017)), and may further restrict market access for those sovereigns that are frequently hit and, thus, more exposed to default (Mallucci (2020)).

Our paper differs from these studies in several ways. From a methodological point of view, we use a panel version of the local projections estimator, which allows us to characterize the dynamic reaction of relevant firm-level variables following the exogenous climate shock. To the best of our knowledge, the local projection method has so far been applied to study the effect of natural disasters only by Tran and Wilson (2020), who investigate their local economic impact on affected counties in the US. Moreover, the sheer majority of existing studies providing firm-level evidence refer to a single region, one or a limited number of countries, and often a single disaster event. By contrast, we employ a rich cross-country dataset covering 17 European countries for the period 2007-2018. While we focus on floods, our setup allows us to derive a comprehensive picture of the effect of this specific type of climate-related hazards on firms in the the context of developed countries, which are increasingly affected by extreme weather events Agency (2019).

The remainder of this paper proceeds as follows. First, Sections 2 and 3 present the data and describe the sample. Then, Section 4 introduces the econometric strategy. Section 5 illustrates the main results of the impact of floods on firm-level outcomes. Section 6 concludes.

2 Data

Flood data are from the Risk Data Hub (RDH) loss dataset compiled by the Joint Research Centre of the European Commission (Faiella et al. (2020)). The dataset is a harmonized collection of multiple databases and metadata of past natural disasters in Member States. The data available 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. Quantitative information on the event – such as the area affected, the number of injured and dead people – is available only for about half of the sample.

We focus on floods (river floods, flash floods and coastal floods) and retain events for which the affected areas could be identified at the NUTS3 level. Furthermore, we drop from the sample countries with no or very few events recorded during the 2007-2018 period.[5] The final sample includes 17 European countries, accounting for about 86 per cent of the GDP of the EU28.[6]

Financial data and information on firms' location are retrieved from the Orbis historical dataset, the largest international database for firms compiled by Bureau van Dijk, a Moody's Analytics Company. Orbis collects detailed information on firms' balance sheets and income statements at an annual frequency from official business registers, annual reports, newswires, webpages, and commercial information providers. As the database includes a large universe of firms across the globe,[7] an increasing number of academic papers rely on it (see, e.g., Cravino and Levchenko (2017); Aminadav and Papaioannou (2020)). For each firm, we consider unconsolidated financial information, the sector of activity (NACE Revision 2 codes),[8] and the headquarter's address. We restrict our sample to manufacturing firms over the 2007-2018 period.

The two datasets are linked using firms' location at the NUTS3 level. To further refine the identification of impacted firms, we exploit as much as possible the information on firms' exact location and their distance from the nearest river or coast. We assume that firms which are located closer to a river or the coastline have higher probability of being damaged than more distant firms whenever a flood occurs in the region.

Orbis includes the exact coordinates (latitude and longitude) for the majority of firms (about 55%; see the second row of Table 1). For the rest, we merge firms' postal codes in Orbis with the GeoNames database on geographic coordinates of all postal codes in the relevant countries.[9] 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 1). In about 2 per cent of the cases, the postal codes recorded in Orbis cannot be perfectly matched with the postal codes in Orbis. 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: UK and Ireland – we identified firms' location using 3-digit outward postal codes (fourth and fifth rows of Table 1).[10] 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 1).

[5]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 used to calculate the distance of the firms from the nearest river or coast; see more on this in Section 4.2 – are not available for this country.

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

[7]Yet, coverage varies from country to country, particularly of small firms.

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

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

[10]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 3.7 km $\times$ 2.9 km.

Table 1: Geocode

	Nb. of obs.	%
Missing geographic info	341,504	3.71
Firm geolocalised	5,048,987	54.89
Postal code geolocalised	3,613,313	39.29
Nearest neighbour postal code	166,926	1.81
3-digit postal codes for the UK and IE	26,368	0.29
Not geolocalised	474	0.01

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

The first three rows of Table 2 show the distance (in km) between the firms' geographic location based on their exact coordinates and the location defined by their postal codes for firms for which both sources of location information are available. 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). With full postal codes, the average distance between the firm's location based on its coordinates and the centroid of the area defined by the postal code is 3.1 km, and the median is 1.7 km. The distance increases when less precise postal codes are used (second and third row).

