Productive disasters? –
Evidence from European firm level data

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Productive disasters? – Evidence from European firm level data

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Abstract

This paper examines the impact of floods on firms' capital accumulation, employment growth and productivity by using a difference-in-difference approach and considering firms' asset structure. We find evidence that after a flooding companies in flooded regions show on average higher growth of total assets and employment than firms in areas not affected by flooding. The positive effect prevails for companies with larger shares of intangible assets. Regarding firms' productivity a negative flood effect is observable which declines with increasing share of intangible assets.

JEL Codes: D24, Q54, R10, C21,

Keywords: Natural Disasters, Firm Growth, Productivity, Difference-in-Differences

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1 Introduction

Natural disasters such as hurricanes, earthquakes or floods occur every year and leave their mark on landscape, population and industries. While there is no doubt that disasters are accompanied by human suffering recent studies provide evidence that the consequences of natural hazards on aggregate output can be positive.

In public perception and media coverage reports on disaster losses are dominated by figures on destroyed or damaged capital stock. In contrast, economic literature on the effects of natural catastrophes favours flow variables as loss measurement, because of their comprehensiveness and consistency (Rose 2004, Ikefuji and Horii 2006). The general findings in the existing empirical literature on the impact of disasters on output can be summed up as followed: As a direct effect, natural disasters physically destroy the factors of production; labour (e. g., Anbarci, Escaleras and Register 2005, Kahn 2005, Halliday 2006) and physical capital (Albala-Bertrand 1993). These direct impacts cause business interruptions within the affected firms and set off additional indirect effects at companies up- and downstream in the supply chain (Rose 2004). The aftershock period can follow several paths, that have been simulated in a numerical model by Tol and Leek (1999). If the investment rules of the firms do not change and lost capital is not replaced the level of production is permanently lowered. Given that the destroyed capital stock is replaced, either through insurance, internal reserves or governmental aid, the output might just drop in the immediate aftermath of the event and than increase at an even higher rate. Economic scholars largely agree that the major impetus for this rise in the output-rate comes from an update in technology and/or factor composition. For example, Skidmore and Toya (2002) argue that disasters induce an update of capital stock and provoke the use of new technologies which positively influence long-run growth. Furthermore, the authors highlight the possibility that since the expected return to physical capital decreases due to higher risk to physical capital loss, the relative return to labour input correspondingly increases. This development may lead to higher investment in employment which has the potential to improve company's performance and leads to positive employment effects in the economy. This positive employment effect is in line with the findings in Ewing, Kruse and Thompson (2003) and Ewing, Kruse and Thompson (2007) who provide further evidence on the impact of natural disasters on employment growth and stability. Ewing et al. (2007) explicitly distinguish between initial and post-event effects. While their results indicate that disasters negatively effect total employment in the short run this decline is not permanent. Rather, an increase in the mean employment growth is observable in the post-hazard period. The magnitude of the disaster effect on a firm is not solely determined by the magnitude of the natural process itself (e. g., Richter-scale, water level) but also by company-specific factors such as investment strategies (Tol and Leek 1999, Skidmore and Toya 2002), factor composition (Jovanovic 1982), level of technology (Crespo-Cuaresma, Hlouskova and Obersteiner 2008) or disaster relief (Sobel and Leeson 2006, Shughart 2006). Okuyama (2003) puts forward that older capital stock is more vulnerable to natural disasters.

The analyses so far have a clear mid to long-run perspective. Raschky (2007) provides a short-run analysis of flooding effects. The author points out that in the short-run (within the same year) floods decrease regional income, followed by an increase in the next period. The natural catastrophe might result in investment activity in production factors that goes beyond the sole replacement of disaster losses and result in a less productive factor composition. The idea of an increase in total factor productivity could therefore hold in the long-run, however, this increase seems to be preceded by a decrease in factor productivity in the short-run. Apparently, firms need some time to learn about their productivity and to adjust their composition of production factors to an optimal level (Jovanovic 1982).

