A bit under the Weather? Flood Impacts and Recovery Strategies of Manufacturing Firms*

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Abstract

Economic disaster or creative destruction? The impacts of weather extremes on firm-level financial performance is far from being completely understood. This paper analyses impacts of flood events on European manufacturing firms. Combining a highly granular identification strategy with the Local Projections Difference-in-Difference approach, we estimate firms' dynamic average treatment responses to flood exposure. We find that flood-affected firms experience a 7% reduction in tangible assets two years after the flood compared to non-affected control firms, as well as a decline in firm output, productivity and profitability. However, those effects decline and are not significant after four years, as firms recover and replace damaged asset by newer, more productive technologies. More importantly, we find that increased credit constraint lead flood-affected firms to draw on cash reserve and resort to equity injections to compensate for restricted access to credit. More severe floods exert a stronger and more prolonged effect on firms' productive physical capital and liquidity. Finally, while financially stable firms become more productive and profitable due to damaged assets replacement, distressed firms face significant constraints in leveraging financing to support recovery, leading to long-lasting flood effect. Overall, we find that floods impact firm-level financial performance on the short-term but are insignificant on the long-term. However, under financial stress, floods have the potential to persistently erode firms' balance sheet.

Keywords: Climate risk, disaster resilience, economic damages, floods, local projection Difference-in-Differences, manufacturing firms, natural hazards, recovery.

JEL Codes: C23, D22, G31, Q54.

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1 Introduction

Riverine flooding, a consequence of excessive rainfall, snowmelt, or dam failures, poses significant risks to businesses by disrupting production capacity and causing extensive physical damage. Combined with increased urbanization, climate change is expected to amplify riverine flood-related damages - threefold under a 1.5°C rise, fourfold at 2°C, and sixfold at 3°C (Alfieri et al., 2018; Dottori et al., 2018). These projections underscore the critical need for deeper insight into climate resilience and firm-level adaptive strategies in response to such events.

While significant progress has been made in understanding the economic consequences of extreme weather events, the precise impact of floods on firm-level financial performance still remain unclear. Some studies find that flood-affected firms experience substantial asset losses (Fatica et al., 2024; Leiter et al., 2009; Pan and Qiu, 2022), whereas there is also evidence suggesting that these firms are very resilient or even outperform their unaffected counterparts (Coelli and Manasse, 2014; Noth and Rehbein, 2019), which supports the creative destruction hypothesis that destroyed production assets are replaced by more productive ones. The mixed evidence suggests that the relationship between floods and firm performance is not yet fully understood. This paper investigates the impact of floods using a highly precise approach in identifying flood affected firms and applying a recently developed method to estimate dynamic treatment effects.

Floods inevitably cause physical damage, resulting in the loss of essential machinery and assets, the deterioration of land and buildings, and additional financial burdens for firms. This has been mirrored in previous research, where total assets, productivity and value added, are systematically chosen as main outcome variables (Bernstein et al., 2019; Fatica et al., 2024; Fujin & Wouter, 2021; Leiter et al., 2009). However, a range of mechanisms unfolding in the aftermath of a flood may produce contrasting effects on the financial health of affected firms. These mechanisms could be context-dependent and external to the firm, including factors such as the severity of the flood, the extent of economic damages, the availability of public financial support, and the presence of insurance coverage. At the firm level, however, companies may engage in asset recovery, such as seeking alternative sources of internal or external funding sources to replace damaged resources, which can significantly affect their leverage and liquidity and ultimately their productivity and financial performance.

The contradictory findings in previous studies raise important questions about the underlying reasons for the variation in empirical findings concerning the impacts of floods. It is conceivable that in specific contexts or with certain characteristics, e.g., finically well performing firms, exhibit a degree of resilience that allows them to absorb flood-related financial shocks without major disruption to their activities or significant negative impact to their assets. Another potential explanation is that prior research may have overlooked critical factors related to corporate recovery and disaster management, which could make the impact of floods more nuanced and context-dependent than initially believed. Alternatively, the disparities in findings may stem from differences in the methodologies employed across studies, such as variations in data sources, sample selection, or empirical strategies.

This paper aims to address these questions and shed light on why the findings on the impact of floods on firms seem so inconsistent. We analyse the impact of flood events on European manufacturing firms. We identify firms located in flood-prone areas that were exposed to floods between 2008 and 2017 at the NUTS-3 level. As firms are affected by floods with heterogenous severities at different points in time, and as impacts might evolve over time, we use the recently proposed Local Projections Difference-in-Difference (LP-DiD) approach (Dube et al., 2023). This approach enables us to estimate dynamic average treatment responses for staggered treatments, which may be heterogeneous across groups and dynamic, i.e., gradually occur over time, compared to a clean control group. We then explore effect heterogeneity by analysing the role of flood severity and compare impacts on financially distressed companies compared to stable firms. As a robustness check, we employ a matching procedure to identify the effects for firms with similar pre-flood characteristics.

Our main results are as follows. First, we find that floods negatively affect firms' assets, in particular by damaging or destroying tangible fixed assets, such as plants, machinery, and buildings. Similarly, their sales, productivity, and profitability also decline. Floods further reduce firms' ability to raise debt, which might impede recovery measures. While these impacts persist over several years after a flooding event, they ultimately decrease or even recover to pre-flood levels four or more years after a flood. Second, we find that firm-level impacts are more pronounced in the case of severe floods, likely due to particularly extensive physical damage to production assets such as machinery and buildings. In contrast, firms recover notably faster from minor flood events. Third, we find that firms that are already in financial turmoil before a flood occurs are more vulnerable and less capable to recover. Distressed firms experience significantly higher losses in production assets and face credit constraints, which deter their capacity to recover. In contrast to distressed firms, which experience reductions in profitability, we find that stable firms' returns to assets increase in the aftermath of a flood event. This finding supports the argument of creative destruction that lost production assets are replaced by more productive ones, which can be done particularly well by firms with internal and access to external funding. The robustness checks based on matched firms confirm our main findings.

This paper's contribution to the literature are three-fold. First, we employ a rigorous multi-step geocoding process to achieve the highest granularity in identifying flood-affected firms, which allows us to provide more precise insights into the financial impact of floods at the firm level. Previous papers often identify affected firms based on their location in a flooded or non-flooded administrative region (e.g., Leiter et al., 2009; Noth and Rehbein, 2019). Our approach builds on Fatica et al. (2024), who identify flood-affected firms using hazard maps to identify flood-prone areas. In their approach, Fatica et al. (2024) rely, to a large extend (40% of firms), on postal codes or nearest neighbour postal codes to geolocalise firms. We use the firms' addresses to determine with more accuracy a firms' geocoordinates and more precisely identify flood-affected firms. To the best of our knowledge, this represents the highest level of granularity achieved in studies examining the impact of floods on firms, enabling us to provide more precise insights into the financial impact of floods at the firm level. Our estimated effect sizes are larger than those of previous studies, which might be due to our approach reducing the issue of over-identification of flood-affect firms.

Second, we add to the literature by analysing the role of flood severity and, in particular, by differentiating between financially distressed and stable firms. We provide insights on the opposing effects of substantial losses in assets and productivity (Fatica et al., 2024; Leiter et al., 2009; Pan & Qiu, 2022) as well as the idea of creative destruction (Coelli & Manasse, 2014; Noth & Rehbein, 2019). Our findings indicate that, while firms initially suffer from flooding events, they successfully recover after a few years and, in some cases, even end up more productive and profitable than control firms. Greater flood severity appears to be associated with higher economic damages and longer recovery periods. Similarly, firms already in financial distress before a flood struggle significantly more with recovery, while financially stable firms appears to be financially stronger after a flood. This could explain the opposing previous findings of studies that do not differentiate between affected firms' financial situations.

Third, we explicitly shed light on how firms finance their recovery from flood damages by analysing firms' debt, equity, and liquidity. While most of previous studies focus on firm assets, productivity, or output (Coelli & Manasse, 2014; Fatica et al., 2024; Leiter et al., 2009; Yamamoto & Naka, 2021), only a few papers analyse the outcome variables associated with recovery financing, such as cash holdings (Noth & Rehbein, 2019), debt leverage (Noth & Rehbein, 2019) and demand for debt (Benincasa et al., 2024). This paper adds to the literature by analysing the impacts of floods on different potential funding sources for recovery measures, such as different types of debt and liabilities, equity issuance, and cash and other liquid current assets. Our findings suggest that flood-affected firms seem to be credit constraint, most likely due to the loss in tangible fixed assets that can serve as collateral, and fund recovery measures largely via internal funds or equity.

The paper is organised as follows. We review the relevant literature in Section 2. Section 3 presents the data and outlines our treatment identification strategy. Our empirical strategy is presented in Section 4, followed by the results in Section 5. Section 6 concludes.

2 Literature Review

Floods impact firm productivity and profitability through several channels. Relief, cleaning and reparation raise operational expenditures, whereas diminished labour supply (due to displacement, health, deaths and emergencies), obstructed infrastructures (such as health, communication and transports), and operating assets as well as disrupted lifelines (for example, water, gas and electricity) slow down production. Affected regions might suffer from a decrease in final and intermediate consumption, impacting sales (Pankratz & Schiller, 2024). Finally, on a longer term, a flood event can lead financial institutions and insurance companies to review firm risk perception fees and might increase the cost of capital and insurance premiums, further increasing operational expenditures. Leiter et al. (2009) find that European firms affected by floods exhibit a lower value added within two years post flood. This is consistent with findings of negative impacts of floods on gross output, sales, profit, and value added in New Zealand (Prieto & Noy, 2024), sales growth in Vietnam (Fujin & Wouter, 2021), and the ratio of profit-to-sales in Japan (Yamamoto & Naka, 2021). In contrast, Noth and Rehbein (2019) find that firms located in flooded regions have significantly higher turnover within three years after a flood and Coelli and Manasse (2014) find that the value-added growth of affected firms two years after the flood is 6.9% higher compared to non-affected firms.

Besides short-term production disruptions, floods damage and destroy firms' physical assets. This ranges from losses and damages in tangible assets, such as buildings, plant and machinery, and equipment and vehicles, to destructed business operating assets, such as stock inventories and supplies. Lost assets might be written off the balance sheet, damaged assets depreciated, and flood risk exposure might lead to a devaluation of current assets (e.g., Bernstein et al., 2019). In order to recover, firms to invest in new fixed assets. For instance, Benincasa et al. (2024) find that firms suffering losses from extreme weather exhibit a 6 percentage points greater propensity to invest in fixed assets, in particular land and buildings, as well as machinery and equipment. Asset replacement might, due to the amortization mechanism, building renovation, and investment in more productive technologies, increase the value of tangible assets. The current literature provides ambiguous findings on whether floods lead to an increase or loss of corporate assets. Whereas Fatica et al. (2024) find that flood-affected companies sustain a loss in assets by about 2% in the following year, Fujin and Wouter (2021) and Leiter et al. (2009) report capital growth. In contrast, Prieto and Noy (2024) argue that capital damage might be a more important transmission channel to firm financial performance than productivity losses.

Both, productivity losses and capital damages, are intertwined. Although capital damages negatively affect productivity in the short run, capital replacement can induce productivity growth in the medium- to long-run if it provides a technological upgrade. Erda (2024) finds that plants, which retire capital in a flood year, substantially increase their capital investment by about 24% and subsequently exceed their pre-disaster labour productivity baseline by about 4.5%. Capital replacement could explain the increase in value added found in Leiter et al. (2009) and Coelli and Manasse (2014). However, as we will describe in the following section, not all firms are able to raise capital and therefore, replace lost assets.

Firms' recovery and capacity to replace lost and damaged assets highly depend on availability of financial resources. Following a natural disaster, firms' access to debt might be constrained. However, there are only few studies on the impact of floods on corporate debt at the firm-level and limited signals that affected firms are more levered than non-affected firms. Noth and Rehbein (2019) find that flood-affected firms reduce leverage by 0.2 percentage points and Elnahas et al. (2018) provide evidence that firms in the most disastrous areas are less levered by 3.6 percentage points. Conversely, Benincasa et al. (2024) find that firms suffering losses from extreme weather events are more levered when considering equity injections and government assistance. The authors further show that firms having suffered monetary losses due to weather extremes are 12 percentage points more likely to need bank credit, however, 5 percentage points more likely to have their loan application rejected. There are several reasons behind those rejections. First, floods, through increased risk awareness, high loan spread and weakened value of collateral, deteriorate firms' creditworthiness (Javadi & Masum, 2021). Secondly, banks in affected regions experience deposit withdrawals, credit demand surge and exposure to unexpected losses and are not able to meet the credit demand (among others, Chowdhury et al., 2022; Rehbein and Ongena, 2022). Koetter et al. (2020), for example, find that flooded firms that have a loan with financial institutions located inside the flooded counties significantly decrease their corporate debt by 46% compared to the pre-flood period, whereas firms connected to a bank located outside of the affected area increase their corporate debt by about 16%.

