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Badly Hurt? Natural Disasters and Direct Firm Effects*

Abstract

We investigate firm outcomes after a major flood in Germany in 2013. We robustly find that firms located in the disaster regions have significantly higher turnover, lower leverage, and higher cash in the period after 2013. We provide evidence that the effects stem from firms that already experienced a similar major disaster in 2002. Overall, our results document a positive net effect on firm performance in the direct aftermath of a natural disaster.

Keywords: natural disasters, firm outcomes

JEL Classification: G21, Q54

* We thank Lena Tonzer for valuable feedback and the German Insurance Association for providing the data. Any remaining errors are our own.

Badly hurt? Natural disasters and direct firm effects☆

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We investigate firm outcomes after a major flood in Germany in 2013. We robustly find that firms located in the disaster regions have significantly higher turnover, lower leverage, and higher cash in the period after 2013. We provide evidence that the effects stem from firms that already experienced a similar major disaster in 2002. Overall, our results document a positive net effect on firm performance in the direct aftermath of a natural disaster.

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1. Introduction

The year 2017 has produced a number of tremendous natural disasters: Hurricanes Harvey, Irma and Maria, a triple-earthquake in Mexico, the deadliest wildfires in U.S. history, and one of the most destructive monsoon flooding in South Asia. Alongside the literature that investigates how protection against natural disaster can be enhanced and risks from such events can be shared (Temmerman et al., 2013; Jongman et al., 2014), existing studies in economics and finance have mainly focused on the effects of damages from natural disasters on the macro economy (Noy, 2009; Strobl, 2011; Cavallo et al., 2013; Fomby et al., 2013), banks' risk taking and lending (Klomp, 2014; Garmaise and Moskowitz, 2009; Berg and Schrader, 2012; Lambert et al., 2015; Koetter et al., 2016; Chavaz, 2016; Cortes and Strahan, 2017), and insurance (Froot, 2001; Cummins et al., 2002; Niehaus, 2002; Jarzabkowski et al., 2015; Biener et al., 2017) and labor markets (Kirchberger, 2017). An important assumption in almost all studies is, that natural disasters are destructive for firms, so first order effects on firm performance should be negative. Here, we show that a major flood in Germany in 2013 that caused damages of about 6 billion Euros (Koetter et al., 2016) had a significant positive effect on the performance of small and medium-sized enterprises (SMEs). We further document modest evidence that firms which already experienced a major disaster of the same type have fared even better after the disaster of 2013. There are several explanations for this positive (net) effect. While firms may cut back investment and lay off employees because working capital is destroyed and economic outlook is bad, governments and insurances may compensate the affected firms for some of the losses and thus counteract negative effects. Additionally, replacing old capital due to a disaster might lead to productivity improvements because it enables SMEs to modernize their capital stock. Finally, strong and deep relationships to banks may also benefit firms to recover quickly.

2. Data and Methodology

We use two data sources for our analysis. First, we obtain firm level data from Bureau van Dijk's Amadeus database. After cleaning the data[2] we match affected and unaffected firms with propensity score

[2]The full data set has roughly 8.9 million observations and 1.6 million firms. We drop all firms, for which we have no information about the location to which we can match to the flood data (reduces sample by 494,000 observations). We then drop all duplicate observations (27,000), all inactive firms (761,000), all observations with negative or missing total assets (2,564,000), and for which any balance sheet financial variables are negative (8,000). We also drop all very large firms (72,000), and then drop all years before 2010, so we have a balanced pre and post period (2,007,000). The last step is also done to ensure that the reported data is complete and accurate, as Amadeus for German firms becomes significantly more reliable after 2008, due to an increase in enforcement of existing reporting duties. We also exclude all firms that report two different locations during the period (50). Finally, we require all matching variables to be available in the pre-flood year (100,000) and the presence of outcome variables in the final data set (1,800,000). We also require each firm to have at least one observation in the pre and post period (196,00). Before matching, we are thus left with 800,000 observations for 185,210 firms.

matching.[3] This procedure leads to a final data set containing 217,742 observations for 48,524 firms between 2010 and 2015. Second, to measure the impact of the natural disaster we use data from the German Insurance Association. This is the same data as in Koetter et al. (2016) which provides information about insurance claims for properties that were damaged by the flood of the Elbe river between May 25 and June 15, 2013. Figure 1 presents the regional spread of the damage reported as the percentage of flood-insurance contracts activated during this period (left graph) and also shows the damages from another major flood from 2002 (right graph).

