DNB Working Paper

No 832/March 2025

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DeNederlandscheBank

EUROSYSTEEM

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* Views expressed are those of the author and do not necessarily reflect official positions of De Nederlandsche Bank.

Working Paper No. 832

March 2025

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European SMEs, Corporate Finance, and Economic Resilience to Floods*

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March 17, 2025

Abstract

We investigate how leverage and the debt maturity structure of SMEs influences their resilience to floods. Using a dataset of six million geo-coded firm-year observations across nine European countries and granular flood maps, we employ dynamic difference-in-differences estimators to assess the economic impacts of floods and the mediating effects of leverage and debt maturity. Our findings highlight a non-linear relationship between leverage and resilience. SMEs with high levels of short-term debt and low levels of long-term debt show more severe reductions in their post-flood employment growth.

Keywords: Economic Resilience, Climate Change, Floods, Leverage, Small- and Medium-Sized Enterprises

JEL Codes: G32, J21, Q54

*We thank Jaap Bos, Wouter Botzen, Dirk Broeders, Clemens Kool, Scott Langford, Katrin Millock, Giulia Piccillo, Mark Sanders, and Stefan Straetmans for helpful comments and suggestions. We are grateful for access to Nuvolos cloud computing services through the Nuvolos PhD Scholarship (De Carolis), without which this project would not have been possible. We thank Fien van Solinge and Beau Soderhuizen for generously sharing code and material used to prepare the firm-level datasets for the analysis.

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1 Introduction

Small- and medium-sized enterprises (SMEs) are the backbone of the European economy, representing 99% of all businesses and two-thirds of all private sector jobs (Katsinis et al., 2024). By providing local employment and services, SMEs contribute to the livability of communities and are of both high economic and societal importance (Udell, 2020). At the same time, SMEs are particularly vulnerable to crises and external shocks. When faced with natural hazards, the high spatial concentration of their physical assets, high dependence on local market conditions, and a lack of back-ups, redundancies, and insurance are some of the factors that contribute to their vulnerability (e.g., Miklian and Hoelscher, 2022).

In Europe, floods are the most prevalent and damaging type of natural hazard shock (Centre for Research on the Epidemiology of Disasters, 2021; European Insurance and Occupational Pensions Authority, 2022). The last three decades have been among the most flood-rich periods in Europe in the past 500 years (Blöschl et al., 2020). With unabated climate change, economic losses from extreme precipitation are projected to increase further (European Academies Science Advisory Council, 2018; Intergovernmental Panel on Climate Change, 2022). This raises important questions about how business owners, local communities, and societies at large can strengthen the resilience of the SME sector.

In this study, we address some of these questions by comprehensively assessing how differences in pre-shock leverage and debt maturity influence the resilience of SMEs — measured in terms of employment growth — after major flood events in Europe. Research from academic fields as diverse as disaster management, business studies, geography, and public policy have highlighted common factors of SME resilience to disasters (Linnenluecke, 2017; Miklian and Hoelscher, 2022; Chang et al., 2022). Next to this, there is a large body of literature investigating the role of corporate leverage on default risk and the performance of firms through financial crises and business cycles (Cathcart et al., 2020; Demirgüç-Kunt et al., 2020; Giroud and Mueller, 2021). However, researchers have not yet examined the differential impact of leverage and its maturity structure on the resilience of SMEs to physical climate shocks. Studying this is interesting both because of the increasing materiality of physical climate shocks and because such shocks are more plausibly exogenous at the firm level than financial shocks, allowing us to identify the role of financial structure in SME resilience.

It is ex-ante unclear how corporate financial structure affects SME resilience to flood events, for several reasons. First, higher total leverage may reflect access to capital and promising investments, but it may also increase default risk in the face of unexpected shocks to firms' income and assets. Second, different components of leverage may exert different effects on firm resilience. While offering flexibility in normal times, high reliance on short-term debt may increase debt rollover risks during disruptive events that affect immediate cash flow, collateral values, and credit conditions (Cathcart et al., 2020; Kalemli-Özcan et al., 2022). Firms with access to long-term debt might be in a better position to renegotiate terms with lenders, allowing them to restructure and manage recovery expenses more effectively (Berger and Udell, 2006).