While debt financing remains the preferred choice (Benincasa et al., 2024), flood-affected firms might turn to alternative financing options, such as private equity, crowd-funding. venture capital and trade credit. Baltas et al. (2022) for example, finds that private funding of US companies increases within 3 months after the occurrence of a natural disaster. Using data on Chinese firms, Lai et al. (2022) show that floods lead to a 2.8% increase in trade credit, a financial arrangement where a supplier allows a buyer to purchase goods or services and pay for them at a later date. Both studies suggest that credit constraint is an important predictor of seeking such alternatives and support a substitution hypothesis.

There is, however, only limited research exists on the role of access to credit and financing alternatives on post-disaster financial recovery. Exceptions are Fatica et al. (2024) and Pan and Qiu (2022), who find that pre-disaster financial constraints are an important predictor for post-disaster recovery, as firms with higher pre-flood debt levels suffer a more substantial reduction in assets following a disaster.

Finally, floods may cause changes in affected firms' liquidity. On the one hand, firms might exhibit decrease in cash reserve, as highly liquid assets might be traded to finance tangible assets acquisition and replacement, as well as extra fees occurring in the event of a flood. On the other hand, firms may receive financial support in the form of cash payouts from insurance schemes or governmental disaster relief programmes following a natural disaster. European countries impose different flood insurance regimes, where subscribing to a flood insurance scheme might be mandatory (e.g., in Spain, Belgium, France), voluntary (e.g., Austria, Germany, Italy, Croatia, Slovakia, Bulgaria) or linked to indirect mandates (e.g., Portugal, Poland, Slovenia, Czechia, Hungary) (Bock et al., 2024; Hudson et al., 2019; Tesselaar et al., 2022). In addition to flood insurance, governments often enact ad-hoc government relief programmes post major disasters to aid recovery. This could be decided on a case-by-case basis (as in Germany, Italy and Slovakia), conditional to uptake requirements (such as in Spain, Portugal, France, Belgium), only partially cover losses, such as in Austria, or provide no ad-hoc disaster aid altogether such as in Croatia and Slovenia (Bock et al., 2024). Access to insurance payouts and state relief programme could therefore raise cash holdings for firms. For example, Noth and Rehbein (2019) found that affected firms exhibit an increase of cash holding of 2.1% in the period after 2013. A firm's capacity to recover from a flood event might be highly dependent on their capacity to increase short-term liquidity and raise capital. Much evidence points towards the positive role played by an increase liquidity through state aid and insurance on recovery. Coelli and Manasse (2014) finds that the role of state aid correlated with 2% increase in value added. Similarly, a randomised experiment of access to relief aid on the recovery of Sri Lankan microenterprises show that firms having received randomly allocated grants recover profit levels almost 2 years before other damaged firms (De Mel et al., 2011). Findings are similar on the role of insurance. Bock et al. (2024) find that both insurance penetration and mandatory insurance have a positive effect on economic recovery.

3 Data

This section provides an overview of the data. First, we describe the firm-level data and the process of obtaining firms' geocoordinates. Next, we discuss flood events across the EU and explain how we identify affected areas (i.e., flooded) using flood extent maps. We then outline the methodology for defining the treated and control groups. Finally, we present the final firm-panel data, including key financial indicators.

3.1 Firm-level data

Our firm-level data is obtained from the ORBIS database by Moody's Bureau Van Dijk, which provides detailed information on balance sheets and income statements for more than 40 million listed and private companies from more than 100 countries worldwide. For our analysis, we retrieve financial, sectoral, and geographic data for firms located in European countries that experienced significant flood events between 2007 and 2018. We restrict our sample to manufacturing firms classified under NACE Revision 2 codes, which results in a dataset comprising approximately 11 million observations across 1.9 million firms.

Identifying flood-affected firms necessitates precise geographic localisation of their headquarters. ORBIS provides exact latitude and longitude coordinates for approximately 32% of firms in our dataset. For the remaining firms, we employ a two-step geocoding process. First, we geocode firms' reported addresses using the OpenStreetMap API and successfully assign coordinates to an additional 27.3% of the dataset. Secondly, following Fatica et al. (2024), we use a matching procedure that links postal codes available in ORBIS with those in the GeoNames database, covering an additional 19% of firms. The distribution of geocoded firms by method and country is presented in Table A.1 in Appendix A. Firms for which geographic coordinates cannot be determined (329,922 observations)[1] are excluded from the final estimation sample. Furthermore, countries with insufficient geocoded coverage using the aforementioned methods—such as Ireland—are omitted from the analysis. The final dataset comprises firms from 15 European countries: Austria, Belgium, Bulgaria, Croatia, Czechia, France, Germany, Hungary, Italy, Poland, Portugal, Romania, Slovakia, Slovenia, and Spain. Due to these restrictions we impose, the locations of firms in our sample are more precisely determined than in Fatica et al. (2024), which allows us to better identify flood-affected firms in the next step. A disadvantage is, of course, that we loose observations.[2]

[1]There are several reasons for the absence of geocoordinates. In some instances, the ORBIS database does not provide the postal code (ZIP). In other cases, the ZIP is not available in the GeoNames database. Additionally, for certain countries, the reported ZIP refers to an administrative unit that is too broad to accurately identify flood-affected firms, as is the case in Ireland. Finally, we exclude firms where the reported NUTS3 region does not align with the region derived from the obtained geocoordinates.

[2]Compared to Fatica et al. (2024), we do not include the UK or Ireland in our sample, as only 3-digit

3.2 Riverine floods in Europe

We obtain flood data for selected European countries from the Risk Data Hub (RDH) of the Disaster Risk Management Knowledge Center (DRMKC) (European Commission, Joint Research Centre, 2022). The RDH consolidates, harmonises, and disaggregates data from multiple sources, notably the EM-DAT International Disaster Database (CRED, UCLouvain), the Historical Analysis of Natural Hazards in Europe (HANZE), and the Global Active Archive of Large Flood Events (Dartmouth Flood Observatory (DFO), University of Colorado). While disaster databases are prone to data gaps (Jones et al., 2023), the DRMKC Risk Data Hub Disaster Loss Data is, to the best of our knowledge, the most comprehensive dataset available on floods in Europe. It provides detailed information on the frequency, economic and human impacts, and geographic distribution of natural disasters, up to the smallest regional administrative units (that is, the NUTS3 level).

We focus on river floods from 2007 to 2018 in selected European countries. Riverine floods, unlike coastal and flash floods, are primarily due to overflow of rivers caused by heavy rain or releases from upstream dams, and account for 97% of all reported flood events. The data set includes 1,904 flood observations at the annual and regional levels for the 2007–2018 period. 1 illustrates the geographical distribution of flood events in Europe during this time, with darker blue shades indicating areas with a higher frequency of flood occurrences at the NUTS3 level. The number of NUTS3 regions flooded by country is reported in Table A.2 in Appendix A.

3.3 Identifying flood-affected companies

Firms located in NUTS3 regions that have experienced floods are not necessarily all directly affected. To more accurately identify firms located in flood-prone areas, we follow the approach of Fatica et al. (2024) by overlaying firm-level geographic data with the River Flood Hazard Maps developed by the Joint Research Centre of the European Commission (Dottori et al., 2018). These flood hazard maps delineate inundation areas determined

ZIP codes are available, which refer to rather larger areas.

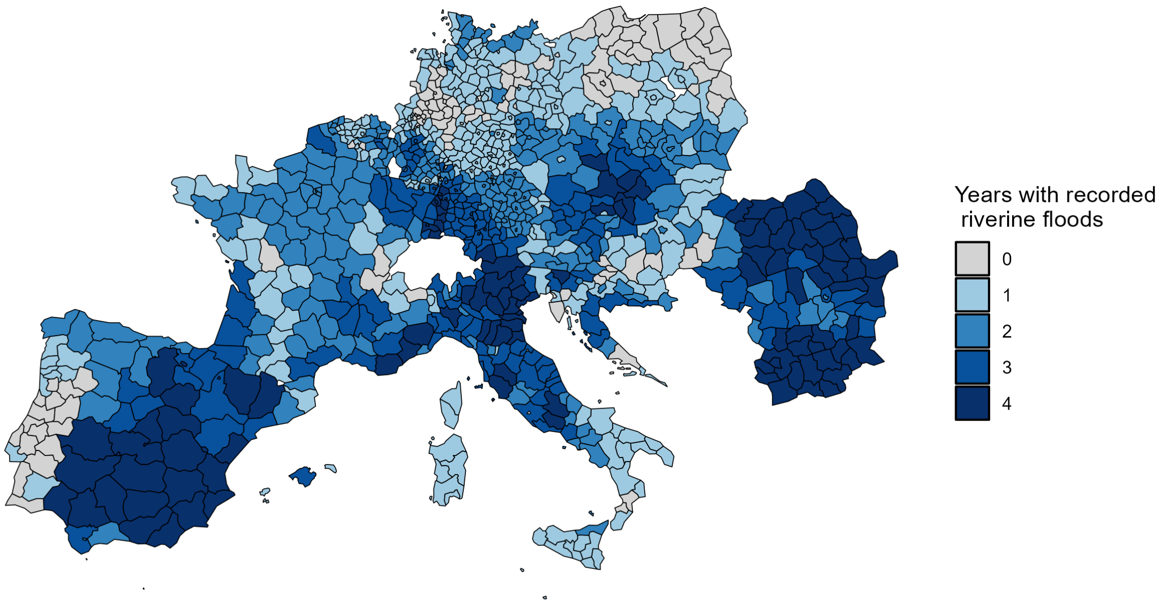


Figure 1: Spatial distribution and frequency of floods events in Europe.

Notes: The map illustrates the number of flood events across NUTS3 regions across selected EU countries between 2007 and 2018.

using a hydrological and hydraulic modelling framework that accounts for existing flood protection infrastructure. Although the maps provide projections of flood extents under different return period scenarios, they have demonstrated strong predictive accuracy in capturing the extent of past flood events. Furthermore, they exhibit significant alignment with both regional and national official flood hazard maps (Alfieri et al., 2015; Dottori et al., 2018).

Given that flood hazard models tend to overestimate flood exposure, leading to potential false positives, we adopt a conservative approach to minimise the over-identification of directly flood-affected firms. Specifically, we focus solely on flood hazard maps with a 1-in-10-year return period. Following the methodology of Fatica et al. (2024), we convert the flood hazard maps, originally provided at a 100-meter grid resolution, into polygons with 300-meter buffers using the 8-connectedness method. Firms are classified as exposed to floods if their geocoordinates fall within a flood-prone area with a 1-in-10-year return period and if their corresponding NUTS3 region experienced flooding in a given year. Based on this methodology, 4.56% of all firms in our dataset were affected by floods at least once during the 2007–2018 period. Among these, 71.56% were flooded only once, 25.42% experienced flooding twice, and 3.02% were affected more than twice. In contrast, we define control group firms as those whose geocoordinates are situated at least 10 kilometres away from any flood-prone area, as identified in the 1-in-500-year hazard map. These firms account for approximately 24.73% of the dataset.

3.4 Data samples and descriptive statistics

To build a suitable dataset for our empirical analysis, we impose several restrictions to refine the sample. Our LP-DiD approach requires that treatment firms are only affected once by a flood such that additional flood events in the post-treatment horizon do not affect the estimated treatment effects. Hence, our final sample includes all never treated firms, which serve as the primary control group, and firms affected by a single flood event in the sample period. For firms affected by more than one flood, we only retain observations up to the second flood event.

Furthermore, we address missing observations and control for outliers. We consider several variables on the firms' asset side and profitability, such as tangible fixed assets, sales, and return on assets. We further derive a measure for labour productivity (sales per employee). On the liability and liquidity side, we consider firm-level measures, such as long-term debt, the costs of debt, cash and cash equivalents, and the quick liquidity ratio, which is defined as current assets minus inventory over current liabilities. Table 1 reports the descriptive statistics of all variables. To ensure consistency, we retain only observations for which at least one of the variables of interest is available. Additionally, we winsorize all variables to the first and ninety-ninth percentile to reduce the impact of outliers and apply a logarithmic transformation to continuous variables, with the exception of the returns to assets.[3] The resulting sample contains 244,122 unique manufacturing firms, of

[3]The variables contains a notable fraction of observations with negative values, i.e., firms with losses, that would be lost after taking logs.