Furthermore, most of the previously mentioned studies examine the mid to long-run economic effects of natural disasters on performance using highly aggregated data. This paper explicitly focuses on the immediate flood effects to European firms. To our knowledge there is no empirical study so far that estimates the short-term effects of natural disasters on firm or plant level.[1] Our study thus augments the existing empirical literature on natural hazards and growth by emphasizing on the firm level effects resulting from disasters in the immediate aftermath of an event. We also take into account the idea of various relevance of 'resilience' depending on the composition of the capital stock. In this paper we analyse the effects of floods on physical capital accumulation, employment and productivity changes using cross-sectional data of European companies. The physical capital stock is measured via firm's total assets, employment is expressed as number of employees and productivity is depicted as value added. We distinguish between affected

[1] In this study either unconsolidated firm level data or lone-standing firm information is used to examine average regional effects of a flood event. Therefore, our data are comparable to plant level information.

and non-affected plants via their location in flooded and non-flooded regions, respectively. In order to identify both direct and indirect effects of a flood disaster we have to include all companies of a region hit by a flood in our analysis. The inclusion of all companies allows us to compute the average effect of a flood on firms directly hit and firms affected indirectly. Limiting the analysis only to firms directly hit would bias the results and deliver an incomplete picture of flood losses on plant-level because of fading out the forward and backward linkages within the supply chain. For example, the destruction of one plant can cause a decrease in production and the cancellation of planned investment of a supplier. Companies in non-flooded areas are included as control group.

Using a difference-in-difference (DID) approach we find that physical capital accumulation and employment growth is significantly higher in regions experiencing a major flood-event. The positive effect prevails for companies with a high share intangible assets (e.g., R&D, patents, software, trademarks). Regarding productivity a negative flood effect is observable which declines with increasing share of intangible assets.

The following sections describe the procedure and findings in detail. Section 2 presents the data and descriptive statistics, Section 3 discusses the model and the econometric procedure, Section 4 provides the estimation results. Finally, Section 5 concludes.

2 Data

The investigation of immediate direct and indirect effects of natural disasters on firm level requires data on firm performance as well as information on natural disasters. The firm level data are provided by the AMADEUS Database.[2] As mentioned above, for our investigation we have to rely on data from lone-standing firms and unconsolidated balance sheet and profit and loss data to assure that the observed units are directly affected by the flood event. The information used captures the time period from 1993 until 2004. In the final dataset we focus on manufacturing companies to make sure that only enterprises which use potentially destructible capital stocks in their production processes are considered.

The data on the natural disaster event (flood) is provided by the EM-DAT dataset collected by the Centre for Research on the Epidemiology of Disasters (CRED) in Brussels. A flood event has to fulfill at least one out of the following criteria in order to be included in the EM-DAT: 10 or more killed people, 100 or more affected people, declaration of emergency or a call for international assistance as a consequence of the flood incident (see Raschky 2007). The EM-DAT database also includes more detailed information on the affected locations within a country. This information was used to identify the regions actually hit by a flood. The AMADEUS and EM-DAT databases are merged using the information about the regional location of the companies and the regional occurrence or non-occurrence of flood events. Regarding the

[2]The Bureau van Dijk distributes the AMADEUS database, which includes financial statements, profit and loss accounts and information on companies' organizational structure of 8.8 million firms located in 40 European countries.

spatial dimension we choose NUTSII-level as this is the most disaggregated level that allows an accurate spatial assignation of the flood event on regional level.

The aim of this empirical investigation is to analyze the effects of one major flood on the average firms' performance in the affected region. For this reason a flood event has to be selected which occurred somewhere in the middle of the time series to identify possible effects on firm performance. Within the years 1996 and 2001 the largest flooding took place in the year 2000 and affected 30 NUTSII regions in Europe. To assure that firms in the affected areas were only confronted to the flood in 2000, all companies in regions where another flood event occurred before and/or after 2000 are eliminated from the data sample.