The distribution of the distance measures can also be used to spot likely errors in the location data: if the distance defined above exceeds a certain threshold, either the firm level latitude and longitude data or the postal code is probably inaccurate. We classify an observation as outlier if the distance measure is more than 5 times the interquartile range above the third quartile. The number of outliers is reported in the last row of Table 2. In these 115,689 cases (1.3% of the sample), the geolocalisation based on the full postal codes is accepted.[11]

Hydrographic data are taken from the US National Centers for Environmental Information. The shapefiles contain high resolution geographic coordinates of all rivers, lakes, and shorelines/coastlines worldwide.[12] As before, geodesic distances between firms' location and the geographic location of rivers and coastlines are calculated using Vincenty's formula. The shortest distance to any river or coast is recovered using an iterative process.

[11]The choice of trusting the information on the postal code rather than the firm's coordinate recorded in Orbis is based on random inspection of the data. A few outliers are also detected when the nearest neighbour or 3-digit postal codes are used. In these cases, we keep the firms' location data in Orbis.

[12]We use high resolution shapefiles for both the shoreline and the river database. The data are distributed in several levels. For the shoreline data, we keep only (L1) continental land masses and ocean islands, and (L2) lakes. Islands in lakes, ponds in islands within lakes, and data on Antarctica (L3 to L6) are not considered. As for the rivers, we consider (L1) Double-lined rivers (river-lakes); (L2) permanent major rivers; (L3) additional major rivers; (L4) additional rivers; (L6) major intermittent rivers; (L7) additional intermittent rivers; and (L9) major canals. Minor rivers (L5) and intermittent rivers (L8), as well as irrigation canals (L11) are disregarded.

Table 2: Distances (in km) between spatial data points defined by the firms' geographic location, the postal codes and the nearest river or coast

	Distances between the firms' location and the centroid of the area defined by the postal code			Distances from the closest river or coast	
	Postal code	Nearest neighbor postal code	3-digit postal codes (UK and IE)	All firms	Firms in impacted regions
Mean	3.133	7.729	5.408	15.401	15.434
Std.	3.929	7.390	7.316	14.991	14.938
Min.	0.001	0.018	0.028	0.002	0.002
P5	0.055	0.701	0.310	0.677	0.714
P25	0.527	2.601	1.014	3.347	3.423
Med.	1.715	5.210	2.519	10.884	10.906
P75	4.153	9.612	5.602	22.890	23.158
P95	11.339	21.587	23.753	46.015	45.828
Max.	23.823	53.065	37.862	108.254	108.254
Nb. of outliers*	115,689	552	238		

*Notes: The first three rows of the table show the distance (in km) between the firms' geographic location based on their exact coordinates and the location defined by their postal codes for firms for which both sources of location information are available. The last two rows present the distribution of the distances between the firm location and the nearest river or coast, separately for all firms in the database and for firms located in impacted regions. *An observation is classified as outlier if the distance measure is more than 5 times the interquartile range above the third quartile.*

The last two rows of Table 2 present the distribution of the distances between the firm location and the nearest river or coast, separately for all firms in our database and for firms located in impacted regions. The distance varies between 0 and 108 km, with a mean of 15.4 km and a median of 10.9 km. The method for estimating the relevant distance below which a firm is considered as impacted by the flood is presented in Section 4.2.

3 Recent floods in Europe

In the past three decades Europe suffered from one of the most flood-rich periods over the past 500 years. Not only floods have become more frequent and bigger in extent since the early '90s, but the recent period also differs from previous flood-rich periods in the timing of the floods and the relationship between flood occurrence and air temperatures. While previous flood-rich periods were associated with relatively (about 0.2 – 0.3 °C) lower average air temperatures, global warming with increasing air temperatures (about 1.4 °C warmer than the previous interflood period) is one of the main drivers of the current flood-rich period (Blöschl et al. (2020)).