Table 1: Descriptive statistics

	Obs.	Mean	Median	SD
Treatment	1183147	0.11	0	0.31
Log(tangible fixed assets)	1040546	4.93	4.72	3.12
Log(sales)	890407	6.59	6.41	2.74
Log(labour productivity)	649973	4.76	4.68	1.83
Return on assets	979576	0.0064	0.011	0.17
Log(cash)	1113497	3.48	3.41	3.17
Log(quick liquidity)	1046880	-0.0083	0.0031	1.35
Log(long-term debt)	575532	5.40	5.13	2.96
Log(cost of debt)	694602	-4.87	-4.38	1.84
Log(trade credit)	804966	4.74	4.64	2.86
Log(issued capital)	1147337	3.75	3.33	2.78
Log(total assets)	1183147	6.51	6.33	2.83
Log(employment)	730002	2.10	1.95	1.45
Log(other shareholder funds)	838175	5.43	5.20	3.03
Log(debt to assets)	1167540	-0.52	-0.34	0.97
Log(cash liquidity)	1022101	-2.23	-1.94	2.54
Log(current liquidity)	1066036	0.40	0.31	1.21

which 44,265 have been affected by a flood and a clean control group of 199,857 never treated firms.

Given that previous studies have applied different methods and reported contradictory results, we develop an alternative data sample to evaluate the robustness of our findings under varying sample restrictions and methodologies. Hence, we create a sample with matched treated and control firms. For each firm affected by a flood, we identify the best match from the population of never affected firms using observable pre-flood firm characteristics. We impose that treatment and control firms are exactly matched within the same country and level 3 NACE industry classification. Following the approach of Noth and Rehbein (2019), the matching variables are the log of total assets, the debt-to-asset ratio, and the cash-to-asset ratio one year before treatment. The matching procedure employs a nearest neighbour matching with replacement, which minimises the Mahalanobis distance between observed covariates of treated and non-treated firms. (Almeida et al., 2017). The Mahalanobis distance measures how far a point is from the mean of a distribution while accounting for correlations and differences in scale, enhancing sample balance and outlier detection, compared to the sole Euclidean distance (Abadie et al., 2004). We apply a caliper of 1, meaning that we exclude weak matches by dropping observations with a Mahalanobis distance greater than one from the sample. We obtain a matched sample of 26,848 firm pairs (treated and control). Table A.3 in Appendix A reports the matching performance. In contrast to the unmatched sample (Panel B), the differences between the treated and matched control firms' characteristics are close to zero and not statistically significant.

4 Empirical Strategy

Our empirical analysis seeks to estimate the impact of flood exposure on affected firms. In this analysis, we use the Local Projections Difference-in-Differences (LP-DiD) approach recently proposed by Dube et al. (2023), which addresses the concerns of staggered treatment with heterogenous and dynamic treatment effects. While difference-in-difference designs are typically used to estimate the treatment effects, they rely on key assumptions, such as parallel trends and no anticipation of the treatment, and become more complex with treatments being staggered (timings of treatment differ between groups), heterogeneous (effects differ across groups) and dynamic (effects can occur gradually over time) (Dube et al., 2023). The two-way fixed effects (TWFE) model, which is commonly used to estimate treatment effects with staggered treatments, does not fully address heterogeneous and dynamic treatment effects and can lead to biased estimators. Similar to alternative DiD estimators proposed by, among others, Callaway and Sant'Anna (2021), de Chaisemartin and D'Haultfœuille (2020), and Sun and Abraham (2021), the LP-DiD method addresses those shortcomings.

The LP-DiD design builds upon the local projection approach of Jordà (2005). The method was introduced in a time-series context to estimate dynamic impulse responses to shocks and has been widely used to estimate dynamic average treatment responses. The LP-DiD approach combines this approach with the clean control approach of Cengiz et al. (2019). For each time horizon h, the impact of a treatment on the variable of interest is recursively regressed for each period t. The clean control approach allows to account for staggered adoption, as for each treatment, the data sample is restricted to compare units entering treatment at t and units that are never treated or not yet treated at $t+h$. Recent literature demonstrated that bias in DiD models with staggered adoption comes from unclean comparisons, i.e., comparisons to treated units. The sample restriction ensures that treated units are only compared to never treated units and eliminates the bias. Given the size of our dataset, we employ an even more conservative approach by solely comparing never treated firms - firms located at least 10 kilometres away from the flood-prone areas – to newly treated firms – firms located in flood-prone areas but that haven't been exposed to floods at the period post treatment year – without considering treated firms prior to the treatment period as a control group. Finally, the LP-DiD estimator recovers the weighted average of all cohort-specific (restricted sample) treatment effects for each time horizon, or in other words, the variance-weighted average treatment effect on the treated (ATT).

Our LP-DiD regression model builds on a static base model, similar to a static TWFE regression, which can be described as follows:

$$y_{it} = \beta D_{it} + \alpha_i + \delta_t + \epsilon_{it}, \tag{1}$$

where y_{it} is the respective outcome variable of interest of firm i in year t and D_{it} is the treatment indicator. If a firm i is affected by a flood occurring at time f, then $D_{it} = 1$ for $t \geq f$ and zero otherwise (absorbing treatment). α_i are firm-specific fixed effects, δ_t are common time-specific fixed effects, and ϵ_{it} is the error term.

In order to estimate the effect of floods using LP-DiD, we take long differences of Equation (1) and sequentially estimate the specification

$$y_{i,t+h} - y_{i,t-1} = \beta_h \Delta D_{it} + \gamma_h y_{i,t-1} + \delta_t^h + \epsilon_{it}^h \quad \text{for } h = 0, ..., H; \quad h \neq -1. \tag{2}$$

sequentially for different values of h by imposing a sample restriction, where a firm i is included in the estimation if it is following one of the following condition:

$$\begin{cases} \text{newly treated} & \Delta D_{it} = 1 \quad \text{and} \quad \sum_{\tau=0}^{h} \Delta D_{i\tau} = 1 \\ \text{never treated (clean control)} & \Delta D_{it} = 0 \; \forall t. \end{cases} \tag{3}$$

$y_{i,t+h} - y_{i,t-1}$ is the cumulative change in the outcome variable of firm i between the year before the flood $(t-1)$ and period $t+h$, and β_h is the effect of a flood in period t on a firm-level outcome in h years after the flood occurred. Due to the differencing, the LP-DiD specification does not contain firm fixed effects in contrast to Equation (1). In the empirical analysis, we further also include negative values of h in order to evaluate the parallel trends assumption. In addition, we include the lagged term of our respective variable if interest, $y_{i,t-1}$, in order to control for pre-existing trends.

Due to the clean controls in Equation (3), the effects are estimated from clean comparisons between firms that enter treatment at time t and units that are never treated.[4] The advantage of this restriction compared to the 'ordinary' local projection approach is that it renders the need to control for (lagged) effects of previous treatments and treatments in the future time horizon, i.e., between $t+1$ and $t+h$, as these observations are removed from the control group (Dube et al., 2023). Finally, the LP-DiD estimates might suffer from composition effects, as the set of control firms changes across time horizons h. In order to avoid this, we keep a constant set of control firms across time horizons. As highlighted by Dube et al. (2023), this comes at a cost, i.e., a loss of observations and hence statistical power. Our dataset, however, has a large number of units compared to a relative short time period, and in particular a large set of potential control firms, such that cost of the loss of observations is relatively small compared to the benefits of avoiding composition effects.

[4]In the general LD-DiD framework proposed by Dube et al. (2023), the restriction on clean controls is weaker, as it includes both never treated and not yet treated units. Given the large sample of never treated, we use the more restricted clean control restriction. However, including not yet treated firms in the control group does not affect the results.

5 Results

This section presents the results, starting with the main results based on the whole sample in Section 5.1. We first present flood impacts of firms' assets and productivity and then discuss impacts firms' liquidity and their funding strategies for recoveries. In Section 5.2, we explore effect heterogeneity by analysing the role of flood severity and compare impacts on financially distressed compared to stable firms. Finally, we present results using the sample of matched firms as a robustness check in Section 5.3.

5.1 Main results

5.1.1 Assets and productivity

Figure 2 plots the LP-DiD event-study estimates for firm assets, sales, productivity, and profitability from Equations (2) and (3). All event-study plots report the cumulative change in the respective outcome variable of firm i between the year before the flood $(t-1)$ and period $t+h$, with $h = 0, ..., 5$.

Our findings indicate that floods have a significant negative impact on firms' financial assets. Panel a in Figure 2 illustrates the effects of floods on firms' tangible fixed assets, including machinery, buildings, land, and equipment. From the year of the flooding event up to three years afterward, we observe increasingly negative effects on tangible fixed assets. Two years after a flood, affected firms experience a 7% decline in tangible assets compared to their non-affected counterparts. A similar pattern emerges for total assets, which also show a 7% reduction up to four years post-flood (Figure B.1 in Appendix B). However, in the long term, firm assets show signs of recovery. From the fourth year onward, the cumulative negative effect diminishes, suggesting that firms begin reinvesting in tangible assets. By the fifth year, tangible fixed assets return to pre-flood levels as firms replace damaged assets. This finding helps reconcile previous studies that report both asset losses (e.g., Fatica et al., 2024) and asset growth post-flood (e.g., Fujin and Wouter, 2021), particularly when considering three-year average asset levels (Leiter et al., 2009; Noth & Rehbein, 2019). In contrast, total assets do not exhibit clear signs of full

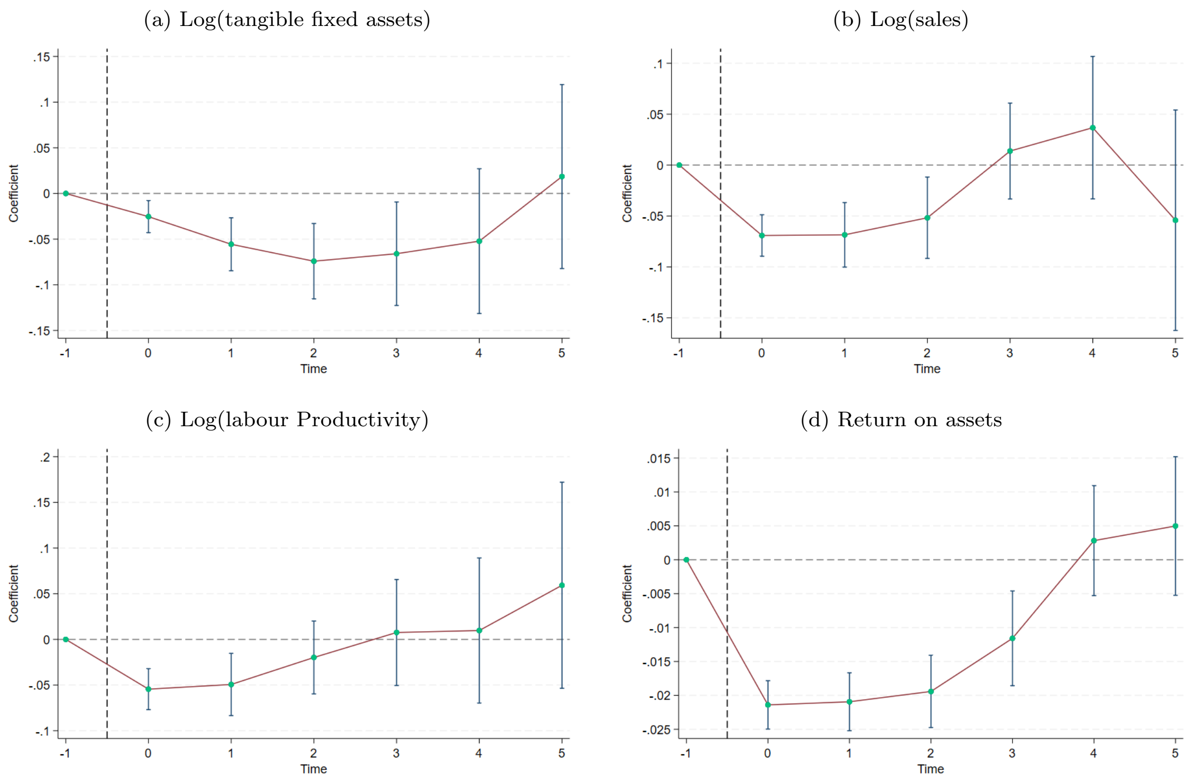


Figure 2: The effects of floods: assets, productivity, and profitability

Notes: The figure plots event-study estimates for the effect of a flood event on tangible fixed assets (Panel a), sales (Panel b), labour productivity (Panel c), and return on assets (Panel d) with 90% confidence intervals using the LP-DiD specification from Equations (2) and (3). All event-study plots report the cumulative change in the respective outcome variable of firm i between the year before the flood $(t-1)$ and period $t+h$, with $h = 0, ..., 5$. Standard errors are clustered at the firm level.

recovery after five years, implying that while firms may restore physical assets, overall financial recovery remains uncertain.