Table 1 about here

Table 1 shows the number of manufactoring firms located in countries where at least one region has been affected by a flooding in 2000. Firms in flooding areas define the treatment group while all other companies in the non-flooding regions represent the control group. Firms located in countries unaffected by a flood in 2000 are not included in the final dataset in order to reduce unnecessary large cross-country variation in the data. For a DID estimation the treatment and the control group should be approximately balanced in terms of sample size. Table 2 reveals that the treatment (affected) and control groups (non-affected) are well balanced.

Table 2 about here

2.1 Descriptive Statistics

This section gives a short summary statistics of the variables which will be used for estimation in Section 3.

Table 3 reports the mean, standard deviation, minimum and maximum of the dependent variables in the estimated models. Companies which are located in the non-flooded regions are larger in terms of labour (expressed as number of employees). On average, these areas also tend to be more productive than firms in flood-affected regions. Total assets, employment and average productivity measured via value added of firms in affected and non-affected regions are higher in the post-flood period.

Table 4 reports the same data attributes for the explanatory variables. Companies in affected and non-effected regions also differ on average in initial values of total assets, employees and their level of intangible assets. The average age of the companies in affected and non-affected regions is rather similar.

Table 3 about here

Table 4 about here

3 Empirical strategy

We infer our empirical model of physical capital accumulation and employment growth from the Gibrat's Law firm size literature (e. g. Evans 1982, Sutton 1997, Fotopoulus and Louri 2004). In these studies, initial values of the firm size and age of the company are included as explanatory variables.

The effect of hazards on productivity changes is examined using a procedure analogous to the Cobb-Douglas production function framework.

3.1 Explanatory variables

The econometric implementation follows the DID approach described in Wooldridge (2002). We consider two time periods – before and after flooding – and split our sample into two groups – flooded and non-flooded regions. The former (latter) is called the treatment (control) group. The time dummy which equals 1 for the period after the flooding and equals 0 otherwise, allows us to account for aggregate changes over time which are relevant for both groups. The treatment dummy (1 if a firm is located in a flooding area, 0 otherwise) considers initial differences between the treatment and control group. The interaction of the time and flood dummy represents the DID estimator. It equals one for treatment group members in the after flood period. This estimator solely measures the flood effects on capital accumulation, employment and productivity changes, respectively, since we control for the general group- and time-specific effects. The econometric advantage of using the occurence of flooding as treatment is its exogeneity. I. e., the occurrence of such an event is independent on study designs and country specific characteristics.[3]

[3]We are aware that the inclusion of a flood event in the EM-DAT database may be for example correlated with a country's ability to prevent floods and/or mitigate their potential for damage and thus directly affecting the event's magnitude. However, as the classification of an event as natural disaster does not solely depend on (financial) damages but also on other consequences (e. g., fatalities, people affected, state of emergency) and as the group of countries considered is rather homogeneous in terms of economic development we think that the inclusion of an event in the database is rather independent on country specific characteristics such that the classification of floods as an exogenous treatment should be justified.

Additionally we include the initial values of physical capital and employment, respectively, age of the firm, the share of intangible assets in total assets and an interaction term of the DID dummy with the share of intangibles in the physical capital and employment regressions. The motivation for the inclusion of the interaction term stems from the assumption that the consequences of floods on capital accumulation and employment changes may differ depending on the vulnerability of the input factors. We assume that tangible (intangible) assets are potentially more (less) exposed to floods. Productivity (measured by total value added) is regressed on capital and labour inputs, ratio of intangible assets to total assets, interaction of this share of intangibles with the DID estimator, and DID, time and treatment effects. While the assets and employment estimates analyse the direct effects of floods, the productivity function refers to indirect flooding impacts.