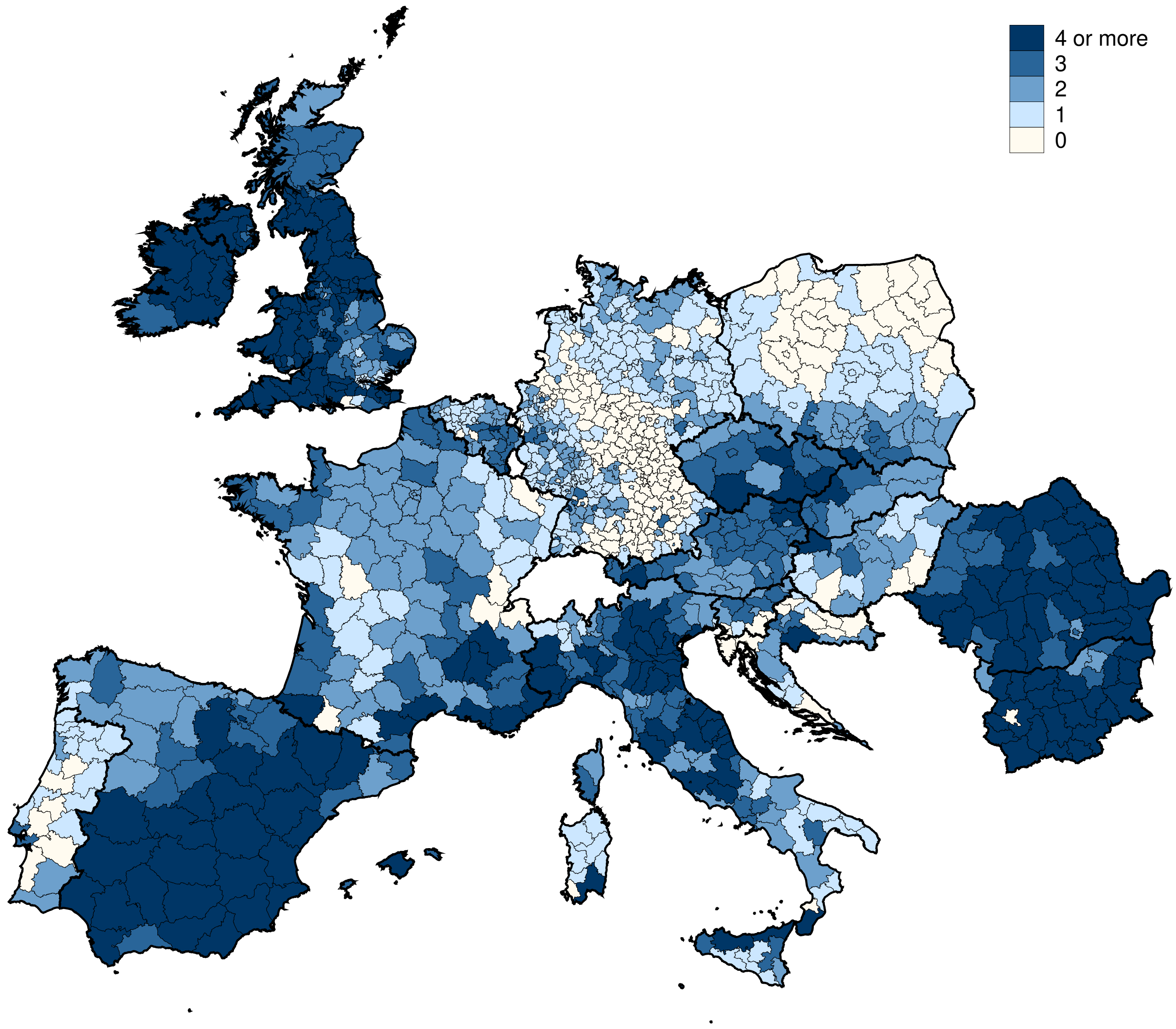
Figure 1 shows the geographical distribution of flood events in Europe between 2007 and 2018, with darker blue colours indicating a higher frequency of flood events in the region. Floods are particularly frequent in the Mediterranean basin area, where enhanced evaporation and convective activity have 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 region, floods are typically associated with prolonged heavy precipitation hitting large areas, which is 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)).

Overall, about 78 per cent of the NUTS3 regions in the selected countries have been hit at least once by a flood during the 2007-2018 period (see the last column of Table 3). Out of the 1,026 affected regions, 681 have been deluged more than once. In some regions, in particular in the United Kingdom, Spain, and Romania, floods are so frequent that they represent the norm rather than the exception (Table 3). Conversely, Germany, Poland and Croatia experienced relatively fewer flood events. In these countries, 33 - 43 per cent of the regions have been spared flooding during the period considered. This is, however, at least partly related to the higher spatial granularity of the areas defined at the NUTS3 level, especially for Germany and Croatia.[13]

Repeated floods in the same regions present a challenge for isolating the long-term economic impact of one particular flood. The 345 regions with only one flood event during the 2007-2018 period provides an important piece of information for the identification of firms' dynamic responses to floods. In the rest of the impacted regions, firms' performance after a specific flood is also contaminated by the persistent impact of past floods. As shown in Table 4, on average, the temporal distance between flood events in regions affected by multiple floods is about three years. Expectedly, the average number of years between events is decreasing with the number of events in a given region. It is thus 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).