We further find that, in the short term, exposure to floods negatively impacts both productivity and profitability. As shown in Panel b in Figure 2, firms experience significant losses in sales revenue, with a 7% decrease compared to non-affected firms immediately following a flood, and a 5% decrease persisting even three years later. This decline in sales is related to a reduction in the productivity of production factors. Panels c and d in Figure 2 present the dynamic effects of floods on labour productivity (sales per employee) and return on assets, respectively. One year after a flood, labour productivity declines by approximately 5%. Initially, this decline appears to be mostly driven by reduced sales (Panel b), while employment levels drop by 2% in the first year and up to 4% by the third year (B.1). Similarly, the results show negative and statistically significant effects on return on assets for affected firms between $h = 0$ and $h = 3$, with returns 2 percentage points lower than those of non-affected firms.

However, floods have a limited impact on long-term productivity. Labor productivity and return on assets begin to gradually recover from the second or third year after the flood. As sales and labour productivity recover, employment gradually rebounds (B.1). By four years post-flood, there is no significant difference in sales, labour productivity, or return on assets between affected firms and their non-affected counterparts. These trends suggest that, while initial capital losses and damages hinder output and productivity, asset replacement enables firms to recover over time. Interestingly, our findings indicate that productivity and profitability return to pre-flood levels sooner than tangible fixed assets and total assets. Similarly, five years post-flood, affected firms appear to outperform their non-affected counterparts, with labour productivity higher by 5% and return on assets greater by 0.5 percentage points. This finding aligns with the findings of Benincasa et al. (2024), suggesting that replacing damaged assets with new, potentially more technologically advanced equipment can lead to improvements in productivity.

Overall, the results show statistically and economically significant negative impacts of flood events on firms that, however, disappear in the medium term.

5.1.2 Liquidity, credit constraints, and firm recovery strategies

A focus on assets and firm output alone does not fully capture the extent of floods' impact on firm financial health. In the aftermath of a flood, the financial structure of a company's balance sheet is likely to change, not only as a direct effect of the economic damage caused by the flood, but also as a consequence of the corporate strategies for addressing and recovering from that economic damage. As argued above, such strategies could include conversion of cash holdings, debt and equity injections. In this next step of our analysis, we investigate how flood consequently impact firms' liquidity and solvency in the aftermath of a flood.

Figure 3 plots the LP-DiD event-study estimates focussing on cash positions and firm liabilities. Beginning with impact of floods on cash holdings, Panel a in Figure 3 reveals a significant decline in cash and cash equivalents, lasting for at least two years before gradually recovering. In the first year post-flood, affected firms hold 15% less cash than non-affected control firms. These results reinforce the argument that firms draw on their cash reserves to fund the restoration and replacement of damaged assets. The current findings do not indicate that firms receive additional cash through insurance payouts or government support after a flood. However, two important considerations should be noted. First, variations in insurance penetration, national insurance structures, and government aid programmes result in uneven access to financial assistance across firms and flood events. Secondly, while such mechanisms may provide additional cash, their magnitude may be insufficient to fully offset the negative impact of floods on firm cash holdings. However, insurance payouts and state aid may still increase cash reserves and help mitigate the otherwise stronger negative impact of floods on firm cash holdings. Therefore, based on our current findings, we cannot conclude that affected firms receive additional cash inflows increasing firm liquidity. Only Noth and Rehbein (2019) have explicitly examined the impact of floods on cash holdings, finding that firms hold, on average, 2.1% more cash than their unaffected counterparts. While our findings differ, this discrepancy may be attributed to the fact that their study focused on the 2013 flooding in Germany, which caused total damages of EUR 8 billion, of which EUR 1.65 billion was insured, and compensation was provided through a flood relief fund amounting to EUR 8 billion (Thieken et al., 2016).

Expectedly, the changes in cash holdings are reflected in a reduction in corporate liquidity. The quick liquidity ratio, shown in Panel b in Figure 3, represents the availability of liquid assets, namely cash, marketable securities and accounts receivable, in relation to a firm's current liabilities and measures the ability of a firm to pay its short-term financial obligations by having assets that are readily convertible into cash. We find that the firm quick liquidity ratio deteriorates with no clear sign of recovery within five years of the floods. The current liquidity ratio and the cash ratio show similar trends (Figure B.1), although the cash ratio recovers as firms rebuild their pre-flood cash reserves.

Firms may also resort to external financing, such as loans, to finance assets recovery and replacement. Therefore, we next analyse the impact of floods on long-term debt. As

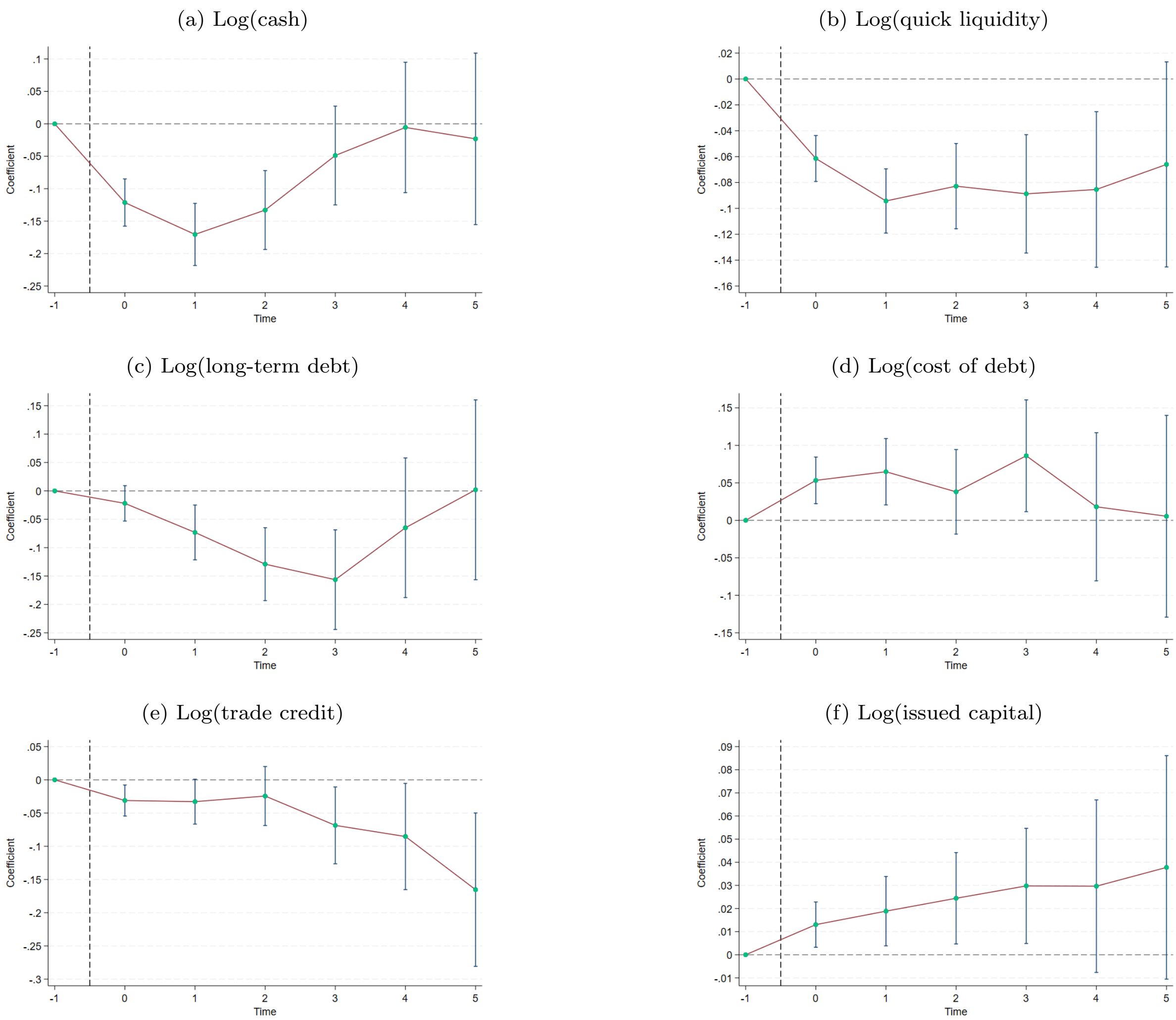


Figure 3: The effects of floods: liabilities and liquiditiy

Notes: The figure plots event-study estimates for the effect of a flood event on cash and cash equivalent (Panel a), quick liquidity (Panel b), long-term debt (Panel c), cost of debt (Panel d), trade credit (Panel e), and issued capital (Panel f) with 90% confidence intervals using the LP-DiD specification from Equations (2) and (3). All event-study plots report the cumulative change in the respective outcome variable of firm i between the year before the flood $(t-1)$ and period $t+h$, with $h = 0, ..., 5$. Standard errors are clustered at the firm level.

depicted in Panel c in Figure 3, we find a significant reduction in affected firms' long-term debt, but only from one year after the occurrence of the disaster onwards. The cumulative change of firms' long-term debt of flood-affected firms is 15% less than non-affected firms. This is consistent with recent findings on the effect of floods on leverage from Elnahas et al. (2018) and Noth and Rehbein (2019).

However, lower debt levels do not inherently signal better financial health. Rather, as highlighted by (Benincasa et al., 2024), it may point to credit constraints that reduce firms' likelihood of securing financing. In addition to the reduction in credit supply in flood-prone areas, as outlined in Section 2, firms may experience lower collateral value and increased risk perception. The reduction of tangible fixed assets, which can serve as collateral for debt, can hinder the access to, in particular long-term, debt and increase its costs (Besanko & Thakor, 1987; Graham et al., 2008; Kempa & Moslener, 2022; Valta, 2012). Our findings align with these financial dynamics. First, the 5% rise in the cost of debt for flood-affected firms relative to non-affected firms, persisting up to two years after the disaster, provides additional evidence of credit constraints (Panel d in Figure 3). Second, while firms reduce their debt levels, asset values decline even more substantially. Consequently, affected firms exhibit significantly lower solvency, as indicated by the debt-to-asset ratio (Figure B.1).

Finally, we analyse whether firms substitute expensive post-disaster debt with alternative financing sources. In particular, we investigate two key mechanisms: trade credit and private funding. Trade credit is a form of commercial financing that allows customers to purchase goods or services and defer payment until a later scheduled date. Contrary to Lai et al. (2022), our findings indicate that trade credit decreases by 3% for flood-affected firms compared to their non-affected counterparts in the year of the flood. Thus, our findings do not indicate that firms, on average, turn to alternative commercial credit. On the contrary, suppliers may be less willing to offer such agreements in the immediate aftermath of a flood. Nonetheless, there is evidence that firms seek alternative funding sources for recovery. Panel F shows a significant increase in issued capital, suggesting that firms rely on equity injections, consistent with the findings of Baltas et al. (2022).

To conclude, firms affected by floods exhibit lower levels of liquidity and solvency in the short term. Asset recovery and replacement appear to be primarily driven by the use of cash reserves and equity injections. Although firm assets and productivity revert to their baseline levels, the recovery of liquidity and solvency is less pronounced. Overall, the analysis of cash holdings and funding structures indicates that floods can, over time, significantly deteriorate a firm's balance sheet, access to finance, and profitability.