3.2 Estimation procedure

To analyse which factors determine physical capital accumulation and employment growth we run OLS and 2SLS regressions for both, the physical capital stock and the employment level, as mentioned in equations (1) and (2). Both equations state that firm size follows an AR(1), where the growth rate becomes independent from firm size when $\beta_1 = 1$ or $\gamma_1 = 1$. The reduced form equations allow to examine the impact of the flood event on firms in the treated regions over time.

The motivation to use IV-estimation arises from the fact that the initial values of total assets and the initial number of employees, which are 1997 values, are themselves generated by each firm's growth process and might capture unobserved firm characteristics. This would lead to an endogeneity problem.

We take the logarithm of all continuous variables before we include them in the regression functions.[4] In the OLS case we regress total assets (*ltoas*) and number of employees (*lempl*), respectively, on its corresponding initial value (*ltoasi*) or (*lempli*), firm's age (*lage*), share of intangible assets compared to total assets (*SIA*), time (*time*), treatment (*treatment*) and DID (*DID*) dummies, the interaction of the share of intangibles with the DID dummy (*SIA*DID*), industry (*ind*) and country (*country*) specific effects and on a constant:

$$\begin{aligned} Ltoas_{ijrct} = &\beta_0 + \beta_1 * ltoasi_{ijrc} + \beta_2 * lage_{ijrc} + \beta_3 * SIA_{ijrct} + \beta_4 * time_t + \\ &\beta_5 * treatment_r + \beta_6 * DID_{rt} + \beta_6 * (SIA * DID)_{ijrct} + \\ &\varphi * ind_i + \iota * country_c + \epsilon_{ijrct} \end{aligned} \tag{1}$$

$$\begin{aligned} Lempl_{ijrct} = &\gamma_0 + \gamma_1 * lempli_{ijrc} + \gamma_2 * lage_{ijrc} + \gamma_3 * SIA_{ijrct} + \gamma_4 * time_t + \\ &\gamma_5 * treatment_r + \gamma_6 * DID_{rt} + \gamma_6 * (SIA * DID)_{ijrct} + \\ &\lambda * ind_i + \kappa * country_c + \nu_{ijrct} \end{aligned} \tag{2}$$

[4]The share of intangible assets is calculated using differences in logs of intangible assets and total assets. Therefore, this variable takes on only negative values.

The indices represent a company i in industry j located in region r[5] in country c at period t.[6] In the IV regression we instrument the initial capital (labour) values using (i) the average amount of total assets (average number of employees) in each NACE industry and (ii) the industry specific minimum efficient scale.[7] A Hausman specification test is used to identify the appropriate model.

The model for productivity is embedded in a Cobb-Douglas production function framework and takes the following form:

$$\begin{aligned} Y_{ijrct} = {} & \delta_0 + \delta_1 * ltoas_{ijrc} + \delta_2 * lempl_{ijrc} + \delta_3 * SIA_{ijrct} + \delta_4 * time_t + \\ & \delta_5 * treatment_r + \delta_6 * DID_{rt} + \delta_6 * (SIA * DID)_{ijrct} + \\ & \phi * ind_i + \upsilon * country_c + \eta_{ijrct} \end{aligned} \tag{3}$$

with Y, *ltoas* and *lempl* representing value added, total assets and number of employees, respectively. Again, i, j, r, c and t index company, industry, region, country and period, respectively.

Estimation of productivity effects at the firm or plant level induces econometric problems. A firm has (at least to a certain extent) information on its productivity when choosing the level of factor inputs. Therefore, the factor input decision is not independent from firm specific productivity which in-

[5]In this paper region is defined in terms of exposure, i. e., the dummy describes the flooding and non-flooding areas.

[6]i varies between different estimation equations and ranges from 82,652 (employment) to 116,024 (productivity); j from 1 to 103; c from 1 to 6; r=1,2 and t=1,2. The initial size variables do not vary over time. Age is constructed relative to a reference year and is therefore also constant before and after the flooding.