To disentangle these heterogeneous effects, we employ a dataset of six million firm-year observations in nine European countries over 2012-2020 from Bureau van Dijk's Orbis/Amadeus database. We geocode the locations of around 923,000 SMEs and combine this with spatially granular data on 26 major flood events gathered from the international disaster database EM-DAT and the Dartmouth Flood Observatory, affecting around 130,000 firms. We estimate the dynamic economic impacts of floods on SMEs using conventional and modern difference-in-differences estimators (Sun and Abraham, 2021; de Chaisemartin and D'Haultfœuille, 2024). We then investigate the role of leverage in moderating flood impacts on SME employment using triple difference-in-differences and sample-split heterogeneity analyses. To rule out the possibility that our results are driven by structural differences across industries, we utilise industry-normalized and standardized measures of leverage in addition to firm-specific reported leverage.

We show that floods have a statistically and economically significant impact on various dimensions of SME performance, including employment growth, asset growth, turnover, and income. For instance, floods cause annual employment growth to fall on average by 1.7 percentage points over the three years after the event, which represents around 1/3 of the mean employment growth rate. Extrapolating this to the population of flood-affected SMEs in the countries included in our sample, this implies a loss of around 1,800 jobs in SMEs each year. Given the localised nature and the infrequent occurrence of major flood events, this represents considerable harm to local labour markets.

We discover a non-linear, inverted U-shaped relationship between leverage and the resilience of SME employment, i.e., the extent to which employment growth in SMEs is affected by floods. The maturity structure of debt plays a crucial role in this. High leverage exacerbates the negative consequences of floods, an effect particularly prevalent among firms with high short-term leverage. Firms with high short-term leverage face increased rollover risk and may have limited access to additional financing (Kalemli-Özcan et al., 2022). When this coincides with an unexpected shock that disrupts cash flows and requires repair or replacement of damaged assets, SMEs reduce employment. At the same time, SMEs with low levels of long-term debt, which may suggest limited access to external financing, exhibit lower resilience to the impacts of floods. Importantly, these results are robust when we account for industry-specific structural differences in firm leverage. This indicates the existence of an optimal level of leverage with respect to flood risk, at which firms can access external capital to maintain operations during shocks and invest in long-term adaptive measures, without incurring the risks associated with excessive short-term debt.

We contribute to several strands of literature. First, we provide novel evidence on the impact of major floods on European SMEs. Extant research has come to contradictory conclusions regarding the impacts of floods on European firms, with some studies suggesting positive and others negative effects (Leiter et al., 2009; Noth and Rehbein, 2019; Fatica et al., 2022; Clò et al., 2024). Improvements in the availability and granularity of disaster data seem to lead to a consensus that disasters have negative consequences for affected regions and firms, but spillovers to unaffected entities may offset some of these losses (Felbermayr et al., 2022; Fatica et al., 2022). Our evidence is consistent with the view that the direct effects of floods on affected firms are negative.

Moreover, the growing concern about physical climate risks and the experience of recent crises such as the global financial crisis or the Covid-19 pandemic have led to an increase in academic interest in factors that explain the resilience of firms, particularly SMEs. Linnenluecke (2017); McKnight and Linnenluecke (2019); Miklian and Hoelscher (2022); Chang et al. (2022) provide reviews of this research. As insurance and government aid gaps may widen if risks accumulate (European Central Bank and European Insurance and Occupational Pensions Authority, 2023; Deryugina, 2022), this begs the question of what firms (and their financiers) can do to strengthen their resilience in preparation for future shocks. We contribute to this field by identifying a so far disregarded factor in SME resilience: Leverage and the maturity structure of debt.