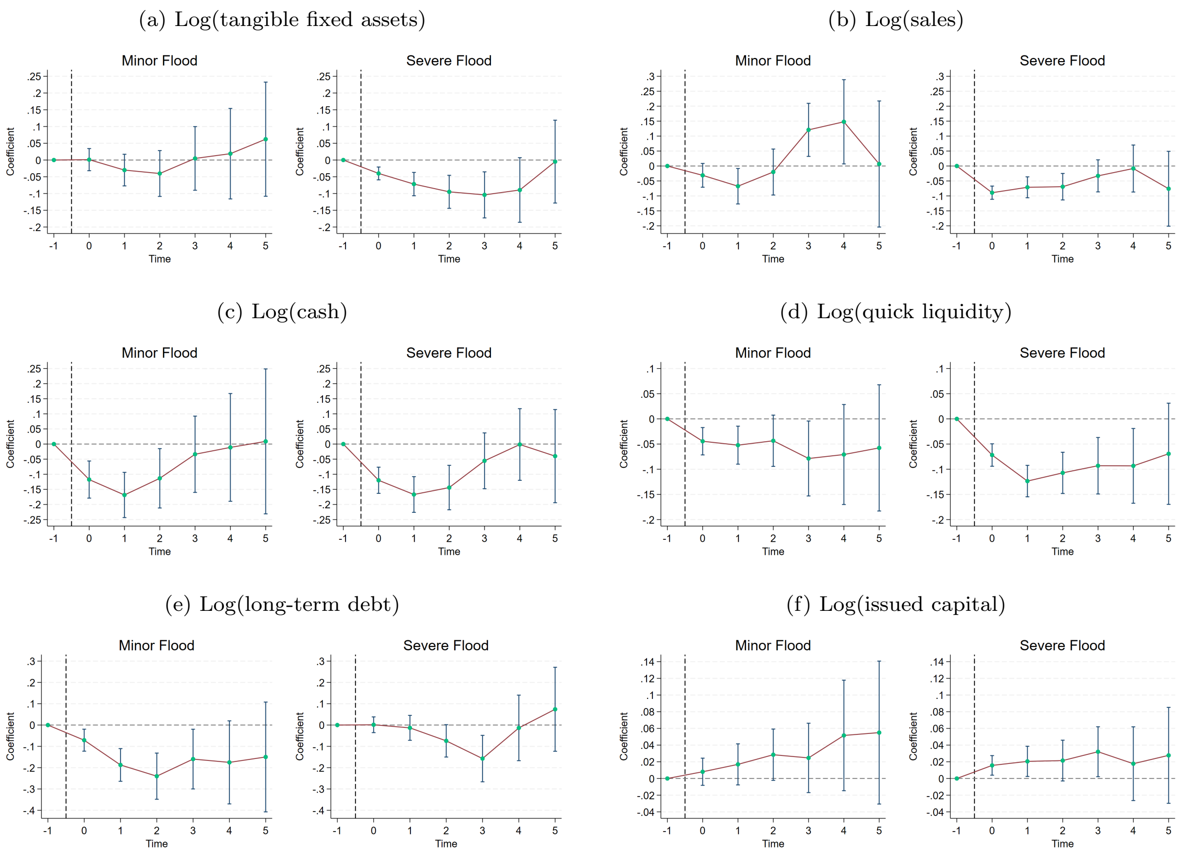
5.2 Effect heterogeneity

5.2.1 The impact of flood severity

In this section, we investigate treatment heterogeneity by considering the severity of a flooding event on the effect on firm outcomes. We identify the severity of flooding events based on information on the estimated economic damages on the NUTS3 level. The economic damages are reparation costs as reported in the DRMKC Risk Data Hub. It is important to note that this proxy could carry important biases, as the main source for losses data are insurance and reinsurance data, as well as official reports. To this extend, those estimations could reflect national disparities and may have limited strength when estimating the real impact of floods on firms, as high reparation cost could hide important insurance coverage and governmental support following a given flood. We use this information, which is available for around 75% of treated firms, to study treatment heterogeneity associated with flood severity. We differentiate between firms affected by severe floods, i.e., floods with above median reparation cost in the sample, and firms affected by minor floods, i.e., floods with below median damages. As in the main analysis, we estimate the dynamic treatment effects on all firm-level outcome variables from Equations (2) and (3) considering either firms affected by minor or severe floods in order to investigate how flood severity affects impacts on firms.

Figure 4 plots the LP-DiD event-study estimates for the effect on tangible fixed assets, sales, cash reserve, quick liquidity, long-term debt and issued capital. Figure B.2 further reports the effect on trade credit, cost of debt, return on assets and labour productivity. For each outcome, we differentiate between minor and severe floods, i.e., the respective left plots report the estimates for firms affected by minor floods, whereas the respective right plots report those for firms affected by severe plots.

As shown in Panel a in Figure 4, severe floods lead to a decline of up to 10% in tangible fixed assets relative to pre-flood levels. In contrast, minor floods result in smaller reductions that are not statistically significant. This suggests that damage to fixed production assets increases with flood severity, a pattern also observed in firm sales (Panel b). Immediately after a flood, some financial variables do not exhibit significant differ-



(a) Log(tangible fixed assets) (b) Log(sales) (c) Log(cash) (d) Log(quick liquidity) (e) Log(long-term debt) (f) Log(issued capital)

Figure 4: The effects of severe versus minor floods

Notes: The figure plots event-study estimates for the effect of a flood event on tangible fixed assets (Panel a), sales (Panel b), cash reserve (Panel c), quick liquidity (Panel d), long-term debt (Panel e), and issued capital (Panel f) with 90% confidence intervals using the LP-DiD specification from Equations (2) and (3). All event-study plots report the cumulative change in the respective outcome variable of firm i between the year before the flood $(t-1)$ and period $t+h$, with $h = 0, ..., 5$. For each outcome variable, we differentiate between minor and severe flooding events based on economic damages on the NUTS3-level as reported in the DRMKC Risk Data Hub. Standard errors are clustered at the firm level.

ences between firms affected by severe and minor floods. Firms affected by both severe and minor floods experience a 15% decline in cash holdings (Panel c), a 5% reduction in labour productivity (Panel c in Figure B.2), and a loss of over 20% in return on assets (Panel d in Figure B.2). These findings indicate that, in the short term, flood severity does not differentiate the impact on firm-level cash reserve, productivity, and profitability.

Second, the higher damages to production assets can prolong affected firms' recovery periods. This can be seen, e.g., for the case of sales (Panel b in Figure 4). After minor floods, sales recover within two years and may even exceed pre-flood levels. In contrast, recovery from severe floods takes approximately four years. Additionally, severe floods put significant pressure on firm liquidity. As illustrated in Panel d in Figure 4, severe flooding leads to a pronounced and longer-lasting decline in quick liquidity, likely driven by the financial burden of asset replacement, a reduction in readily convertible assets, and/or an increase in current liabilities. A similar trend is observed for sales (Panel b). While minor floods negatively impact firm sales in the first year, they recover quickly, surpassing non-affected firms by 10% on average after three years. In contrast, major floods lead to significant and prolonged losses, with sales remaining 6% lower on average up to three years post-flood and no clear signs of recovery beyond this period. Similarly, while both severe and minor floods negatively impact cash holdings and liquidity, Panels c and d indicate that firms recover more quickly after minor floods.

The heterogeneity analysis on flood severity offers important insights into the financial strategies of flood-affected firms. The post-flood evolution of cash holdings (Panel c) suggests that firms, regardless of flood severity, initially draw on cash reserves to fund asset recovery. However, severe floods have a greater impact on firm liquidity than minor floods (Panel d). While both reduce quick liquidity, the effect is more pronounced for severe floods, with a 12% decline after one year compared to 5% for minor floods. Interestingly, firms affected by minor floods experience a significant 20% decline in long-term debt after two years (Panel e). Conversely, firms affected by severe floods exhibit no significant short-term changes but experience a 15% decline in long-term debt after two years. The reason firms affected by minor floods hold less debt than those impacted by severe floods remains unclear. One possibility is that firms experiencing minor floods remain operational and generate cash flow, as reflected in their sales performance, enabling them to prioritise debt repayment. In contrast, firms hit by severe floods may face higher repair and recovery costs, increasing their reliance on external financing. On the other hand, flood severity may be linked to higher perceived risk, greater insurance coverage, or increased access to government aid and payouts (Bhattacharyya & Hastak, 2024). Firms affected by severe floods may receive insurance or government support, which could help secure external financing. In contrast, firms exposed to minor floods may not qualify for such aid, leaving them more financially constrained. This may also be linked to the previously discussed bias, as the economic costs of flooding events in our dataset are frequently derived from insurance data (DRMKC). Consequently, severe floods may also be those with the highest levels of insurance coverage. Surprisingly, severe floods result in a slight increase in the cost of debt after one year, with no significant effects beyond that (Panel b in Figure B.2). In contrast, firms affected by minor floods experience a 10% increase after one year and a 12% increase after three years compared to the control group. This could indicate that firms impacted by minor floods face greater financial constraints than those affected by major floods. This may reflect a selection process, wherein firms exposed to severe floods are unable to bear the higher costs of debt and therefore refrain from seeking expensive credit. Alternatively, it may indicate that lenders do not differentiate in their risk assessment between firms located in areas affected by minor or severe floods. Finally, supporting the credit constraint hypothesis, firms affected by severe floods turn to equity injections. In contrast to firms exposed to minor floods, they show a significant 2% increase in issued capital after one year compared to non-affected firms (Panel f in Figure 4).

In conclusion, the severity of floods is crucial for the size and persistence of negative impact on firm assets and sales. Crucially, more extensive damage to production assets can lead to longer recovery periods for affected firms. As such, floods have the potential to progressively erode firm assets and productivity over time.

5.2.2 Financially distressed versus stable Firms

In this section, we analyse how firms' financial distress affects the impacts of flood events. The core idea is that firms in financial distress before a flood are at a higher risk of prolonged disruption and recovery challenges. Such firms may lack the necessary internal resources and struggle to secure external financing, such as debt, to replace damaged assets. In contrast, firms with strong financial stability are generally better positioned to quickly restore their production assets, facing fewer obstacles in the process. We measure firms financial distress using Altman's Z-Score model, which is a predictor of firm's bankruptcy based on key financial ratios developed by Altman (1968). The original Z-Score model only relies on a firm's market value and hence can only be applied to publicly traded companies. Hence, we employ a modified version, the so-called the Z"-Score, which is a measure of default risk for private firms. Altman et al. (2017) investigate the performance of the Z"-Score model in predicting firm bankruptcies based on a comprehensive international dataset and find a prediction accuracy of approximately 75%. We compute the Z"-Score for all treated firms in the year of prior to being affected by a flood event.[5] We define firms in the top quartile as financially safe firms, and firms in the bottom quartile as financially distressed firms and estimate the dynamic treatment effects on all firm-level outcome variables for both firm types.

The LP-DiD event-study estimates are depicted in Figure 5 and reveal the results reveal notable heterogeneities between both between financially distressed and financially stable firms. First, while both financially distressed and stable firms suffer significant economic consequences from floods, the effects differ in both magnitude and persistence. In the year of the flood, financially stable firms exhibit smaller reductions in tangible fixed assets than distressed firms, suggesting either rapid asset replacement within the accounting year or lower overall impact, potentially due to prior investments in resilient infrastructure (Panel a in Figure 5). This disparity extends to sales performance, where distressed firms experience a decline exceeding twice that of financially stable firms (Panel a in Figure B.3). Furthermore, the economic impact of floods persists longer for distressed firms. For financially stable firms, fixed tangible assets gradually decline before recovering, with no significant effects remaining after three years. The stability of sales suggests that these firms compensate for asset losses through investments in modern, more productive technologies. Financially distressed firms, on the other hand, show a sharp decline in tangible assets and show no signs of recovery, with an average reduction in tangible assets of 25% five years after the flood compared to pre-flood levels. The higher reduction in fixed assets also seem to affect the sales of distressed firms, which are significantly lower in the first two years after the flood. As depicted in Panel c, a similar pattern can

[5] The Z"-Score can be computed as follows (Altman et al., 2017):

$$Z'' = 3.25 + 6.56 \times X_1 + 3.26 \times X_2 + 6.72 \times X_3 + 1.05 \times X_4,$$

where $X_1 = \textit{Working Capital/Total Assets}$, $X_1 = \textit{Retained Earnings/Total Assets}$, $X_3 = \textit{EBIT/Total Assets}$, and $X_4 = \textit{Book Value of Equity/Book Value of Debt}$.