– Figure 1 about here –

We use the data to run our baseline analysis

$$Y_{irt} = \gamma_i + \gamma_t + \beta_1 \left(\text{Post } 2013_t \times \text{Affected } 2013_i\right) + \epsilon_{it}, \tag{1}$$

which is a difference-in-difference regression explaining firm i's outcomes in year t (the firm resides in region r). We focus on four variables here which are firms' turnover, (tangible) fixed assets, the leverage ratio, and cash. The main explanatory variables are Affected 2013, which is a dummy separating affected firms from unaffected firms and Post 2013, which is a dummy equal to one in the years 2013–2015 (and zero before). Thereby, β_1 shows the differential effect on firm outcomes for firms residing in affected regions after the Elbe flooding relative to firms in unaffected regions prior to 2013. Figure 2 shows the separation of regions into affected and unaffected one (for both disaster periods). We further employ firm (γ_i) and year (γ_t) fixed effects to control for unobserved constant factors that may influence firm outcomes. In all our analyses, we use clustered standard errors on the firm level. We provide a detailed explanation of all variables in Table OA2 and descriptive statistics in Tables OA3 and OA4 in the Online Appendix.

– Figure 2 about here –

3. Results

Baseline results. We provide our baseline results in Table 1. The first column investigates firms' turnover and we find a positive and significant coefficient that indicates that firms affected by the Elbe flood of 2013 increase their turnover after 2013 by 1.4% compared to the group of unaffected firms relative to the period before 2013. If we turn to firms' fixed assets in Column (2), we find no significant effects due to the Elbe flood. However, Columns (3) and (4) show, that affected firms managed to have significant lower leverage

[3] We provide details for the matching procedure in the Online Appendix and also provide statistics for the matching performance in Table OA1.

ratios and more cash in the period after 2013. All our regressions deliver a good fit since we are able to explain between 77% and 96% of the variation of the dependent variables.[4]

Surprisingly, our results document mostly positive effects from the Elbe flood of 2013 on affected firms. We also provide descriptive evidence, that even in the year of the disaster, there is no indication of a negative effect on firms' outcomes (see the development over time in Figure OA1 in the Online Appendix). There are several possible explanations for this finding: disaster assistance to affected firms by insurance markets and/or (local) governments; strong relationship-banking effects; and/or increased demand due to reconstruction works. Disentangling these explanations is difficult due to the lack of data. Nevertheless, the net effect appears to be positive instead of negative as frequently assumed in the scientific literature and conventional wisdom might dictate.

– Table 1 about here –

Our results are robust to several variations for which we provide results in the Online Appendix. There, Table OA4 and Figure OA1 provide evidence that the parallel trend assumption for both groups are valid. Also, Table OA6 shows that our results remain intact when we collapse the sample on the time dimension, taking care of potential auto correlation that may bias results (Bertrand et al., 2004). Further, Table OA7 shows that our results vanish when we artificially shift the flood event into 2011 and use 2011 and 2012 as the post period of the event. In Table OA8 we show that our results stay robust when we exclude any fixed effects from our regressions. The results are even stronger when using an unmatched sample of firms (Table OA9) and also survive when we use the matching variables as controls (except for cash holdings, Table OA10).

The flood of 2002. We make use of the information whether a firm was already affected by a major flood in 2002 (see the right graph of Figure 1 and 2).[5] To analyze whether this affects firm outcomes after the 2013 flood, we augment Equation (1) by interacting all dummy variables with Affected 2002, which is a dummy variable equal to one if a firm existed in 2002 and resided in a region that was already hit by the flood of 2002. Our particular interest is on the coefficient for the interaction term Post 2013$\times$ Affected 2013$\times$Affected 2002, which tells the differential effect for firms affected by both floods for the period starting in 2013 relative to firms only affected by the flood of 2013 and the period before 2013.

– Table 2 about here –

[4] This comes mostly from the firm and time fixed effects. The difference-in-difference dummies explain around 1% to 3% only as shown in Table OA8 in the Online Appendix.

[5] Table OA5 in the Online Appendix show that our main results remain intact when we use only firms that already existed in 2002 in our baseline regression.

The columns of Table 2 show three things. First, our baseline results are much weaker for firms that did not experience the flood of 2002 as indicated by the double interaction term Post 2013×Affected 2013. Second, for the sample of firms that were also affected by the Elbe flood of 2002, the bottom of Table 2 shows much stronger (and significant) effects which shows that our main results are driven by firms affected by both floods. Third, however, the triple interaction effect Post 2013×Affected 2013×Affected 2002 indicates that the differences between both samples are not statistically significant. Thereby, we have only weak evidence for the fact that firms already involved in a natural disaster can use this experience to navigate better through similar events.