[13]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. Districts in Germany and provinces in Spain correspond to NUTS3 regions.

Figure 1: Map



Notes: Canary Islands, Overseas France, the Azores and Madeira are not shown.

Table 3: 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: Number of regions by frequency of floods. The column "Total" displays the total number of regions affected by a flood at least once between 2007 and 2018. The last column shows the percentage of the regions in a given country with at least one flood event recorded in our sample.

Table 4: 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 regions affected by multiple floods during the 2007-2018 period.

4 Identification strategy

4.1 The econometric models

To assess the impact of a flood on manufacturing firms, we rely on three interrelated econometric models. In our first model, we use local projections (LP) to investigate the firms' dynamic responses to flood events. The general LP method is documented in Jordà (2005). In a panel framework, the impulse response function is estimated sequentially for each horizon $h = 0, ..., H$ using the following equation:

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

where $y_{i,t+h} - y_{i,t-1}$ is the cumulative change in the outcome variable of firm i between time $t-1$ and $t+h$; D_{it} is the treatment dummy indicating that the firm i is impacted by a flood in time t; $\sum_{\tau=0,\tau\neq t}^{h} \theta_\tau D_{i\tau}$ is a set of dummies controlling for all other floods that occurred before the current event or between the current disaster and the horizon of interest h; and δ_{sch} are region- and industry-specific (NUTS3×NACE3) fixed effects. In addition, a 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; the share of tangible, intangible and fixed assets in total assets; leverage; and the firm's age. To control for the cyclical position of the economy, we also include in vector X 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 impulse response function 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. Assuming that the error-terms ε_{ith} are independent and identically normally distributed, the $H + 1$ equations can be estimated separately for each horizon using simple ordinary least squares (OLS). Tran and Wilson (2020) use a similar LP method to study the local, county-level impact of natural disasters in the U.S. on a broad range of outcome variables.

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 $1/\hat{\Pr}$, whereas non-treated firms receive a weight equal to $1/(1-\hat{\Pr})$. 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_{sch}), 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.