[7]Our measure of minimum efficient scale (MES) is the 50 percent percentile of the initial total assets (employment) distribution within a NACE industry within our data sample and is therefore only a proxy for the real MES.

duces a simultaneity bias. Olley and Pakes (1996) and Levinsohn and Petrin (2003) provide estimation procedures which allow a consistent estimation of production functions using panel data. The basic idea of this approaches is to use lagged information on the input choice as well as the level of intermediate inputs to instrument the contemporaneous level of factor inputs. Unfortunately, these approaches are unfeasible for the cross sectional structure of our data. However, we try to control for the simultaneity problem using average industry-region levels for the endogeneous inputs as instruments in the production function and compare the IV results with the OLS approach via the Hausman specification test.

4 Results

In the first step we focus on the effects of floods on capital accumulation and employment growth. Columns (5.1) and (5.2) of Table 5 depict the results estimating Equation (1), columns (5.3) and (5.4) report regression results for Equation (2).

Table 5 about here

In all four equations, the initial values of capital stock and level of employment reveal a positive influence on the corresponding present values (dependent variables). The level of the OLS-coefficients of the initial values in (5.1) and (5.3) and the IV-parameter in (5.4) indicate that companies with low initial values face higher input growth (total assets and number of employees, respectively) than firms with large initial stocks. I. e., as these coefficients are significantly smaller than one we conclude that small companies grow faster than their larger counterparts. This observation corresponds to empirical findings in the firm size literature (e. g. Fotopoulus and Louri 2004, Blonningen and Tomlin 2001) but contradicts the argument of Gibrat (1931) who proposes that growth of companies is independent of its initial size. However, the coefficient of initial total assets in column (5.2) do not significantly differ from 1 and supports *Gibrat's law*. Company's age reveals a significant and negative impact on total assets and employment changes, respectively, in all four regressions indicating, that capital stock and employment growth of young firms are larger. This finding is in line with results in studies examining determinants of firm growth (e. g. Evans 1982, Sutton 1997). Also a consistent picture is observable regarding the time effects. The time dummy captures the variation in physical capital stock and level of employment between the before and after flood period. In all equations it reveals a positive influence on growth of total assets and number of employees. The treatment dummy shows that total assets and employment grow is on average lower in the treatment group but this difference is only significant for labour. We also control for industry and country specific effects by including industry and country dummies and find that they are jointly significant determinants of the dependent variables.

Some authors point at the different resilience of assets regarding disasters (e. g., Okuyama 2003, Skidmore and Toya 2002). We take this idea into account by introducing the structure of firms' assets and distinguishing between intangible and tangible assets. While the latter is potentially exposed to flood the former is not. Hence, a higher (lower) positive (negative) DID effect is expected the higher the share of intangible assets is. Consequently, the key parameters for our analysis are the share of intangible assets (SIA), the DID estimator (time*treatment) and its interaction with the asset share (time*treatment*SIA). The OLS-coefficient of SIA in (5.1) and (5.3) indicates that total assets growth and employment significantly decrease with an increasing proportion of intangible assets. However, the IV-parameter in column (5.4) suppose a significant rise in employment growth with increasing shares of intangibles. The importance of the asset structure in determining the economic consequences of floods is strengthened by the coefficients of the DID variable and its interaction with the share of intangibles. As can be seen in Table 5 the corresponding parameters are significantly positive across all estimation models. The DID coefficient indicates that – ceteris paribus – companies in affected regions on average tend to possess higher total assets and employment growth after a flooding occurs than firms in non affected areas.

In order to choose the appropriate estimation model for total assets and employment growth we conduct Hausman specification tests. The results of the test statistics are reported in the bottom of Table 5 and indicate that the IV model should be favoured over the OLS estimates in case of total assets. For employment, the OLS version outperforms the IV alternative.