4. Conclusion

It is a difficult empirical exercise to disentangle the different channels that affect firm outcomes after a natural disaster. We document the absence of a negative effect of natural disasters on firms and highlight that there is likely a multitude of factors, that may lead to a positive net effect for firms in the aftermath of huge disasters. Our results also indicate that learning effects play a minor role – if any – in the management of natural disasters on the firm level. On the positive side, our results indicate that the support after natural disasters seems to work – at least in the case of Germany – as affected firms fared comparably well.

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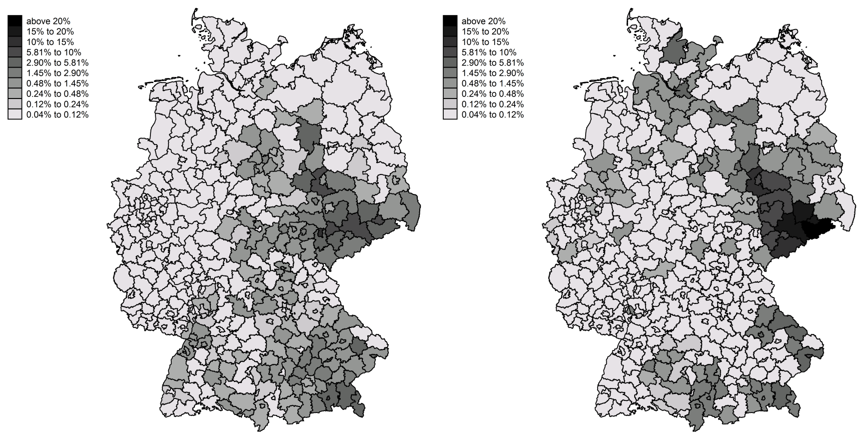
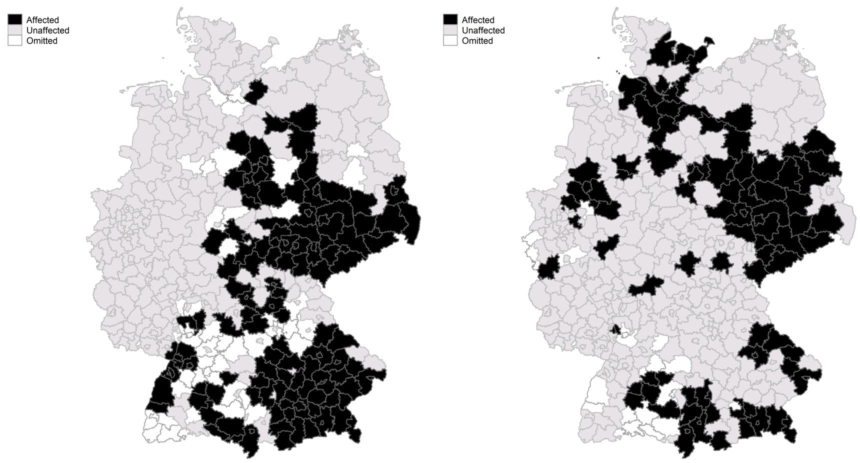
Figures and Tables

Figure 1: Distribution of flood damages in Germany 2013 and 2002



This figure shows the distribution of flood damages according to the German Association of Insurers (GDV). The damages are shown as the percentage of insurance contracts activated during the flooding period, according to the legend. The left-hand side displays the flood related damage distribution of the 2013 flood, while the right-hand side displays the damage distribution for the 2002 flood.

Figure 2: Distribution of flood damages in Germany 2013 and 2002



This figure shows the distribution of affected and unaffected regions. Regions which are designated as category 4 or higher in the insurance data (c.f. Figure 1) are classified as affected. Regions in category 1 are designated as unaffected and regions of categories 2 and 3 are omitted as a buffer category. The left-hand side displays the categorization for the 2013 flood and the right-hand side for the 2002 flood.