Second, our research relates to a growing body of research exploring the linkages between corporate financial structure and firm resilience to crises in general, and the role of finance in resilience to physical climate shocks explicitly. For the former, Giroud and Mueller (2016) report that more highly leveraged firms lost more workers during the 2008/09 financial crisis. Cathcart et al. (2020) demonstrate that leverage has a greater impact on the default risk of SMEs than of larger firms. Kalemli-Özcan et al. (2022) find that firms entering the Global Financial Crisis with higher debt levels reduced their investment more after the crisis. Greater reliance on short-term debt plays an important part in the latter two studies. Fatica et al. (2022) and Peters et al. (2023) suggest that high pre-disaster leverage may decrease resilience and increase the vulnerability of affected entities. As a distinct contribution of this paper, we highlight the heterogeneous consequences of leverage and debt maturity in the aftermath of floods in SMEs. Generating this knowledge is highly important for business owners, banks, and policymakers invested in increasing economic resilience in the face of climate change.

The remainder of the paper is structured as follows. Section 2 discusses related literature and carves out the research gap our paper occupies. Section 3 introduces our data. Section 4 outlines the methodological approach we choose to test our main hypotheses. Section 5 discusses the main results and additional robustness checks. Section 6 provides a discussion and overall conclusion of our findings.

2 Background and hypotheses

2.1 Natural hazard shocks and economic resilience

An extensive literature analyzes the economic impacts of natural hazard shocks at aggregate country or regional levels (see e.g., Klomp and Valckx (2014), Lazzaroni and van Bergeijk (2014) or Botzen et al. (2019) for overviews). Studies on firm-level impacts have surfaced more recently, driven by the increased accessibility of reliable and highly granular microdata. In one of the first firm-level studies in this strand focusing on Europe, Leiter et al. (2009) analyse a major flood event in the year 2000 that affected regions in France, Italy, Spain, and the United Kingdom. According to their results, firms located in affected NUTS 2 regions[1] respond on average by increasing their total assets and employment. At the same time, productivity deteriorates, especially in firms with large shares of tangible assets. In a similar vein, Noth and Rehbein (2019) report that German firms located in counties affected by the 2013 Elbe River floods show on average *higher* turnover, lower leverage, and higher cash holdings after the shock.

A potential issue with many earlier studies is the coarse treatment assignment resulting from limitations of the available data: Considering all firms in a given administrative region as treated, e.g., all firms in a NUTS 2 region, may obscure more granular patterns such as spillovers from affected to unaffected firms within an administrative area and bias the estimated treatment effects towards zero (Botzen et al., 2019; Felbermayr et al., 2022). Using geolocated flood maps, Fatica et al. (2022) report significant and persistent negative effects of flood events on European manufacturing firms, with assets, sales, and employment stunted up to seven years after the event. Highly indebted firms and firms with more tangible assets seem to fare worse, while nearby but unaffected firms gain economically, demonstrating how economic activity is reallocated in the aftermath of a shock. Cathcart

[1] A NUTS 2 region is a territorial unit within the EU's statistical classification system, representing basic regions for regional policy implementation, typically with a population of 800,000 to 3 million inhabitants. For detailed definitions and classifications, see the official Eurostat website: NUTS - Nomenclature of Territorial Units for Statistics (Eurostat, 2024).

et al. (2023) use small-gridded temperature and precipitation data to estimate the impact on the default probability of small and micro firms in six European countries. They find increased susceptibility to these risks, particularly in micro and financially constrained firms. For the case of Italy, Clò et al. (2024) find that firms in municipalities hit by hydrogeological disasters have higher default probabilities, lower revenue, and lower employment after the shock.

In light of the more frequent and severe occurrence of natural hazard shocks, but also other crises like the Global Financial Crisis and COVID-19, the determinants of economic resilience receive increasing attention in the economic literature (Noy and Yonson, 2018). Articles focusing specifically on the recovery of firms find that smaller and local businesses are particularly vulnerable to disasters (Chang et al., 2022; Miklian and Hoelscher, 2022; McKnight and Linnenluecke, 2019). Their assets are highly spatially concentrated, they are highly dependent on local market conditions, and they lack backups and redundancies. Moreover, they are less likely to be insured for such events (e.g., Davlasheridze and Geylani, 2017; Basker and Miranda, 2018; Collier et al., 2020).