The overall flood effect is given by the derivative with respect to DID. The overall marginal effects of a major flood event for total assets and employment growth are reported in columns (7.1) and (7.2) of Table 7. The calculations refer to companies located in affected regions after the flooding occurred. The estimates regarding total assets clarify that the overall increase in capital growth does not hold for all companies. Rather, firms with high tangible assets are negatively affected by floods which is expressed as decrease in total assets. From the 70^{th} percentile of intangibles upwards a significantly positive flood effect is observable. A monotonic increase in growth is recognisable for employment. The higher the amount of intangible assets of companies, the more pronounced is the positive employment growth effect in the post-flood-period.

To summarize, in the short run floods positively influence employment growth and to some extent firms' physical capital accumulation. This may be traced back to (replacement) investment in new and more valuable equipments. The increase in employment is more distinct for firms with high intangible assets which may be a result of the durability of intangibles regarding the physical impacts of floods. In terms of total assets, a positive flood effect only prevails for firms which possess high shares of intangibles. We interpret these impacts as 'direct' effects of floods as the production factors capital and labour are immediately affected by flooding.

Indirect effects may occur due to the consequences of floods on input factors which are passed on the production process. We measure the indirect effects of a flooding via their impact on value added using OLS and IV estimation procedures and apply a Hausman test to define the accurate specification. The test statistics favour the IV over the OLS method. The corresponding estimates for both specifications are reported in Table 6.

Table 6 about here

The outcome when using the OLS and IV estimation procedure is quite similar with one exception: While the OLS estimates suggest that a high share of intangible assets induces lower value added, the coefficient on *SIA* in the IV model describes a positive influence of intangibles. In both specifications, the coefficients on total assets and employment point at higher changes in productivity the more input factors are used. Different from the asset and employment estimates the time dummy reveals a negative impact and suggests – ceteris paribus – lower productivity in period $t+1$. On the other hand, the coefficient on the treatment dummy indicates a significant difference in firms' productivity between companies in affected (flooded) and non affected regions. The average firm which is located in a flood region tend to be more productive than the average firm in the control group.

Also in the productivity equation, the flood effects on companies in the treatment group are depicted by the DID estimator and its interaction with the share of intangibles. To determine the overall flood effect the first derivative of equation (6) with respect to DID is of relevance. Column (7.3) of Table 7 shows the corresponding overall effects for different shares of intangible assets. Our short-run results regarding firm's productivity changes reveal that the (partly) positive direct effects on factor inputs do not lead to higher productivity. In fact, the occurrence of floods significantly reduces the efficiency of companies in affected areas. Overall, a major flood event reduces productivity of firms located in the affected region and is most pronounced for firms which do not use intangible assets in their production process. We interpret this as evidence that companies in affected areas with less assets at risk are confronted with diminishing negative effects on the value added while firms with large tangible assets may face more severe negative consequences due to floods. Particularly companies with a higher share of tangible assets are potentially confronted to replacement and/or restructuring of assets damaged by floods. The adoption of an appropriate composition of factor inputs is accompanied by a time consuming learning process (Jovanovic 1982).

Table 7 about here

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5 Conclusions and Discussion

In economic terms, natural disasters can initiate a sudden, exogenous shock for firms' production factors. The corresponding consequences do not only evolve through the physical destruction per se but may be accompanied by effects on labour and productivity.

In this paper we examine the average consequences of floods on firms' factor endowment and productivity and differentiate between highly and less flood-resistant endowments. Using a DID approach we distinguish between affected and non-affected regions and two periods – before and after flooding – to analyse the average change in total assets, in employment and in productivity induced by a flooding. Our estimates provide evidence that post-flooding employment growth for companies in flooding areas is higher. This positive impact is increasing with higher shares of intangible assets. The overall effect of a major flood on physical capital stock accumulation depends on the inserted share of intangible assets in the production process. After flood physical capital stock accumulation increases at least for companies with high intangible assets.

Contrary to this trend, the post-flooding effect on productivity in the treatment group is negative. However, this effect slows down with increasing shares of intangible assets. We interpret the findings regarding the impact of floods on total assets accumulation, employment growth and productivity changes as evidence that firms with high intangibles are less vulnerable regarding flood impacts.