Table 1: Baseline Regressions

	(1) log(turnover)	(2) log(tangible fixed assets)	(3) leverage ratio	(4) log(cash)
Post 2013 ×Affected 2013	0.014^{***}	-0.004	-0.004^{***}	0.021^{*}
	(0.003)	(0.009)	(0.001)	(0.012)
N	217,742	217,742	217,742	217,742
Number of Firms	48,524	48,524	48,524	48,524
Treatment Group	24,262	24,262	24,262	24,262
Adjusted R^2	0.958	0.915	0.871	0.772
Firm Fixed Effects	YES	YES	YES	YES
Time Fixed Effects	YES	YES	YES	YES

This table presents the results of the direct effects of flooding on firms for several different outcomes: Turnover, tangible fixed assets, leverage and cash. Affected 2013 is a dummy variable based on the firms location with regard to the flood (c.f Figure 1). It is set equal to 1 if the firm is located in a county with a damage category of 4 or higher and set equal to 0 if it is in an unaffected county. Firms in counties with damage categories 2 and 3 are omitted from the analysis. The regression is based on a matched sample using 2012 values of the following variables: Cash/TA, Long term debt/TA, log(total assets), regional unemployment rate, regional GDP per capita, regional insolvency applications per capita, and regional public debt per capita. All regressions include firm and year fixed effects. Clustered standard errors on the firm level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 2: Firms affected by two floods within 12 years

	(1) log(turnover)	(2) log(tangible fixed assets)	(3) leverage ratio	(4) log(cash)
Post 2013×Affected 2013	0.008^{*}	0.001	-0.003^{*}	0.006
	(0.004)	(0.012)	(0.002)	(0.016)
Post 2013×Affected 2002	0.001	0.004	-0.000	-0.009
	(0.006)	(0.018)	(0.002)	(0.025)
Post 2013×Affected 2013×Affected 2002	0.009	-0.004	-0.002	0.047
	(0.008)	(0.022)	(0.003)	(0.030)
N	199,375	199,375	199,375	199,375
Number of Firms	44,470	44,470	44,470	44,470
Treatment Group2013	21,850	21,850	21,850	21,850
Treatment Group2002	14,613	14,613	14,613	14,613
Triple Interaction	11,105	11,105	11,105	11,105
AdjustedR^2	0.959	0.915	0.873	0.771
Partial Effect 2013	0.017	-0.003	-0.005	0.053
Partial Effect p-value	0.016	0.862	0.066	0.043
Firm Fixed Effects	YES	YES	YES	YES
Time Fixed Effects	YES	YES	YES	YES

This table presents the results of the direct effects of being flooded twice within 12 years for several firm-level outcomes: Turnover, tangible fixed assets, leverage and cash. Affected 2013 is a dummy variable based on the firms location with regard to the 2013 flood. Affected 2002 is a dummy variable based on the firms location with regard to the 2002 flood (c.f Figure 1). Both variables are set equal to 1 if the firm is located in a county with a damage category of 4 or higher for the respective flood and set equal to 0 if it is in an unaffected county. Firms in counties with damage categories 2 and 3 are omitted from the analysis. The regression is based on a matched sample using 2012 values of the following variables: Cash/TA, Long term debt/TA, log(total assets), regional unemployment rate, regional GDP per capita, regional insolvency applications per capita, and regional public debt per capita. All regressions include firm and year fixed effects. Clustered standard errors on the firm level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

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— Online Appendix —

Matching procedure

All regressions are based on a matched sample of firms, in order to improve the compatibility of affected and unaffected firms. We employ propensity score matching that estimates the probability of being selected into the treatment group (p(x)), based on observable characteristics (x).

$$p(x) = \Pr(\text{Affected 2013} = 1 | \, X = x) \tag{1}$$

X are firm level and regional variables: Cash (share of TA), long term debt (share of TA) and size; Unemployment (%), GDP per capita, insolvencies per capita and public debt per capita. Variable Definitions can be found in Table OA2. We use values of these variables before the flood in the year 2012, as to ensure that the matching parameters are not themselves affected by the flood. After estimating the propensity score, we find exactly one match (without replacement) for firms in the treatment group. We additionally employ a caliper band of 0.01, meaning that no firms propensity score match can be further away than 0.01. Using this method, we identify a comparable control groups (in terms of their observables) for 24,262 firms. We then use only these firms and their controls in all further regressions (for which we use the full sample years). Table OA1 displays the reduction in sample bias due to matching. We achieve a reduction in difference of observables for all matching variables over 80% with the exception of GDP per capita. Furthermore, matching reduces all previously statistically significant differences between control and treatment groups for the firm level variables. The difference in regional variables is however more difficult to overcome. Due to the limited number of flooded regions, the variation is not large enough to remove all significant differences in these variables between the treatment and control group. Note however, that as long as the Parallel trend assumptions holds, level differences between treatment and control group do matter for difference-in-difference estimation. We confirm that trends are parallel both visually (Figure OA1) and by analyzing the pre-flood differences over time (Table OA4). Both tests confirm that the parallel trends assumption holds in our setting.