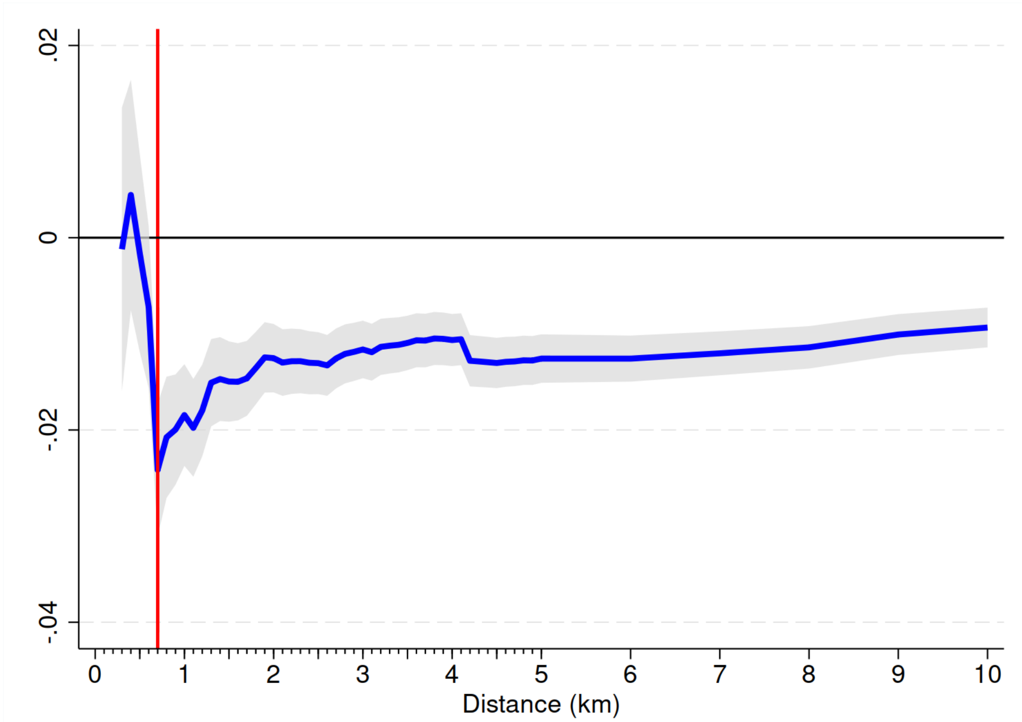
4.2 The treated and the control groups

Firms impacted by a flood are not directly observed. As explained in Section 2, the flood events are recorded in our database at the NUTS3 regional level only. Nonetheless, the whole region is unlikely to be affected whenever a flood occurs in the region.

To better distinguish between firms affected by the flood and those in the same region which haven't been damaged, we assume that the likelihood of being affected depends on the distance between the firms' geographical location and the nearest river or coast. This distance is calculated as explained in Section 2. To identify the relevant distance below which an average flood is likely to cause damage, we recursively re-estimate eq. 1 by taking different threshold values for the distance from nearest river or coast below which the firm is considered as treated (and more distant firms are placed in the control group). In each iteration, the treated group and the control group are redefined according to the given threshold. The outcome variable is the change in firms' total assets between one year before and one year after the flood event. That is, we fix $h = 1$ for each estimation. Even if the flood occurs close to the end of the year, we expect the impact of the flood on the treated firms' total assets to be detectable in the following year.

Figure 2 presents the results of this exercise. The X-axis shows the relevant distance in km, and the Y-axis presents the estimated impact of the flood on the firms' total assets (in log) one year after the flood event. The blue line is the estimated coefficient $\hat{\beta}_1$ of eq. 1 for a threshold starting from 300m up to 10km away from the closest river or coast, and the grey area is the corresponding 95% confidence interval. The model is re-estimated for every 100m up to 5km, then every km up to 10km.

Figure 2: Impact on total assets & distance from the closest river or coast



Notes: the figure shows the estimation results from the LP model with $h = 1$ for different threshold values for the relevant distance from the closest river or coast above which the firm is considered as treated. In each iteration, the treated group and the control group are redefined according to the the given threshold. The X-axis shows the distance in km, and the Y-axis presents the estimated impact of the flood on the firms' total assets (in log) one year after the flood event. The blue line is the estimated coefficient $\hat{\beta}_1$ of eq. 1 for a threshold starting from 300m up to 10km away from the closest river or coast, and the grey area is the corresponding 95% confidence interval. The model is re-estimated for every 100m up to 5km, then every km up to 10km.

Results reveal that the largest difference between the treated and the control groups is identified when 700m is taken as the threshold for the distance that discriminates between the two groups. Above this threshold, more and more unaffected firms are considered as treated. As a consequence, the difference between the firms' total assets in the treated and the control groups one year after a flood event slowly converges towards zero as the threshold is increased. Conversely, as we approach closer and closer to the river or the coast, we misclassify more and more affected firms by placing them into the control group. As a result, the difference between the outcome for the treated and the control groups quickly disappears.

In our empirical specifications, we thus define treated firms those which are located up to 700m away from the closest river or coast in an impacted region. Overall, about 5% of the firms are directly exposed to a flood of an average size (see Table 2 in Section 2). By taking into account the number of regions affected by a flood event and the frequency of floods in our sample, we arrive to the conclusion that, on average, about 1% of the manufacturing firms suffer from water damage every year in the countries considered. The location of the affected firms is displayed on a map in Figure A.1 in Appendix A.

To make sure that the control group does not include affected firms, we drop from the estimation sample all firms that are located at a distance between 700m and 10km from the nearest river or coast. 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.

5 Estimation results

The purpose of the first step of the AIPW and the doubly robust AIPW models is to rebalance the treated and the control groups with respect to all possible pre-treatment characteristics, so that the reweighted sample satisfies the unconfoundedness assumption. The balance tables on the unweighed and the weighted samples – where weights are given by the inverse propensity scores obtained from the first-stage probit (eq. 2) – are shown in Table 5. The unweighted mean and median values of the covariates in the treated and the control groups (first two columns of the table) are reasonably close to each other. When propensity scores are used (last two columns), the resulting groups are almost perfectly balanced with respect to all observed characteristics.