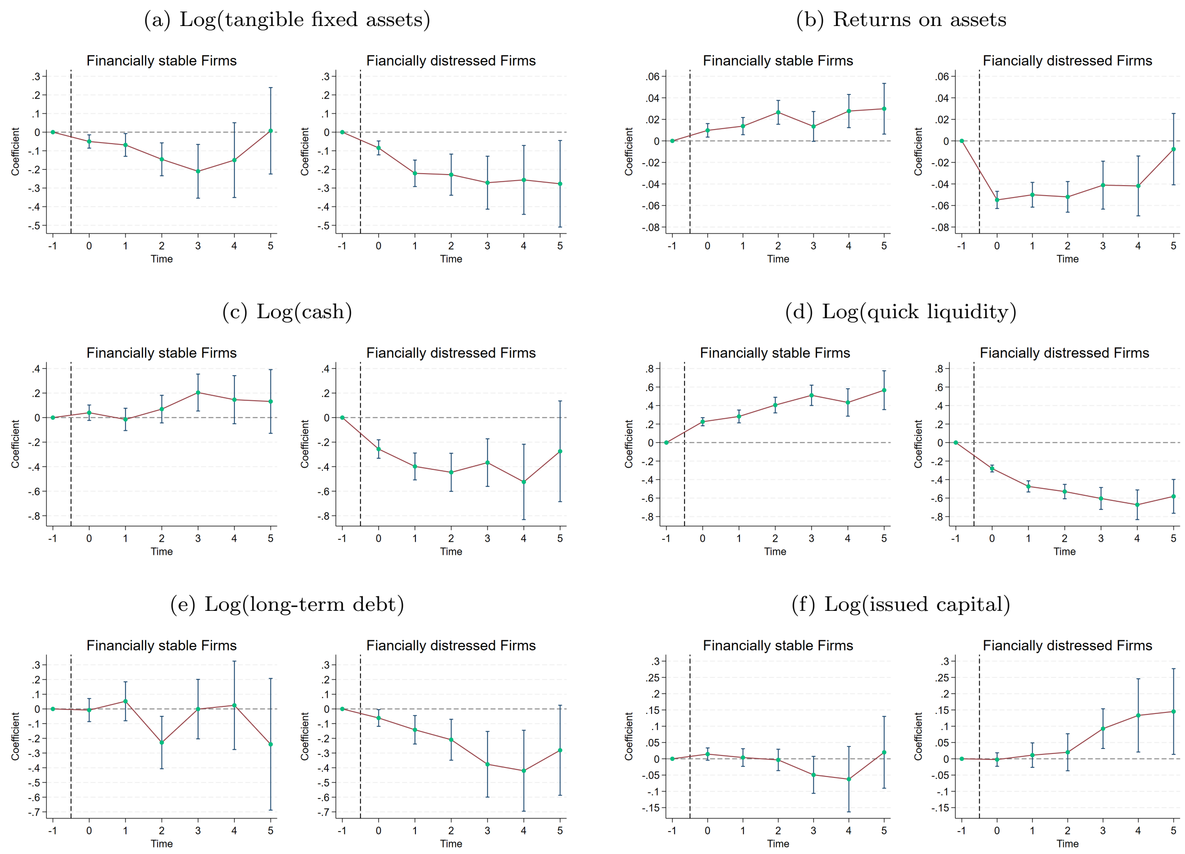


Figure 5: The effects of floods on financially distressed versus stable firms

Notes: The figure plots event-study estimates for the effect of a flood event on tangible fixed assets (Panel a), returns on assets (Panel b), cash and cash equivalents (Panel c), quick liquidity (Panel d), long-term debt (Panel e), and issued capital (Panel f) with 90% confidence intervals using the LP-DiD specification from Equations (2) and (3). All event-study plots report the cumulative change in the respective outcome variable of firm i between the year before the flood $(t-1)$ and period $t+h$, with $h = 0, ..., 5$. For each outcome variable, we use the Altman's z-score to differentiate between financially distressed firms and financially stable firms. Standard errors are clustered at the firm level.

be observed in the case of labour productivity, which is also likely driven by the reduction in production plants and machinery (Panel c of Figure B.3).

The comparative analysis of financially distressed and solvent firms further substantiates the trends observed in the main sample regarding the impact of floods on liquidity and credit constraints (Section 5.1.2). Financially distressed firms continuously deplete their cash reserves, with levels remaining 40% lower than pre-flood values even after four years (Panel c in Figure 5). This affects overall liquidity, as high-default-risk firms face a persistent decline in their quick liquidity ratio, whereas financially stable firms remain more liquid post-flood (Panel d in Figure 5). The decline in long-term debt for distressed firms further indicates that flood-affected firms face significant credit constraints, impeding their ability to secure additional debt for recovery (Panel e in Figure 5). This difficulty in raising debt persists, as these firms still exhibit a 40% reduction in debt relative to baseline levels four years post-flood. The significant increase in issued capital further suggests that when firms cannot secure external financing through loans, they increasingly rely on equity injections to fund their recovery (Panel f in Figure 5).

Finally, the resulting and most striking heterogeneity can be observed for firm profitability. As depicted in Panel b in Figure 5, financially distressed firms experience a significant reduction of their returns on assets by around 5 percentage points up to four years after the flood occurred. Only five years after the flood, profitability begins to recover towards pre-flood level. This is a result of the loss of production assets and the resulting decline in productivity and sales combined with these firms' limited ability to recover. In contrast, financially stable firms' returns on assets increase after being affected by a flood. One explanation might be the argument of creative destruction that destroyed production assets are replaced by more productive ones, which can be done particularly quickly by financially not distressed firms with available internal and access to external funding.

In summary, the comparative analysis of financially distressed and stable firms offers valuable insights into corporate recovery strategies following flood events. While floods uniformly affect corporate assets, a firm's financial health significantly influences the speed and effectiveness of its recovery. Firms in stronger financial positions are better equipped to quickly replace damaged assets, limiting the negative impact on sales and profitability. On the other hand, financially constrained firms are forced to rely on cash reserves, delay asset replacement, and seek equity injections to overcome their inability to access credit. Ultimately, firms able to effectively replace lost and damage assets will, on the long-term, present stronger liquidity, productivity, and profitability.

5.3 Robustness checks

As a robustness check, we estimate all models using the sample of matched firms (Section 3.4). Figure B.4 in Appendix B plots the LP-DiD event-study estimates for firm assets, output, and productivity from Equations (2) and (3). Overall, the results confirm the main findings based on the total sample. We find that floods negatively affect firms' assets, sales, productivity, and profitability. There are, however, some notable differences in the results using matched firms.

First, the effect sizes are larger. In the case of tangible fixed assets, for example, the highest cumulative reduction estimated from the total sample is below 8% (Panel a in Figure 2). According the the matched LP-DiD estimates, the highest reduction is more almost twice as high, namely 15% (Panel a in Figure B.4. The same can be observed for all sales, productivity, and profitability. Another example is cash and cash equivalents. In the first year after the flood, affected firms hold 28% less cash than their counterparts, with a 15% shortfall still evident after four years and no indication of recovery after five years (Figure B.5). In the main sample, the reduction in the first year is 15% (Figure 3).

Second, the effects of floods are more persistent according to the results using the matched sample. In the main analysis, all cumulative flood impacts disappear eventually within the analysed time horizon of 5 years. This is, however, not always the case in the matched sample. While we observe a recovery from flood impacts at the end of the time horizon for most variables, these seem to occur later. For example, the LP-DID estimates obtained from the whole sample indicate that labour productivity returns to pre-flood levels three years after the flood event (Panel c in Figure 2. As depicted in Panel c in Figure B.4, however, the recovery of productivity to pre-disaster levels takes more than four years in the case of matched firms. Similarly, the results from the main analysis indicate that tangible fixed assets return to pre-flood levels after five years, whereas the matched results do not provide evidence for this recovery within the analysed time horizon (Panels a in Figures 2 and B.4).

Figure B.5 plots the LP-DiD event-study estimates focussing on firm liabilities and liquidity and shows a similar pattern. The effects obtained from the matched sample are mostly quantitatively larger and more persistent. The negative impact of cash and cash equivalents, for example, is roughly twice as large and does not fully disappear after five years (Panel a in Figure B.5. In contrast, the cash and cash equivalents return to pre-flood levels according to the results based on the full sample (Panel a in Figure B.4).

Overall, the robustness checks confirm our main findings indicate that flood impacts on assets, productivity, and profitability as well as firms' liquidity and their funding strategies for recoveries. Compared to the results using the full sample, the findings based on matched firms indicate that flood impacts may be even quantitively larger and more persistent.

6 Conclusion

This paper analyses the impact of flood events on European manufacturing firms. We identify firms located in flood-prone areas that were exposed to floods between 2008 and 2017 at the NUTS-3 level. We employ a rigorous methodology to achieve the highest granularity in identifying flood-affected firms, which allows us to provide more precise insights into the financial impact of floods at the firm level. We use the recently proposed Local Projections Difference-in-Difference (LP-DiD) approach to estimate dynamic average treatment responses for staggered treatments, which may be heterogeneous across groups and dynamic, i.e., gradually occur over time, compared to a clean control group.

We have three major findings. First, floods negatively affect firms' assets, in particular tangible fixed assets, productivity, and profitability. While these impacts persist over several years after a flooding event, they ultimately decrease or even recover to pre-flood levels four or more years after a flood. Robustness checks based on matched firms confirm these findings.

Second, we find that firm-level impacts crucially depend on the severity of a flood and, in particular, on the financial situation of a firm when it is affected by a flood. In the case of severe floods, the negative impacts are more pronounced, likely due to extensive physical damage, especially to production assets such as machinery and buildings. In contrast, firms recover notably faster from minor flood events.T his is particularly relevant in light of global climate projections, which indicate an increase in both the frequency and severity of floods. Furthermore, firms that are financially distressed before a flood occurs experience higher losses in production assets and face credit constraints, which deter their capacity to recover. In contrast to distressed firms, which experience reductions in profitability, we find that stable firms' returns to assets increase in the aftermath of a flood event. This finding supports the argument of creative destruction that lost production assets are replaced by more productive ones, which can be done particularly well by firms with internal and access to external funding.

Third, we provide insights on how firms finance their recovery from flood damages. With the exception of the firms with the lowest probability of default, firms seem to face issues to raise debt after being affected by a flood, most likely due to the loss in tangible fixed assets that can serve as collateral. We find that firms tend to raise equity or use internal funds to finance recovery measures.

A Appendix: Data

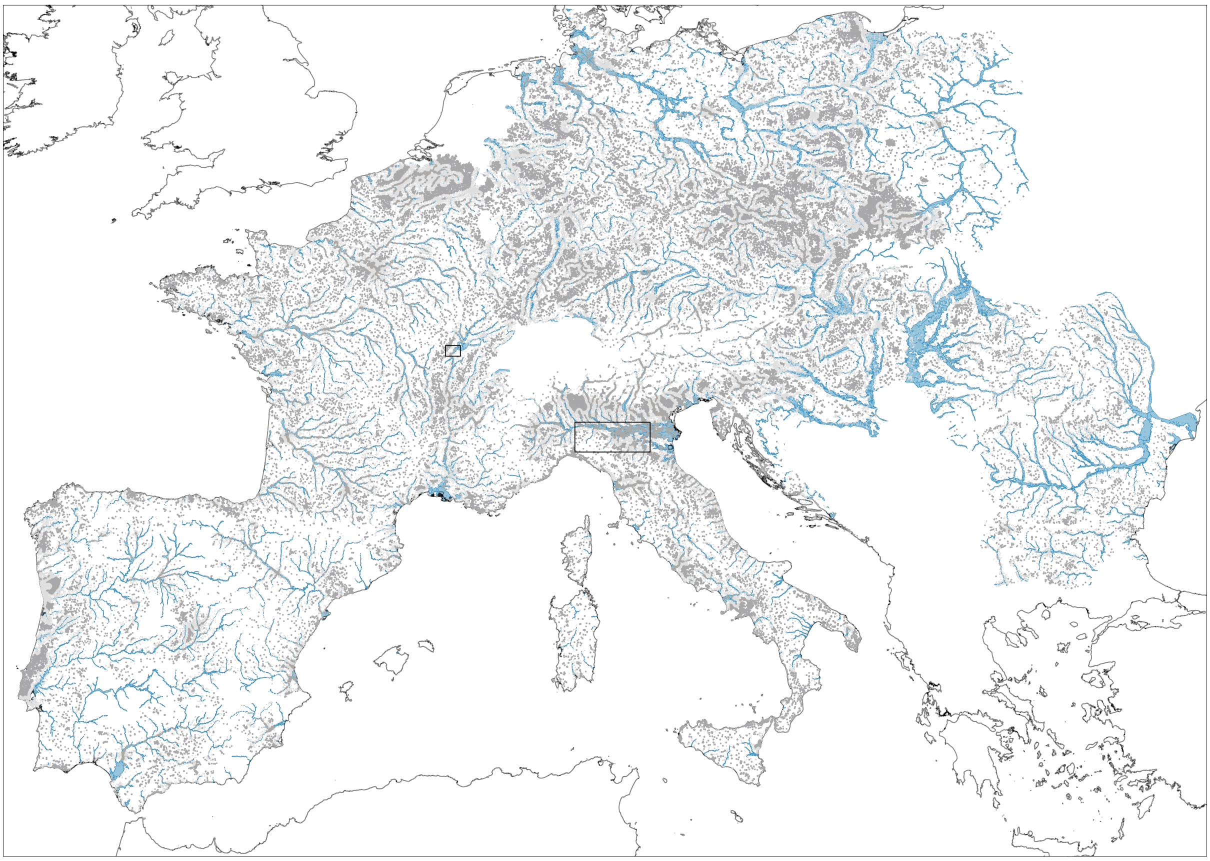
Table A.1: Overview of geocoding methods per country