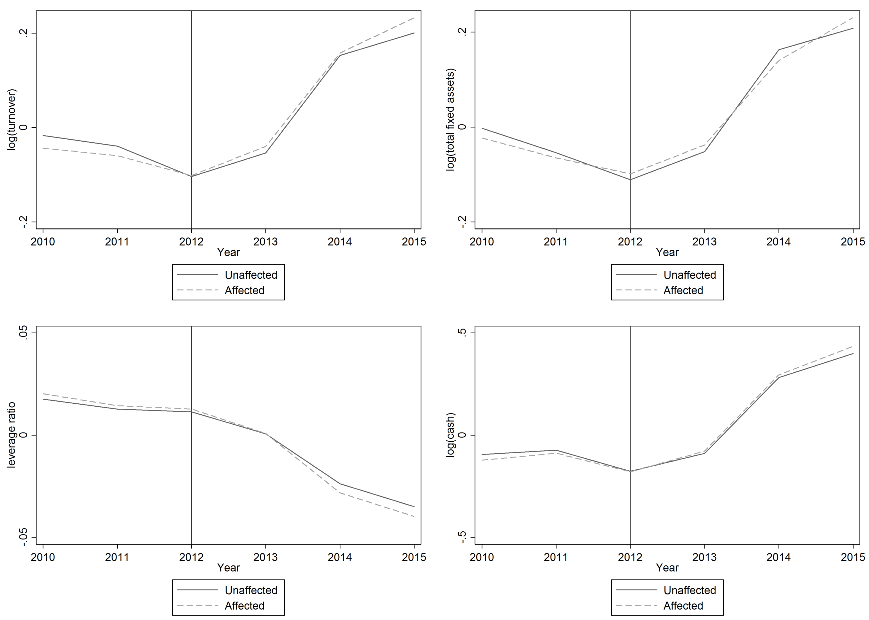
Table OA1: Matching Performance: Before and after sample Comparison

Variable	Match	Mean Treated	Mean Control	% Bias	% Bias reduction	t-statistic	p-value
Cash (share of TA)	U	0.172	0.164	4.5		8.01	0.000
	M	0.172	0.171	0.5	89.4	0.52	0.605
Long term debt (share of TA)	U	0.312	0.317	-1.7		-2.97	0.003
	M	0.317	0.316	0.2	86.1	0.26	0.798
Size	U	13.799	13.767	2.1		3.79	0.000
	M	13.783	13.788	-0.3	84.6	-0.36	0.715
Unemployment (%)	U	5.7366	7.1353	-46.3		-84.32	0.000
	M	6.487	6.5699	-2.8	94.0	-2.95	0.003
GDP per capita	U	36,005	34,457	9.2		17.04	0.000
	M	31,463	32,539	-6.4	30.5	-8.63	0.000
Insolvencies per capita	U	0.0015	0.0020	-97.6		-174	0.000
	M	0.0018	0.0018	6.2	93.6	6.78	0.000
Public debt per capita	U	1,026	2,225	-103.6		-169.2	0.000
	M	1,320	1392	-6.3	93.9	-8.87	0.000

This table presents the outcome of the 1:1 propensity score matching between firms affected and unaffected by the flood used to create the sample for estimation. It displays the means of the matching variables for the sample of unmatched (U) and matched (M) firms, for the affected and unaffected groups. Furthermore it shows the reduction in bias and provides difference in means tests (ttest) for both samples.

Additional Figures and Tables

Figure OA1: Distribution of flood damages in Germany 2013 and 2002



This figure shows the trend of unaffected and affected firms for all four dependent variables over the sample period (2010-2015). All trends have been demeaned, i.e. the overall mean for any given year has been subtracted.

Table OA2: Descriptives Statistics

Variable Name	Definition	Amadeus Code
Identification Variables		
Post 2013	Dummy variable set to 0 for 2010-2012 and set to 1 for 2013-2015.	
Affected 2013	Dummy variable set to 0 if no flood insurance claims were made during the 2013 flood event in the firms region and set to 1 if the firm is located in a county with flood damage category 4 or lager.	
Affected 2002	Dummy variable set to 0 if no flood insurance claims were made during the 2002 flood event in the firms region and set to 1 if the firm is located in a county with flood damage category 4 or lager.	
Dependent Variables		
Turnover (tsd EUR)	Operating Revenue (Turnover) of firms. Used in logs in the regression.	OPRE
Tangible fixed assets (tsd EUR)	Tangible Fixed Assets of firms. Used as logs in the regression.	TFAS
Leverage ratio	Total liabilities (non-current + current) divided by total assets.	(CULI+NCLI) / TOAS
Cash (tsd EUR)	Cash and cash equivalent of firms. Used as logs in the regression.	CASH
Matching Variables		
Size	log(total assets)	ln(TOAS)
Long term debt (share of TA)	Long term debt as the share of firms total assets.	LTDB / TOAS
Cash(share of TA)	Cash and cash equivalent as the share of total assets	CASH / TOAS
Insolvencies per capita	Regional insolvency applications / number of inhabitants in the region. Derived from official statistics.	
Unemployment (%)	Regional unemployment rate in %.	
Public debt per capita	Public debt of the local governments (counties and cities) / by the number of inhabitants in the region	
GDP per capita	Regional GDP / number of inhabitants in the region	