Figure 3 shows the estimated impulse response functions using the LP (graphs on the left-hand side), the AIPW (in the middle) and the doubly robust AIPW models (on the right-hand side) for total assets (in log, first line) and the number of employees (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 grey areas are the corresponding 95% confidence intervals.

The results from the three models are very similar (Figure 3), suggesting that specification errors are negligible. Water damages have a significant and persistent adverse effect on firms' total assets. In the following year after the event, an average flood deteriorates firms' total assets by about 2%. Although the impact of the flood on total assets is not statistically significant after about 5-7 years (depending on the model), the impulse responses do not show clear sign of recovery even after 8 years.

Table 5: Balance table on predetermined variables

	Unbalanced sample		Balanced sample	
	Control	Treated	Control	Treated
Total assets (t-2)	12.898 (13.069)	12.282 (12.445)	13.685 (13.578)	13.685 (13.591)
Total assets (t-3)	12.958 (13.119)	12.391 (12.533)	13.635 (13.537)	13.635 (13.533)
Nb. of employees (t-2)	2.299 (2.197)	2.126 (1.946)	2.461 (2.303)	2.461 (2.303)
Nb. of employees (t-3)	2.324 (2.197)	2.095 (1.946)	2.448 (2.303)	2.448 (2.303)
Share of intangible assets (t-2)	0.029 (0.000)	0.046 (0.000)	0.027 (0.000)	0.026 (0.000)
Share of intangible assets (t-3)	0.028 (0.000)	0.045 (0.000)	0.028 (0.000)	0.028 (0.000)
Share of tangible assets (t-2)	0.268 (0.192)	0.309 (0.170)	0.279 (0.221)	0.276 (0.211)
Share of tangible assets (t-3)	0.271 (0.196)	0.281 (0.172)	0.280 (0.223)	0.277 (0.211)
Share of fixed assets (t-2)	0.306 (0.246)	0.320 (0.229)	0.330 (0.288)	0.327 (0.283)
Share of fixed assets (t-3)	0.311 (0.250)	0.330 (0.235)	0.330 (0.289)	0.327 (0.283)
Share of current assets (t-2)	0.700 (0.754)	0.739 (0.770)	0.671 (0.712)	0.673 (0.717)
Share of current assets (t-3)	0.697 (0.750)	0.700 (0.765)	0.671 (0.711)	0.673 (0.717)
Leverage (t-2)*	0.781 (0.687)	0.846 (0.689)	0.713 (0.672)	0.784 (0.686)
Leverage (t-3)*	0.758 (0.686)	0.809 (0.684)	0.708 (0.684)	0.771 (0.696)
Age	16.603 (13.000)	14.297 (11.000)	20.618 (17.000)	20.617 (17.000)
Output gap	-0.000 (0.001)	-0.011 (-0.015)	-0.007 (-0.006)	-0.007 (-0.002)

*Notes: the table shows the mean values and the medians (in parentheses) of the predetermined variables (two and three years before the flood event) for the control and the treated groups. The first two columns display the raw statistics on the unbalanced sample, while the last two columns correspond to the rebalanced (reweighted) sample. * To remove extreme outliers, the leverage (both the second and third lags) are winsored at the 1st and the 99th percentiles.*

The number of employees reacts more slowly to flood damages. The following year after the event, the number of employees remains unaffected, and it becomes significantly lower than in the control group only after 3 years. The impulse response then follows a prolonged U-shaped path. The magnitude of the shock after 5 years is comparable to that of the total assets. Although the recovery in the number of employees is more visible than in total assets, the point estimates remain negative at least until 8 years after the event.