	Orbis	OpenStreetMap	GeoNames	Missing
AT	0	11594	5182	95
	0%	*68.72%*	*30.72%*	*0.56%*
BE	48468	515	407	493
	97.16%	*1.03%*	*0.82%*	*0.99%*
BG	0	10503	7792	56709
	0%	*14%*	*10.39%*	*75.61%*
CZ	0	81740	158317	578
	0%	*33.97%*	*65.79%*	*0.24%*
DE	0	99951	22421	1335
	0%	*80.8%*	*18.12%*	*1.08%*
ES	119051	1141	6125	58403
	64.45%	*0.62%*	*3.32%*	*31.62%*
FR	137197	10322	8463	7548
	83.9%	*6.31%*	*5.18%*	*4.62%*
HR	0	18952	1249	5801
	0%	*72.89%*	*4.8%*	*22.31%*
HU	0	31685	21500	24510
	0%	*40.78%*	*27.67%*	*31.55%*
IE	0	14	0	10458
	0%	*0.13%*	*0%*	*99.87%*
IT	266043	119591	25302	36149
	59.51%	*26.75%*	*5.66%*	*8.09%*
PL	0	112440	58615	104037
	0%	*40.87%*	*21.31%*	*37.82%*
PT	60290	1524	0	11578
	82.15%	*2.08%*	*0%*	*15.78%*
RO	0	482	48100	56846
	0%	*0.46%*	*45.62%*	*53.92%*
SI	0	24398	716	2222
	0%	*89.25%*	*2.62%*	*8.13%*
SK	0	17573	10892	63160
	0%	*19.18%*	*11.89%*	*68.93%*

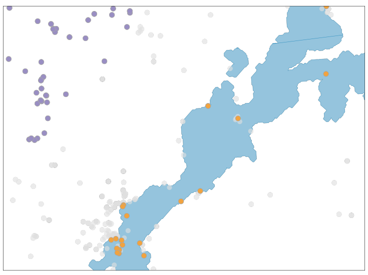
Table A.2: Distribution of Flooding Events in NUTS3 Regions by Country

Country	NUTS3 Regions	1	2	3	4	5	6	7	Flooded Regions	Percentage
AT	35	7	11	15	2	0	0	0	35	100%
BE	44	20	20	2	0	0	0	0	42	95%
BG	28	0	3	5	1	6	11	2	15	54%
CZ	14	2	5	4	2	1	0	0	14	100%
DE	401	179	106	57	9	0	0	0	351	88%
ES	59	12	11	12	11	6	4	1	52	88%
FR	96	22	50	19	1	1	0	0	93	97%
HR	21	6	5	5	0	0	0	0	16	76%
HU	20	10	4	2	0	0	0	0	16	80%
IT	107	30	17	34	12	9	1	0	102	95%
PL	72	24	21	2	0	0	0	0	47	65%
PT	25	9	0	0	0	0	0	0	9	36%
RO	42	0	7	9	10	8	2	6	34	81%
SI	12	3	3	3	1	0	0	0	10	83%
SK	8	2	1	2	3	0	0	0	8	100%

(a) Spatial distribution of European firms and Flood Extent of Flood Hazard Map



(b) Chalon-sur-Saône, France



(c) Lombardy region, Italy

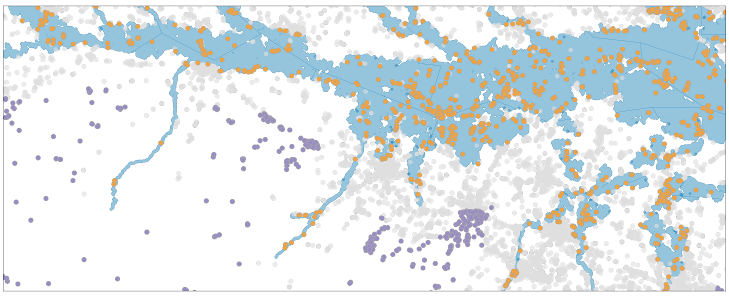


Figure A.1: Spatial Distribution of Firms, Treatment Status, and Flood Extent of Flood Hazard Map

Notes: In all three figures, the light blue spectrum relates to the flood extent as presented in the JRC Flood Hazard Map for a 1-in-10 year return period. Treatment firms are shown in orange, while control firms are purple. Figures b) and c) present a zoom into the map presented in figure a) respectively at the city and region-level. Compared to flood extend of historical flood events (e.g., obtained through satellite imagery, such as events presented in the Global Active Archive of Large Flood Events), this figure shows that our identification strategy is consistent with flood depth at firms' headquarter location.

Table A.3: Matching performance

	A. Matched Sample					
	Treated firms		Control firms		Diff	
	Mean	SD	Mean	SD	Diff	t-stat
Cash to asset ratio	0.16	0.21	0.16	0.22	0.00	(0.65)
Debt to asset ratio	0.82	1.05	0.90	1.27	0.08***	(12.37)
Log(Total assets)	6.94	2.91	6.41	2.78	-0.53***	(-30.59)
Observations	26848		26848		53696	
	B. Unmatched Sample					
	Treated firms		Control firms		Diff	
	Mean	SD	Mean	SD	Diff	t-stat
Cash to asset ratio	0.16	0.20	0.15	0.20	-0.00	(-1.17)
Debt to asset ratio	0.75	0.77	0.74	0.76	-0.00	(-0.60)
Log(Total assets)	7.07	2.83	7.07	2.80	0.00	(0.20)
Observations	29202		854302		883504	

Table A.4: Descriptive Statistics: Matched Sample

	Obs.	Mean	Median	SD
Treatment	299775	0.24	0	0.43
Log(tangible fixed assets)	276591	5.34	4.98	3.27
Log(sales)	235342	7.23	6.93	2.84
Log(labour productivity)	159715	5.19	4.98	1.91
Return on assets	248930	0.015	0.016	0.15
Log(cash)	293389	4.06	3.97	3.30
Log(quick liquidity)	271486	0.053	0.053	1.23
Log(long-term debt)	166163	5.60	5.22	3.21
Log(cost of debt)	194177	-4.85	-4.41	1.73
Log(trade credit)	217747	5.25	5.05	2.91
Log(issued capital)	294770	4.26	3.68	2.94
Log(total assets)	299021	7.18	6.78	2.88
Log(other shareholder funds)	232009	5.95	5.63	3.14
Log(cash liquidity)	267646	-2.23	-1.87	2.54
Log(current liquidity)	272606	0.44	0.35	1.09

B Appendix: Results

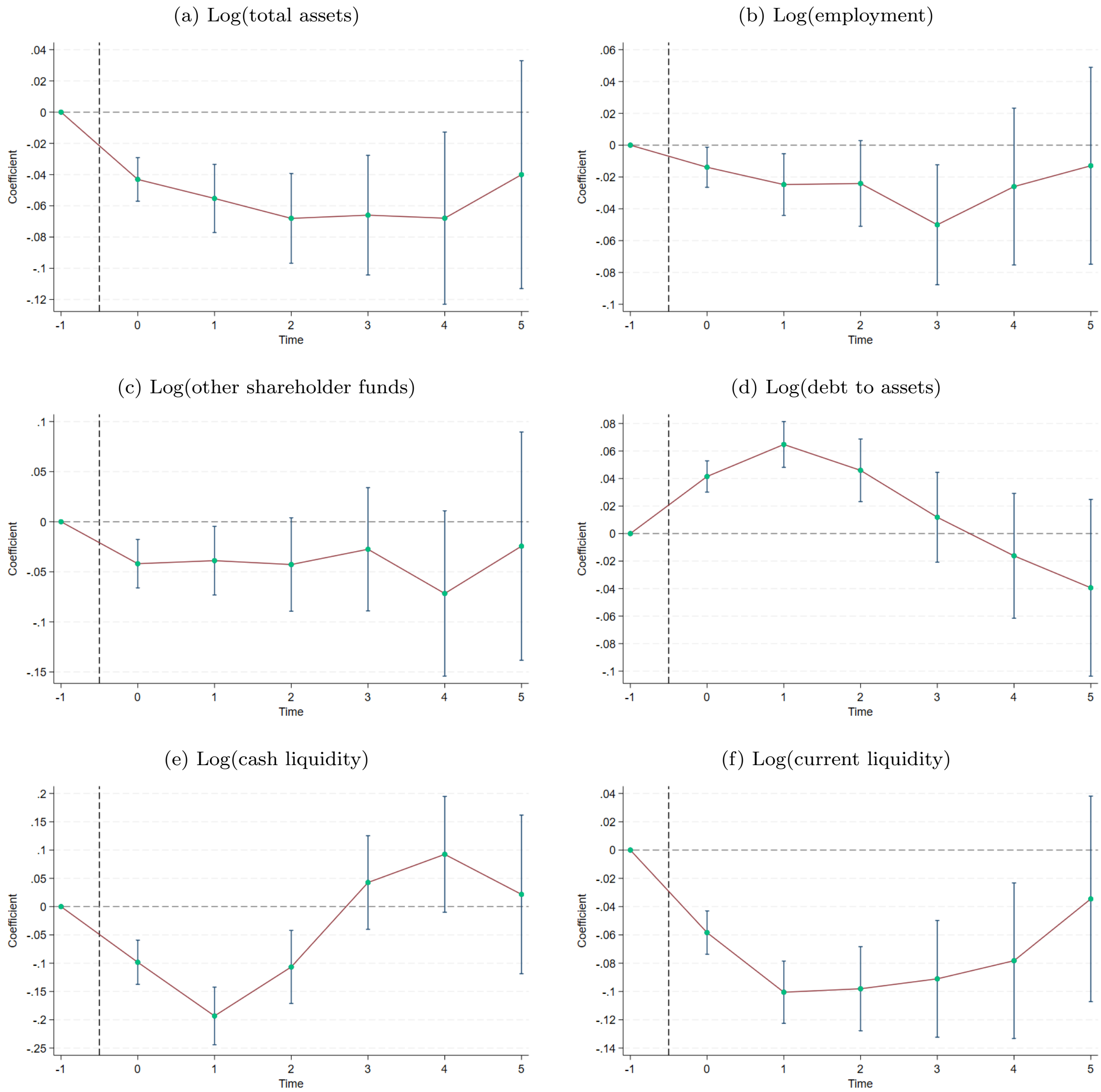
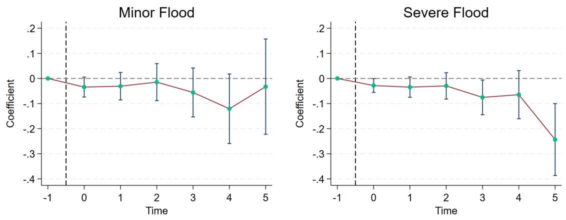


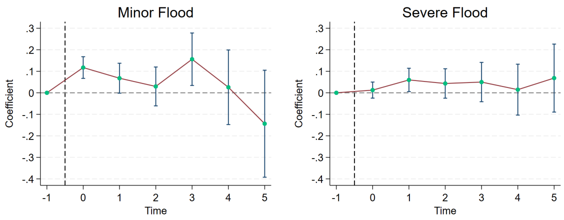
Figure B.1: The effects of floods: additional results

Notes: The figure plots event-study estimates for the effect of a flood event on total assets (Panel a), employment (Panel b), other shareholder funds (Panel c), debt to assets (Panel d), cash liquidity (Panel e), and current liquidity (Panel f) with 90% confidence intervals using the LP-DiD specification from Equations (2) and (3). All event-study plots report the cumulative change in the respective outcome variable of firm i between the year before the flood ($t-1$) and period $t+h$, with $h = 0, ..., 5$. Standard errors are clustered at the firm level.