Access to out-of-the-ordinary funds to replace damaged physical assets and to bridge liquidity gaps when recovering from natural hazard shocks and operations is vital and credit provides a means for firms to fill these gaps and mitigate consecutive negative effects (McDermott et al., 2014; Basker and Miranda, 2018; Collier et al., 2020). However, due to their informational opacity, SMEs are more likely to be financially constrained, both in non-crisis times (Beck et al., 2008) and after disasters, making it hard for SMEs to access external recovery funding when needed (Basker and Miranda, 2018; Collier et al., 2020). Destruction of collateral and increased uncertainty in the aftermath of a disaster further aggravate pre-existing asymmetric information problems associated with small firms Berg and Schrader (2012).[2]

SMEs' pre-shock corporate financial structure may thus have direct consequences for their resilience to natural hazard shocks. Although papers have assessed both the economic and financial consequences of natural hazard shocks, no paper, to our knowledge, has investigated the differential role of leverage and its components in SME resilience in this context. We thus strive to fill an important gap in the literature.

2.2 SME leverage and resilience: Main hypotheses

Firms face trade-offs in their corporate financial structure decisions. Having some leverage may signal access to external finance, allowing firms to make investments without having

[2] Relationship banking helps mitigate some of these issues, also during crises (Beck et al., 2018; Langford and Feldman, 2022; Peters et al., 2024).

to acquire expensive equity or being limited to using retained profits (under the Pecking Order Theory, Myers and Majluf, 1984). Moreover, firms may desire higher leverage as they trade off the tax-saving advantages of debt against higher bankruptcy costs (as posited by the Trade-Off Theory, Kraus and Litzenberger, 1973). During economic and financial crises, however, high leverage may create vulnerabilities, including higher risks of insolvency and default (Giordani et al., 2014; Traczynski, 2017). Recent empirical evidence suggests that both the positive and negative effects of leverage are exacerbated for smaller firms (Cathcart et al., 2020) and SMEs in Europe are typically more leveraged than larger firms within the same industries (Beck et al., 2023).

After a disaster, highly leveraged firms may find it more difficult to secure additional financing. Due to disrupted operations and revenue, they may struggle to meet their debt obligations, and lenders might view them as riskier. We hence expect SMEs with higher leverage to be less resilient to floods:

H.1: SMEs with higher levels of leverage are less resilient to floods.

In addition to total leverage, we investigate the influence of leverage components with different maturities. Theoretical propositions come to different conclusions about the optimal debt maturity structure of firms (Myers, 1977; Diamond and He, 2014). Research on default risks suggests that short-term liabilities may exert a greater influence on default risk than long-term financing. For instance, commonly applied Merton-based models of default risks used by financial analysts and investors typically weigh 100% of short-term debt but only 50% of long-term debt in their default predictions (Merton, 1974; Vassalou and Xing, 2004; Cathcart et al., 2020). The maturity structure of a firm's debt may have heterogeneous implications for flood-affected SMEs. Having a higher proportion of short-term debt implies increased rollover risk if the disruption caused by the shock exerts pressure on cash flows and if lenders adjust interest rates in the aftermath of the shock (Brown et al., 2021; Correa et al., 2022). While short-term debt offers flexibility for borrowers in non-crisis times, it may exacerbate vulnerabilities in the aftermath of an exogenous shock. We hence hypothesize:

H.2: High pre-event levels of short-term debt decrease SME resilience to flood events.

Insofar as high leverage represents access to external sources of financing that provide immediate liquidity to address urgent liquidity needs and enable firms to invest in post-flood growth, leveraged firms may bounce back more strongly. Similarly, high leverage may imply stronger incentives for lenders to support recovery. If due to the loss of collateral through the shock, creditors expect a greater loss if the firm defaults, they may be more inclined to offer forbearance, restructuring, or additional credit facilities to support recovery to avoid the borrower's default. Additionally, these lenders have made specific investments into the borrower-lender relationship, generating soft private information (Agarwal and Hauswald, 2010). If lenders believe in the long-term sustainability of the leveraged firms' business model, they may be inclined to support the continuation of the firm to extract long-term rents from the relationship (Kysucky and Norden, 2016).