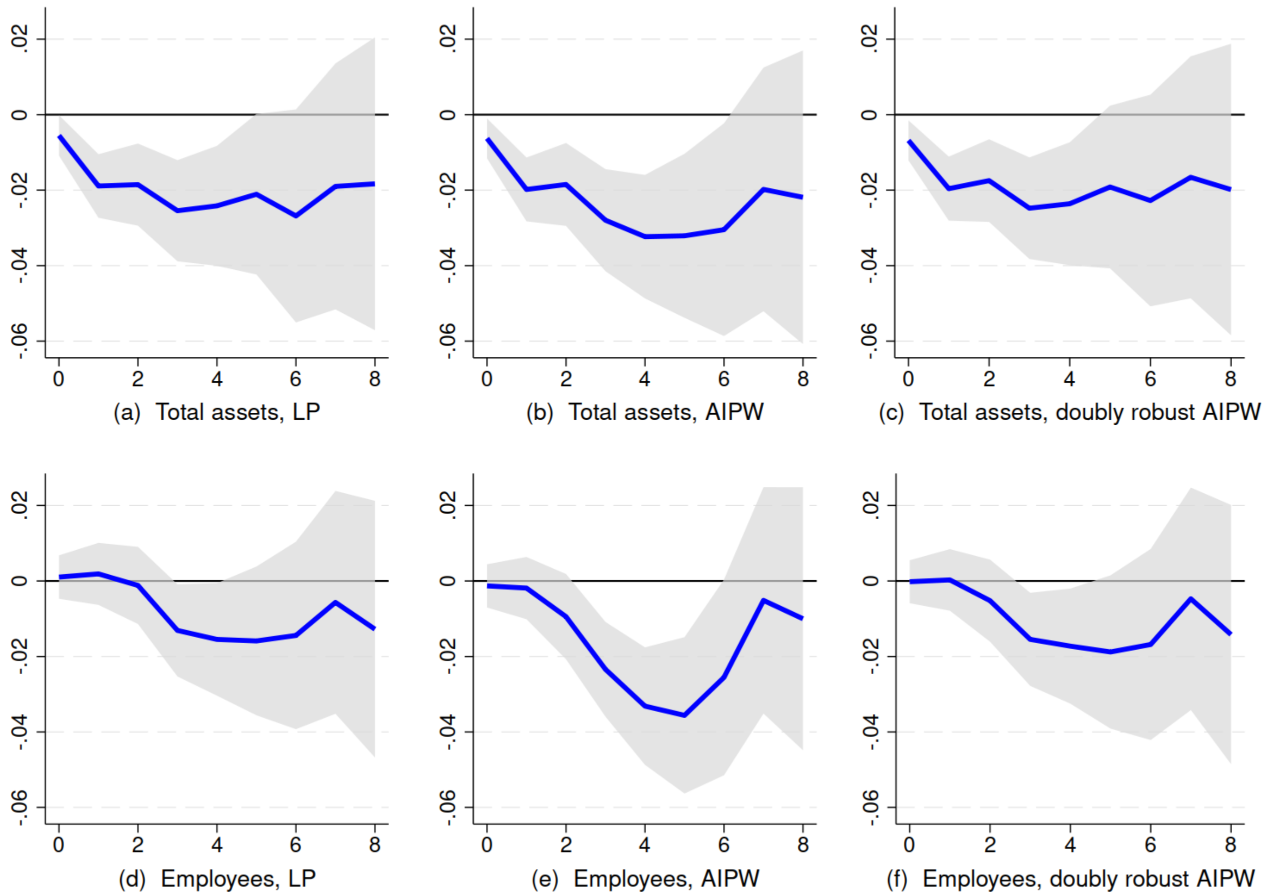
Several factors can possibly explain the sluggish adjustment in employment. For example, legal impediments to dismissal, severance pay, or the activity of the trade unions may all prevent firms to adjust employment in response to shocks. Moreover, employers may find it optimal to choose other means of 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.

Overall, the impact of an average flood on firms and employees is significant and highly persistent, but the magnitude of the shock is rather limited. Every year, about 1% of all manufacturing firms in the 17 countries considered suffer from the consequences of an average flood. By simply multiplying the share of affected firms by the estimated average loss of about 2%, we could conclude that the aggregate impact of an average flood is negligible.

Nonetheless, there are several additional considerations that should be taken into account to get the full picture on the risks related to floods. First, our estimates show the dynamic impact of one flood event. However, many firms are repeatedly damaged by a flood. About 78% of the regions were partly flooded at least once during the 12 years between 2007 and 2018, and more than half of them were flooded at least twice (Table 3). When more than one flood events occurred during this period, the average number of years between the events was less than 3 (Table 4). The damaged firms are presumably always the same ones: those which are located in a floodplain or a coastal area. That is, the majority of these companies have had no time to recover before they were damaged again. Second, our data do not allow us to accurately disentangle large-scale floods from relatively less important events. It is possible (and even likely) that bigger floods have a more damaging impact. Third, our analysis does not take into account the damage caused by the flood in the infrastructure and

– most importantly – in terms of human casualties. Finally, the climate change is likely to amplify both the strength and the frequency of floods. The adverse economic and humanitarian impacts of the floods are thus likely to increase in the future.