This table provides the definitions of the variables used in the regression and the matching procedure.

Table OA3: Descriptives Statistics

	N	Mean	SD	Min	Max
Affected Variables					
Affected 2013	217742	0.50	0.50	0.00	1.00
Affected 2002	199375	0.33	0.47	0.00	1.00
Dependent Variables					
Turnover (tsd EUR)	217742	5094	10754	58.18	69149
Tangible fixed assets (tsd EUR)	217742	1403	4917	0.00	36237
Leverage ratio	217742	0.65	0.27	0.07	1.00
Cash (tsd EUR)	217742	411.5	1053	0.07	7701
Matching Variables					
Size	217742	13.88	1.45	10.64	18.05
Long term debt (share of TA)	217742	0.31	0.30	0.00	0.99
Cash (share of TA)	217742	0.18	0.20	0.00	0.80
Insolvencies per capita	215041	1.73	0.57	0.73	3.60
Unemployment (%)	215041	6.50	3.00	2.20	13.90
Public debt per capita	216591	1332	889.00	45.06	6504
GDP per capita	193753	31998	13836	17431	96641

This table presents summary statistics for all variables used in the regressions and matching process. Affected 2013 is a dummy variable based on the firms location with regard to the 2013 flood. Affected 2002 is a dummy variable based on the firms location with regard to the 2002 flood. Both dummies are set equal to 1 if the firm is located in a county with a damage category of 4 or higher and set equal to 0 if it is in an unaffected county in the respective flood years. Dependent variables are displayed in levels in this table, but used in natural logs in the regressions. Matching variables are used for the pre-estimation, 1:1 propensitiy score matching. Matching is based on pre-flood (2012) characteristics.

Table OA4: Pre-2013 statistics for affected and unaffected firms

	Affected		Unaffected		
	Mean	SD	Mean	SD	ND
Dependent Variables					
ΔRevenue (tsd EUR)	0.184	5.625	0.211	6.863	-0.00
ΔTangible fixed assets (tsd EUR)	27.17	2267	16.043	1281	0.00
ΔLeverage ratio	0.004	0.334	0.002	0.304	0.01
ΔCash (tsd EUR)	9.333	303.8	8.260	123.1	0.00
Matching Variables					
ΔSize	0.005	0.023	0.005	0.023	0.01
ΔLong term debt (share of TA)	24.246	2830	9.687	1098	0.00
ΔCash (share of TA)	7.309	125	6.879	98.77	0.00
ΔGDP per capita	0.032	0.036	0.030	0.032	0.05
ΔUnemployment (%)	-0.076	0.064	-0.049	0.064	-0.30
ΔPublic debt per capita	0.008	0.082	0.020	0.110	-0.09
ΔInsolvencies per capita	-0.052	0.118	-0.048	0.131	-0.02

This table presents average changes (Δ, in percent) for the period 2010-2012 for the all variables used in our analyses for affected and unaffected banks. Detailed definitions of the variables are provided in Table OA3. We provide normalized differences in the last column. A value for normalized differences larger than $|0.25|$ indicates that averages between both groups of banks are significant.

Table OA5: Baseline effect of flooding on firm performance: Non-missing 2002 flood firms

	(1) log(turnover)	(2) log(tangible fixed assets)	(3) leverage ratio	(4) log(cash)
Post 2013×Affected 2013	0.013^{***}	0.000	-0.004^{***}	0.026^{**}
	(0.003)	(0.010)	(0.001)	(0.012)
N	199,375	199,375	199,375	199,375
Number of Firms	44,470	44,470	44,470	44,470
Treatment Group	21,850	21,850	21,850	21,850
AdjustedR^2	0.959	0.915	0.873	0.771
Firm Fixed Effects	YES	YES	YES	YES
Time Fixed Effects	YES	YES	YES	YES