A higher proportion of long-term debt might thus offer some initial relief if repayment terms are more flexible and debt can be restructured. Firms with long-term debt might be in a better position when negotiating with creditors for deferrals or restructuring, as the pressure to repay is not as immediate. Long-term debt may offer more stability and predictability in cash outflows, which can help with planning and managing recovery expenses. However, longer-term debt implies higher interest costs and the destruction of physical assets may reduce the value of collateral, aggravating information asymmetry problems and the risk profile of the debt. Against this background, we test:

H.3: Access to long-term debt improves SME resilience to flood events.

Taken together, we expect the effect of leverage to be dependent on the underlying maturity structure of debt. In Section 4, we propose an event study model and two complimentary estimation strategies to disentangle this relationship. In the next Section, we introduce the data used to test these hypotheses.

3 Data

3.1 Firm-level data

We collect firm-level financial data for European SMEs from the Orbis/Amadeus database. This database, hosted and maintained by Bureau van Dijk, represents the largest and most comprehensive source of financial information for both public and private enterprises in Europe (e.g., Ferri et al., 2019; Kalemli-Özcan et al., 2024). The data is provided in standardized formats, taking care of differences in filing regulations and practices of the national data providers, which include national chambers of commerce, central banks, and statistical offices. The database contains detailed firm-level balance sheet information on firms' assets, equity, investment, indebtedness, and debt maturity, as well as sales, profits, industry codes, and the number of employees, among others (Table A.1 provides a complete overview of the variables we use). Comprehensive address data allows pinpointing firms' locations, as outlined in section 3.2. A useful and distinct feature of the dataset is its extensive and representative coverage not only of large, listed companies but also of SMEs (van Solinge and Soederhuizen, 2023; Kalemli-Özcan et al., 2024).

We collect data for the years 2012-2020. We exclude earlier years because the coverage of our Orbis/Amadeus data deteriorates significantly for those years. To prepare the data for analysis, we follow the cleaning procedure outlined in Kalemli-Özcan et al. (2022) and Kalemli-Özcan et al. (2024) to identify duplicates, drop missings, and handle outliers. Moreover, we apply additional diligence and follow van Solinge and Soederhuizen (2023) by rectifying the data of observations where the accounting identities don't add up in a given year or variables take on illogically negative values. To be able to track the dynamic impacts of floods, we drop firms with less than three consecutive recorded years. In line with our research questions, we keep only unconsolidated balance sheet data for non-financial SMEs active in Manufacturing, Wholesale and Retail Trade, and Accommodation and Food Services Activities (NACE 1 codes). These industries are particularly relevant to study because of their material exposure to physical climate risks (Sustainalytics, 2023).[3] In addition, selecting these industries ensures sufficient data coverage across the country-level sub-samples for our statistical analyses, but implies that our results are not directly representative for other sectors. By retaining only unconsolidated observations we ensure we do not double-count companies that belong to larger, consolidated business groups and multicorporate enterprises. Given the local nature of floods, using unconsolidated information is also consistent with our research questions, because unconsolidated balance sheets represent the situation in the local, directly affected firm rather than at a central, consolidated headquarter level.

In accordance with the European Commission's definition of SMEs (European Commission, 2003), we retain firms with $\leq$ EUR 50 million annual turnover, $\leq$ EUR 43 million annual balance sheet totals, and $<$ 250 employees. After merging with the event data described in Section 3.2, we drop observations from countries for which no relevant events were registered and matched to firms during the sample period. Our final firm dataset consists of 6,053,035 firm-year observations of 923,336 firms across 9 European countries (Austria, Bulgaria, France, Germany, Greece, Ireland, Italy, Poland, and Spain). 130,449 firms in our sample were exposed to a flood in this period.[4]

Table 3.1 reports the number of observations and firms for each country in the sample. Table 3.2 displays summary statistics of the main variables of interest used in our analyses. Table A.1 presents definitions of all variables used.