Figure 3: Impact of an average flood on firms' total assets and the number of employees



Notes: the figure displays the impulse responses 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) and the number of employees (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 grey areas are the corresponding 95% confidence intervals.

6 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. 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 natural hazards and detailed information on firm geographical location to pin down companies that are directly affected by the floods hitting a specific region. 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%, without clear signs of full recovery even after 8 years. While adjusting more sluggishly, employment follows a similar pattern, experiencing growth in negative territory for the same number of years at least. While the estimated order of magnitude may seem negligible, the frequency of flood events suggest a significant compound effects from repeated floods with potentially disruptive economic and social consequences for regions that are hit repeatedly.

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Appendix

A Firms affected by a flood

Figure A.1: Location of firms affected by flood

Notes: Canary Islands, Overseas France, the Azores and Madeira are not shown.

B Number of affected regions

Table B.1: Number and share of affected regions by country

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
AT	21 (60)	6 (17.1)	22 (62.9)	4 (11.4)	0	0	29 (82.9)	1 (2.86)	0	10 (28.6)	0	6 (17.1)
BE	0	10 (22.7)	0	31 (70.5)	6 (13.6)	0	5 (11.4)	0	0	8 (18.2)	0	19 (43.2)
BG	25 (89.3)	0	0	4 (14.3)	0	17 (60.7)	0	21 (75)	23 (82.1)	2 (7.14)	7 (25)	18 (64.3)
CZ	9 (64.3)	0	7 (50)	12 (85.7)	0	0	11 (78.6)	0	0	1 (7.14)	0	2 (14.3)
DE	31 (8.16)	4 (1.05)	23 (6.05)	36 (9.47)	55 (14.5)	6 (1.58)	57 (15)	6 (1.58)	6 (1.58)	49 (12.9)	52 (13.7)	23 (6.05)
ES	37 (62.7)	3 (5.08)	37 (62.7)	18 (30.5)	2 (3.39)	12 (20.3)	21 (35.6)	10 (16.9)	7 (11.9)	21 (35.6)	6 (10.2)	33 (55.9)
FR	12 (11.9)	8 (7.92)	6 (5.94)	14 (13.9)	2 (1.98)	0	17 (16.8)	31 (30.7)	8 (7.92)	39 (38.6)	14 (13.9)	50 (49.5)
HR	0	0	0	6 (28.6)	0	1 (4.76)	3 (14.3)	7 (33.3)	2 (9.52)	0	3 (14.3)	2 (9.52)
HU	1 (5)	0	0	12 (60)	0	0	8 (40)	9 (45)	0	1 (5)	0	0
IE	0	6 (75)	8 (100)	0	3 (37.5)	0	7 (87.5)	0	1 (12.5)	0	6 (75)	7 (87.5)
IT	1 (.909)	11 (10)	29 (26.4)	26 (23.6)	18 (16.4)	34 (30.9)	17 (15.5)	59 (53.6)	25 (22.7)	13 (11.8)	26 (23.6)	37 (33.6)
PL	3 (4.17)	0	27 (37.5)	37 (51.4)	0	0	0	0	0	5 (6.94)	0	0
PT	6 (24)	1 (4)	6 (24)	1 (4)	0	0	0	6 (24)	1 (4)	1 (4)	0	1 (4)
RO	24 (57.1)	6 (14.3)	41 (97.6)	30 (71.4)	0	7 (16.7)	7 (16.7)	32 (76.2)	12 (28.6)	15 (35.7)	0	22 (52.4)
SI	7 (58.3)	0	0	2 (16.7)	0	3 (25)	1 (8.33)	5 (41.7)	0	0	0	3 (25)
SK	4 (50)	0	4 (50)	4 (50)	0	0	3 (37.5)	0	0	0	0	6 (75)
UK	105 (61)	97 (56.4)	61 (35.5)	5 (2.91)	1 (.581)	121 (70.3)	78 (45.3)	14 (8.14)	38 (22.1)	16 (9.3)	51 (29.7)	53 (30.8)

Notes: Number of regions affected by a flood in a given year. Percentage of the total number of NUTS3 regions are in parentheses.