This table presents the results of the baseline regression, for the sample used in the double flood regression, i.e. excluding firms which are excluded due to the definition of the Affected 2002 variable. Affected 2013 is a dummy variable based on the firms location with regard to the flood. It is set equal to 1 if the firm is located in a county with a damage category of 4 or higher and set equal to 0 if it is in an unaffected county. Firms in counties with damage categories 2 and 3 are omitted from the analysis. Post is a dummy set equal to 0 for the pre-flood years (2010-2012) and set equal to 1 for the post-flood years (2013-2015). The regression is based on a matched sample using 2012 values of the following variables: Cash/TA, long term debt/TA, size, regional unemployment rate, regional GDP per capita, regional insolvency applications per capita, and regional public debt per capita. All regressions include firm and year fixed effects. Clustered standard errors on the firm level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table OA6: Robustness: Collapsed sample

	(1) log(turnover)	(2) log(tangible fixed assets)	(3) leverage ratio	(4) log(cash)
Post 2013	0.084***	0.104***	-0.025***	0.172***
	(0.002)	(0.007)	(0.001)	(0.009)
Post 2013×Affected 2013	0.014***	-0.002	-0.004***	0.023*
	(0.003)	(0.009)	(0.001)	(0.012)
Constant	14.299***	11.481***	0.672***	10.822***
	(0.001)	(0.002)	(0.000)	(0.003)
N	97,048	97,048	97,048	97,048
Number of Firms	48,524	48,524	48,524	48,524
Treatment Group	24,262	24,262	24,262	24,262
Adjusted R^2	0.055	0.010	0.045	0.019
Firm Fixed Effects	YES	YES	YES	YES
Time Fixed Effects	NO	NO	NO	NO

This table provides the results of OLS regressions of the baseline on a collapsed sample, in order to address concerns that the results are driven by autocorrelation. The sample is collapsed into the pre-flood and post-flood period for this regression. Affected 2013 is a dummy variable based on the firms location with regard to the flood. It is set equal to 1 if the firm is located in a county with a damage category of 4 or higher and set equal to 0 if it is in an unaffected county. Firms in counties with damage categories 2 and 3 are omitted from the analysis. The regression is based on a matched sample using 2012 values of the following variables: Cash/TA, long term debt/TA, size, regional unemployment rate, regional GDP per capita, regional insolvency applications per capita, and regional public debt per capita. All regressions include firm fixed effects. Clustered standard errors on the firm level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table OA7: Placebo Regression

	(1) log(turnover)	(2) log(tangible fixed assets)	(3) leverage ratio	(4) log(cash)
Post 2013 ×Affected 2013	0.005	0.011	-0.000	-0.016
	(0.004)	(0.011)	(0.001)	(0.016)
N	109,623	109,623	109,623	109,623
Number of Firms	41,350	41,350	41,350	41,350
Treatment Group	24,262	24,262	24,262	24,262
Adjusted R^2	0.968	0.937	0.902	0.795
Firm Fixed Effects	YES	YES	YES	YES
Time Fixed Effects	YES	YES	YES	YES

This table presents the results of a placebo regression, using the year 2011 as the treatment year and excluding the years 2013-2015. Accordingly, post is a dummy set equal to 0 for the year 2010 and set equal to 1 for the years 2011 and 2012. Affected 2013 is a dummy variable based on the firms location with regard to the flood. It is set equal to 1 if the firm is located in a county with a damage category of 4 or higher and set equal to 0 if it is in an unaffected county. Firms in counties with damage categories 2 and 3 are omitted from the analysis. The regression is based on a matched sample using 2012 values of the following variables: Cash/TA, long term debt/TA, size, regional unemployment rate, regional GDP per capita, regional insolvency applications per capita, and regional public debt per capita. All regressions include firm fixed effects. Clustered standard errors on the firm level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table OA8: Effect of flooding on firm performance: No fixed effects

	(1) log(turnover)	(2) log(tangible fixed assets)	(3) leverage ratio	(4) log(cash)
Post 2013	0.085^{***}	0.105^{***}	-0.026^{***}	0.191^{***}
	(0.002)	(0.007)	(0.001)	(0.008)
Affected 2013	-0.094^{***}	0.027	-0.004^{*}	0.028
	(0.012)	(0.023)	(0.002)	(0.020)
Post 2013×Affected 2013	0.015^{***}	-0.003	-0.004^{***}	0.022^{*}
	(0.003)	(0.009)	(0.001)	(0.012)
Constant	14.350^{***}	11.476^{***}	0.674^{***}	10.814^{***}
	(0.009)	(0.017)	(0.002)	(0.014)
N	217,742	217,742	217,742	217,742
Number of Firms	48,524	48,524	48,524	48,524
Treatment Group	24,262	24,262	24,262	24,262
R^2	0.004	0.001	0.003	0.003
Firm Fixed Effects	NO	NO	NO	NO
Time Fixed Effects	NO	NO	NO	NO