[3] Other industries considered vulnerable to physical climate risks, e.g., mining and utilities, are not included because few companies in these sectors are SMEs.

[4] Note that the numbers of observations in the regression tables will differ from these numbers because not all firms report data on all variables in all years.

Table 3.1: Sample composition.

	Firms		Firm-Year Obs.		Treated Firms	
	N	% (of Total)	N	% (of Total)	N	% (of Firms)
Austria	30,177	3.27	203,157	3.36	7,826	25.93
Bulgaria	108,746	11.78	725,480	11.99	48,914	44.98
France	182,824	19.80	1,198,833	19.81	40,860	22.35
Germany	130,142	14.09	929,146	15.35	20,040	15.40
Greece	12,113	1.31	76,400	1.26	217	1.79
Ireland	8,981	0.97	48,168	0.80	1,023	11.39
Italy	284,748	30.84	1,869,969	30.89	9,072	3.19
Poland	20,582	2.23	114,216	1.89	597	2.90
Spain	145,023	15.71	887,666	14.66	1,900	1.31
Total	923,336	100.00	6,053,035	100.00	130,449	14.13

Table 3.1 presents the overall composition of the firm sample. Columns (2) and (4) present the absolute numbers of firms and firm-year observations by country. Columns (3) and (5) show each countries share in the total number of firms and firm-year observations respectively. Column (6) shows the total number of treated firms by country. Column (7) shows the share of firms affected by a major flood out of the country's total number of firms in the sample.

3.2 Floods

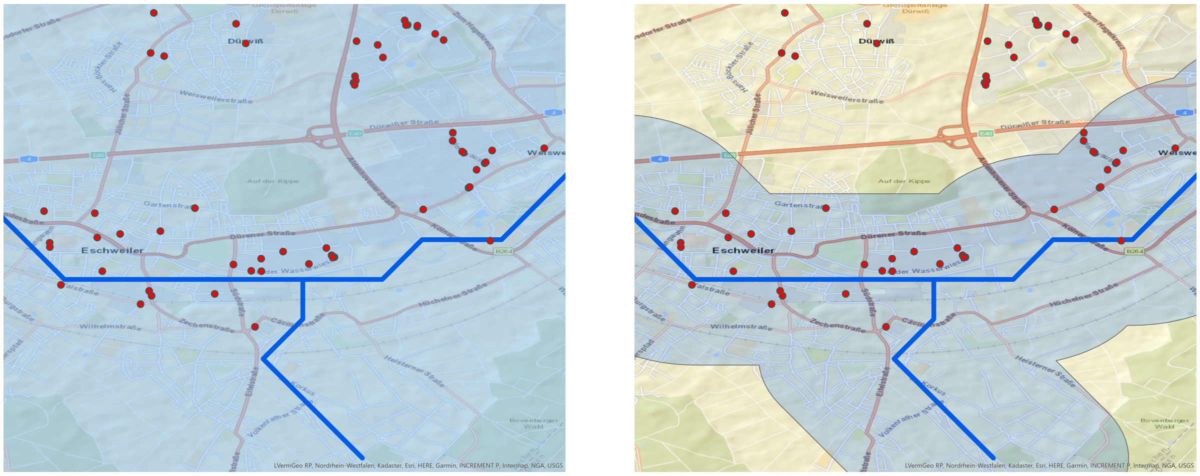
To compute the exposure of European SMEs to flood events, we use combined data from the Dartmouth Flood Observatory's (DFO) Active Archive of Large Flood Events (Brakenridge, 2021) and the EM-DAT International Disaster Database of the Centre for Research on the Epidemiology of Disasters (Centre for Research on the Epidemiology of Disasters, 2022; Delforge et al., 2023). Both databases provide global coverage of floods including estimates of associated direct impacts (people affected, fatalities) and damages. EM-DAT data is compiled from various sources, such as UN agencies, non-government organizations, reinsurance companies, research institutes, and press agencies. The DFO combines news, governmental, instrumental, and remote sensing sources. For inclusion in the EM-DAT database, an event must have led to (a) ten fatalities, (b) 100 people affected, injured, or homeless, *and/or* (c) a call for international assistance or an emergency declaration. For inclusion in the DFO Archive, a flood must meet at least one of these criteria: (a) significant damage to structure or agriculture, (b) fatalities, (c) at least a 1-2 decades-long interval since the last similar event. While no currently available disaster database is completely accurate, both of these established sources are considered reliable and comprehensive, particularly in the context of developed economies (e.g., Jones et al., 2022).