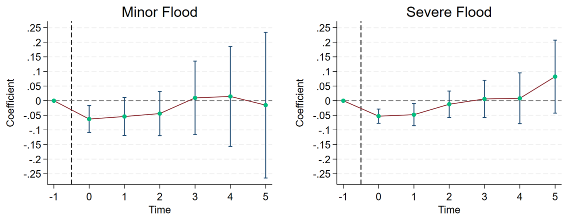
(a) Log(trade credit)



(b) Log(Cost of Debt)



(c) Log(labour productivity)



(d) Returns on assets

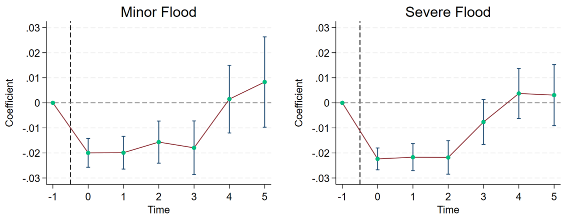
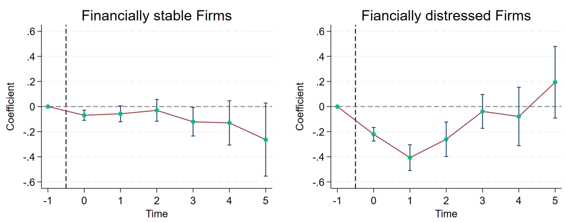


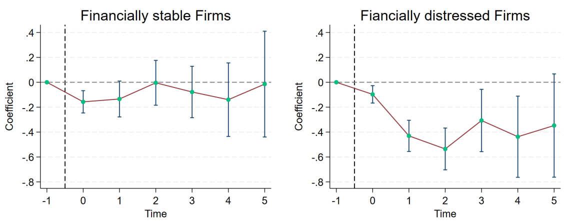
Figure B.2: The effects of severe versus minor floods: additional results

Notes: The figure plots event-study estimates for the effect of a flood event on trade credit (Panel a), issued capital (Panel b), labour productivity (Panel c) and return on assets (Panel d) with 90% confidence intervals using the LP-DiD specification from Equations (2) and (3). All event-study plots report the cumulative change in the respective outcome variable of firm i between the year before the flood $(t-1)$ and period $t+h$, with $h = 0, ..., 5$. For each outcome variable, we differentiate between minor and severe flooding events based on economic damages on the NUTS3-level as reported in the DRMKC Risk Data Hub. Standard errors are clustered at the firm level.

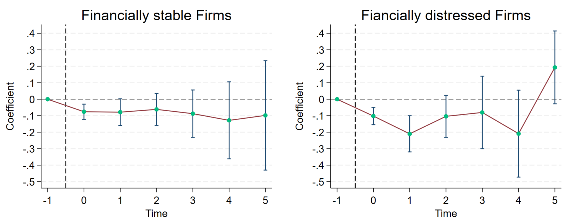
(a) Log(Sales)



(b) Log(Cost of Debt)



(c) Log(labour productivity)



(d) Log(trade credit)

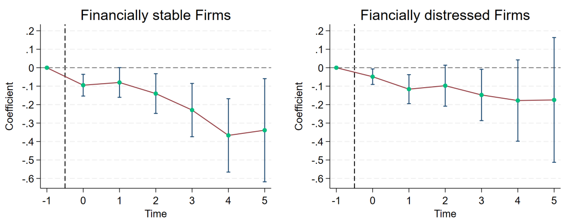


Figure B.3: The effects of floods on financially distressed versus stable firms: additional results

Notes: The figure plots event-study estimates for the effect of a flood event on sales (Panel a), cost of debt (Panel b), labour productivity (Panel c) and trade credit (Panel d) with 90% confidence intervals using the LP-DiD specification from Equations (2) and (3). All event-study plots report the cumulative change in the respective outcome variable of firm i between the year before the flood $(t-1)$ and period $t+h$, with $h = 0, ..., 5$. For each outcome variable, we use the Altman's z-score to differentiate between financially distressed firms and financially stable firms. Standard errors are clustered at the firm level.

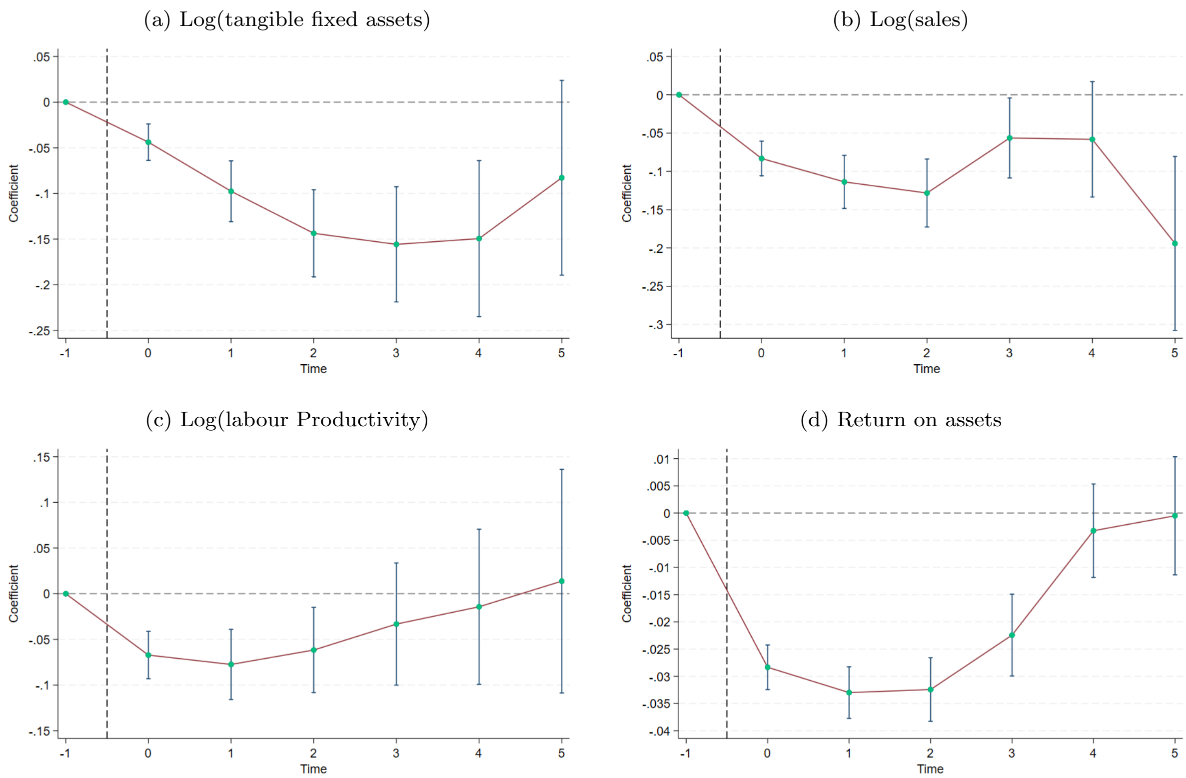


Figure B.4: The effects of floods basted on matched sample: assets, productivity, and profitability

Notes: The figure plots event-study estimates for the effect of a flood event on tangible fixed assets (Panel a), sales (Panel b), labour productivity (Panel c), and return on assets (Panel d) with 90% confidence intervals using the LP-DiD specification from Equations (2) and (3). All event-study plots report the cumulative change in the respective outcome variable of firm i between the year before the flood $(t-1)$ and period $t+h$, with $h = 0, ..., 5$. The estimates are based on the matched sample (Section 3.4 for details on the matching procedure). Standard errors are clustered at the firm level.

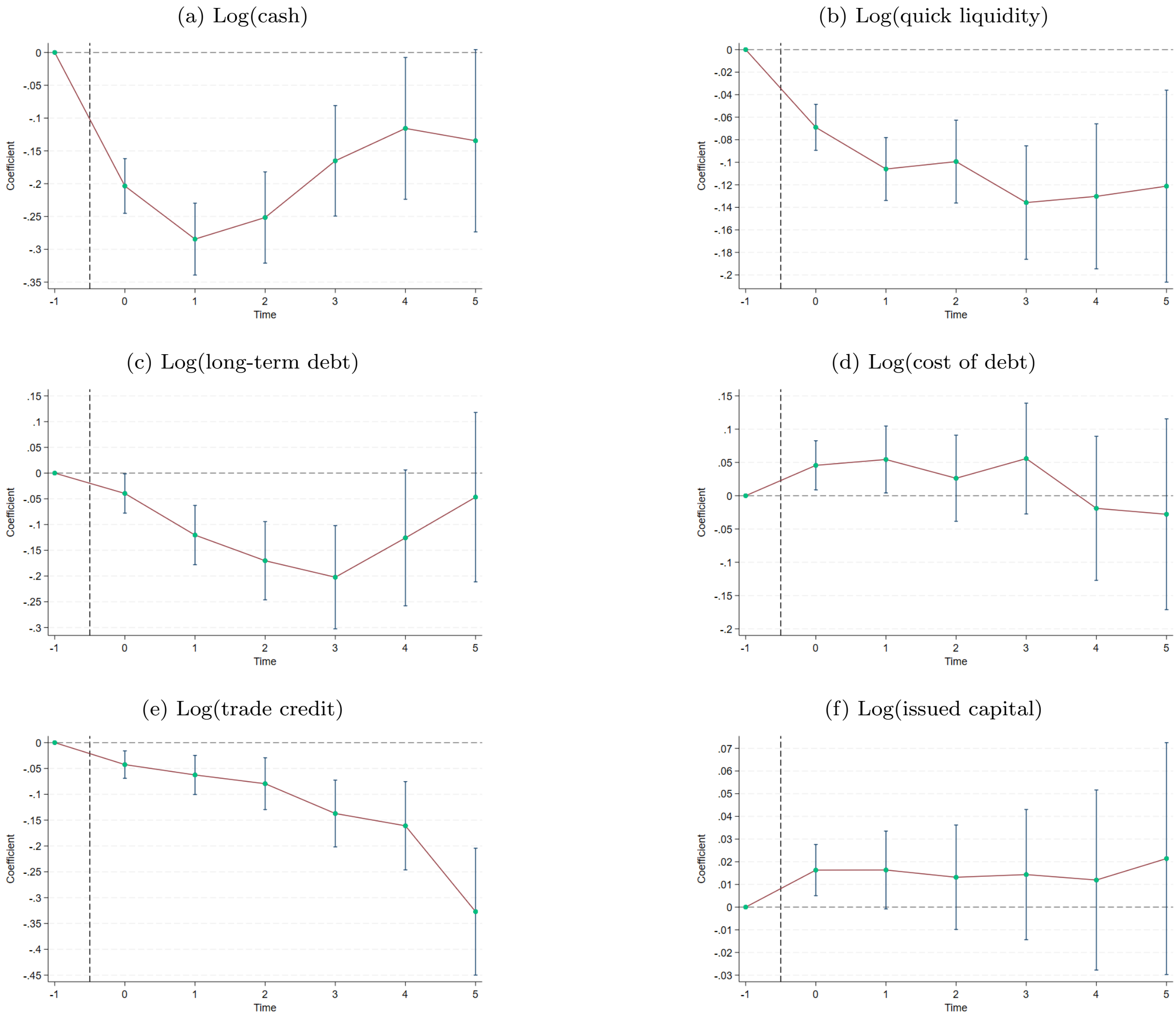


Figure B.5: The effects of floods basted on matched sample: liabilities and liquiditiy

Notes: The figure plots event-study estimates for the effect of a flood event on cash and cash equivalent (Panel a), quick liquidity (Panel b), long-term debt (Panel c), cost of debt (Panel d), trade credit (Panel e), and issued capital (Panel f) with 90% confidence intervals using the LP-DiD specification from Equations (2) and (3). All event-study plots report the cumulative change in the respective outcome variable of firm i between the year before the flood ($t-1$) and period $t+h$, with $h = 0, ..., 5$. The estimates are based on the matched sample (Section 3.4 for details on the matching procedure). Standard errors are clustered at the firm level.

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