This table presents the results of a difference-in-difference estimation of the direct effects of the 2013 flooding on firms for several different outcomes, without including fixed effects. Affected 2013 is a dummy variable based on the firms location with regard to the flood (c.f Figure **??**). It is set equal to 1 if the firm is located in a county with a damage category of 4 or higher and set equal to 0 if it is in an unaffected county. Firms in counties with damage categories 2 and 3 are omitted from the analysis. Post is a dummy set equal to 0 for the pre-flood years (2010-2012) and set equal to 1 for the post-flood years (2013-2015). The regression is based on a matched sample using 2012 values of the following variables: Cash/TA, long term debt/TA, size, regional unemployment rate, regional GDP per capita, regional insolvency applications per capita, and regional public debt per capita. Clustered standard errors on the firm level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table OA9: Effect of flooding on firm performance: Unmatched dataset

	(1) log(turnover)	(2) log(tangible fixed assets)	(3) leverage ratio	(4) log(cash)
Post 2013×Affected 2013	0.027^{***}	0.032^{***}	-0.005^{***}	0.052^{***}
	(0.002)	(0.006)	(0.001)	(0.007)
N	662,744	662,744	662,744	662,744
Number of Firms	151,943	151,943	151,943	151,943
Treatment Group	54,609	54,609	54,609	54,609
AdjustedR^2	0.954	0.907	0.866	0.766
Firm Fixed Effects	YES	YES	YES	YES
Time Fixed Effects	YES	YES	YES	YES

This table presents the results of the baseline regression, for an unmatched sample of firms. Affected 2013 is a dummy variable based on the firms location with regard to the flood. It is set equal to 1 if the firm is located in a county with a damage category of 4 or higher and set equal to 0 if it is in an unaffected county. Firms in counties with damage categories 2 and 3 are omitted from the analysis. Post is a dummy set equal to 0 for the pre-flood years (2010-2012) and set equal to 1 for the post-flood years (2013-2015). All regressions include firm and year fixed effects. Clustered standard errors on the firm level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table OA10: Effect of flooding on firm performance: Matching variables as controls

	(1) log(turnover)	(2) log(tangible fixed assets)	(3) leverage ratio	(4) log(cash)
Post 2013×Affected 2013	0.009^{***}	-0.005	-0.002^{*}	0.007
	(0.003)	(0.009)	(0.001)	(0.010)
Cash (share of TA)	0.048^{***}	-0.855^{***}	-0.148^{***}	6.788^{***}
	(0.011)	(0.033)	(0.004)	(0.040)
Long term debt (share of TA)	-0.044^{***}	0.124^{***}	0.125^{***}	-0.032^{**}
	(0.005)	(0.014)	(0.002)	(0.015)
Size	0.323^{***}	0.887^{***}	0.058^{***}	0.821^{***}
	(0.007)	(0.020)	(0.002)	(0.013)
GDP per capita	0.000^{**}	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment (%)	-0.003	-0.006	-0.000	0.005
	(0.002)	(0.007)	(0.001)	(0.007)
Public debt per capita	-0.000^{***}	-0.000	0.000^{**}	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Insolvencies per capita	5.887	10.477	-1.435	6.425
	(4.392)	(12.164)	(1.449)	(14.419)
N	190,958	190,958	190,958	190,958
Number of Firms	48,430	48,430	48,430	48,430
Treatment Group	24,262	24,262	24,262	24,262
AdjustedR^2	0.965	0.929	0.895	0.855
Firm Fixed Effects	YES	YES	YES	YES
Time Fixed Effects	YES	YES	YES	YES

This table presents the results of the direct effects of flooding on firms affected by the flood on several different outcomes. The regression includes the matching variables as control variables. Affected 2013 is a dummy variable based on the firms location with regard to the flood (c.f Figure **??**). It is set equal to 1 if the firm is located in a county with a damage category of 4 or higher and set equal to 0 if it is in an unaffected county. Firms in counties with damage categories 2 and 3 are omitted from the analysis. The regression is based on a matched sample using 2012 values of the following variables: Cash/TA, long term debt/TA, ln(Total assets), regional unemployment rate, regional GDP per capita, regional insolvency applications per capita, and regional public debt per capita. All matching variables are used as control variables in this regression. All regressions include firm and year fixed effects. Clustered standard errors on the firm level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

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