Since we aim to examine the impact of one flooding on firm performance we had to exclude companies in regions where more floods took place during the observation period to avoid overlapping effects of various events. However, the examination of the dynamic economic effects of several temporally correlated exogenous flood events might be an interesting question for further research.

Table 1: Number of firms listed by country

Country	Number of Firms	Percent
France	31,231	22.34
Greece	1,053	0.75
Hungary	1,583	1.13
Italy	68,082	48.69
Spain	30,052	21.49
United Kingdom	7,819	5.59
Total	139,820	100.00

Table 2: Number of firms in non-affected and affected areas

	Number of Firms	Percent
No-Flood	70,143	50.17
Flood	69,677	49.83
Total	139,820	100.00

Table 3: Summary statistics of dependent variables

Variable	Treatment/Period	Observations	Mean	Std. Dev.	Min	Max
Total Assets	0/0	51,090	11,051.600	126,740.200	0	18,576,594.330
	0/1	51,090	12,267.150	141,879.300	0	18,495,455.330
	1/0	47,307	11,101.120	121,798.200	0	14,058,479.330
	1/1	47,307	12,701.000	146,968.000	0	18,217,461.330
Employees	0/0	38,979	73.451	339.315	1	31,393.000
	0/1	38,979	76.866	277.824	1	13,121.670
	1/0	42,474	57.316	349.522	1	28,128.330
	1/1	42,474	65.359	505.564	1	82,815.500
Value Added	0/0	43,436	3,540.288	28,227.760	−1,096,014.000	3,534,083.000
	0/1	43,436	3,584.032	31,690.770	−97,977.000	4,299,011.000
	1/0	44,519	3,398.755	30,611.560	−84,494.330	3,062,248.000
	1/1	44,519	3,608.459	44,336.870	−418,642.000	5,826,378.000

Notes: Total assets are measured in 1000 US-Dollars.

Table 4: Summary Statistics of explaining Variables

Variable	Treatment/Period	Observations	Mean	Std. Dev.	Min	Max
Initial Total Assets	0/0	42,173	11,358.020	121,147.500	0	18,576,594.330
	1/0	38,946	12,123.530	135,847.800	0	15,131,069.000
Inital Employment	0/0	27,609	82.039	324.663	1	14,565.000
	1/0	32,895	63.746	403.082	1	40,556.000
Age	0/0	27,140	18.172	16.520	0	302.000
	1/0	33,572	18.887	14.731	0	202.000
Sh. o. Int. Assets	0/0	50,665	.031	.073	0	1
	0/1	50,665	.032	.071	0	1
	1/0	47,210	.036	.074	0	1
	1/1	47,210	.037	.073	0	.911

Notes: Initial total assets are measured in 1000 US-Dollars. Companies age is calculated using 1999 as reference year

Table 5: Estimates of flood event on total assets and employment growth

Variable	(5.1) OLS	(5.2) IV	(5.3) OLS	(5.4) IV
Initial Total Assets	0.907*** (0.001)	1.010*** (0.009)		
Initial Employment			0.897*** (0.001)	0.980*** (0.008)
Age	−0.094*** (0.002)	−0.149*** (0.005)	−0.056*** (0.002)	−0.100*** (0.005)
Share o. Int. Assets (SIA)	−0.011*** (0.001)	0.000 (0.001)	−0.002* (0.001)	0.003* (0.001)
Time	0.109*** (0.004)	0.109*** (0.004)	0.160*** (0.004)	0.163*** (0.004)
Treatment (Flood)	−0.002 (0.004)	−0.004 (0.004)	−0.028*** (0.004)	−0.025*** (0.004)
Time * Treatment (DID)	0.086*** (0.010)	0.073*** (0.010)	0.090*** (0.009)	0.083*** (0.010)
Time * Treatment * SIA	0.018*** (0.002)	0.016*** (0.002)	0.013*** (0.002)	0.011*** (0.002)
Industry Dummys	yes	yes	yes	yes
F-Stat	15.739***	7.294***	13.586* * *	8.696***
(df; df)	(102; 95,123)	(102; 95,123)	(102; 82,537)	(102; 82,537)
Country Dummys	yes	yes	yes	yes
F-Stat	174.703***	175.052***	47.032***	43.131***
(df; df)	(5; 95,123)	(5; 95,123)	(5; 82,537)	(5; 82,537)
Sargan Test[1]		1.003 (0.3166)		1.780 (0.1821)
Hausman Test	141.680** (0.040)		100.160 (0.8191)	
R^2	0.898	0.890	0.886	0.880
Observations	95,238	95,238	82,652	82,652

Notes: Standard errors are given in parenthesis. The symbols *, ** and *** stand for 10%, 5% and 1% significant.

Included instruments: average firm size in NACE-classification industries, minimum efficient scale.

[1] P-Values are given in parenthesis.

Table 6: Estimates of flood events on productivity changes

	Value Added OLS	Value Added IV
Total Assets	0.432*** (0.001)	0.395*** (0.006)
Employment	0.562*** (0.002)	0.615*** (0.006)
Share of Int. Assets (SIA)	−0.003*** (0.001)	0.016*** (0.002)
Time	−0.077*** (0.003)	−0.081*** (0.003)
Treatment (Flood)	0.094*** (0.003)	0.093*** (0.003)
Time * Treatment (DID)	−0.005 (0.007)	0.027 (0.019)
Time * Treatment * SIA	0.008*** (0.001)	0.014*** (0.002)
Industry Dummys	yes	yes
F-Stat	73.647***	58.647***
(df; df)	(102; 111,549)	(102; 111,549)
Country Dummys	yes	
F-Stat	2836.380***	2220.743***
(df; df)	(4; 111,549)	(4; 111,549)
Sargan Test[1]		1.314 (0.2516)
Hausman Test	180.50*** (0.000)	
R^2	0.922	0.920
Observations	111,663	111,663

Notes: Standard errors are given in parenthesis. The symbols ** and *** stand for 5% and 1% significant.

Included instruments: average region-industry inputs (total assets, employment, share of intangibles assets, share of intangibles assets*DID), average region-industry materialcosts per employee.

[1] P-Values are given in parenthesis.

Table 7: Overall (marginal) effects of a flood for different shares of intangible assets (SIA)

	(7.1)		(7.2)		(7.3)	
Variable	Total Assets		Employment		Value Added	
Mean	0.003	(0.280)	0.033***	(37.000)	−0.035***	(70.760)
10% Percentile	−0.034***	(21.120)	0.002	(0.130)	−0.068***	(39.890)
20% Percentile	−0.020***	(9.890)	0.013**	(5.070)	−0.056***	(53.510)
25% Percentile	−0.015**	(6.100)	0.017***	(9.300)	−0.053***	(61.050)
30% Percentile	−0.011*	(3.290)	0.021***	(14.290)	−0.048***	(68.690)
40% Percentile	−0.003	(0.250)	0.028***	(26.220)	−0.041***	(79.000)
50% Percentile	0.005	(0.610)	0.034***	(39.690)	−0.034***	(65.820)
60% Percentile	0.012	(3.960)	0.040***	(53.100)	−0.027***	(34.780)
70% Percentile	0.019***	(9.900)	0.046***	(65.920)	−0.020***	(12.550)
75% Percentile	0.023***	(13.710)	0.049***	(71.840)	−0.017**	(6.580)
80% Percentile	0.027***	(17.890)	0.053***	(77.180)	−0.013*	(3.050)
90% Percentile	0.038***	(28.260)	0.062***	(86.830)	−0.003	(0.120)
Observations[1]	25,720		23,695		31,494	

Notes: Values of F-Statistic from non-linear Wald test given in parenthesis. The symbols ** and *** stand for 5% and 1% significant.

[1] Number of Firms which are located in flood regions.

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