Table 3.2: Summary statistics: All firms.

Variables	Mean	Median	SD	Min	Max	N
Employees	15	6	25	0	249	4,197,720
Employment Growth	0.06	0.00	0.35	-0.61	2.00	3,295,694
Firm Age	17.20	14.00	14.38	0.00	363.00	5,325,841
Turnover	2,522.43	701.65	5,368.36	-9,069.56	49,998.85	4,874,951
Net income	89.55	11.92	344.29	-1,858.07	4,563.80	4,782,102
Total Assets	1,962.19	654.93	3,927.54	0.00	42,999.04	6,053,035
Total Assets Growth	0.07	0.03	0.26	-0.64	1.19	5,077,069
Tangible Assets	473.80	62.39	1,484.96	0.00	42,808.30	5,991,861
Tangible Assets Growth	0.03	-0.05	0.53	-1.42	2.51	4,517,541
Tangible / Total Assets	0.20	0.11	0.23	0.00	0.93	5,991,861
Current / Total Assets	0.72	0.81	0.27	0.04	1.00	6,053,035
Total Liabilities	1,118.83	350.87	2,384.21	0.00	42,925.68	6,053,035
Current Liabilities	722.95	179.23	1,757.94	0.00	41,308.64	6,053,035
Non-current Liabilities	395.88	68.51	1,128.72	0.00	41,422.94	6,053,035
Leverage Ratio	0.86	0.84	0.46	0.00	2.00	5,539,456
Short-term Leverage Ratio	0.63	0.57	0.43	0.00	2.00	5,539,456
Long-term Leverage Ratio	0.26	0.15	0.31	0.00	2.00	6,053,035
Leverage Ratio (Normalized)	1.00	0.98	0.54	0.00	2.84	5,539,456
Short-term Leverage (Norm.)	1.00	0.90	0.69	0.00	4.19	5,539,456
Long-term Leverage (Norm.)	1.00	0.58	1.19	0.00	9.85	6,053,035
Leverage Ratio (Standardized)	0.00	-0.03	1.00	-2.15	2.93	5,539,456
Short-term Leverage (Std.)	0.00	-0.15	1.00	-1.74	3.90	5,539,456
Long-term Leverage (Std.)	0.00	-0.36	1.00	-1.08	6.55	6,053,035
Leverage Growth	0.01	-0.02	0.32	-0.83	1.69	4,435,769

Table 3.2 presents summary statistics for all variables used in the subsequent regressions. Detailed variable definitions can be found in Table A.1 in the Appendix. Monetary values in 1000 EUR and adjusted to 2015 real values. Growth rates and asset ratios are winsorized at the 1% and 99% level. Normalization and standardization of leverage as specified in equations 3 and 4.

We take the subset of flood events registered in both EM-DAT and the DFO's Archives and use information in the form of flood maps (polygons) provided by the DFO to geolocate flood-affected areas precisely. We pre-process the information on floods by keeping only the area of floods that is within 1 km of distance from the closest river, based on European river networks maps (Lehner et al., 2006). Figure 3.1 illustrates the difference between impacted areas using DFO polygons and those corrected for distance from the river network, illustrated by the July 2021 floods in Germany. In Panel (a) the blue line is the river. The red dots indicate the locations of SMEs in that region. The area where a major flood occurred in July 2021 according to the DFO polygons is the blue shaded area that overlays all SMEs locations. In Panel (b), the blue-shaded area around the rivers is considered flooded and only comprises SMEs with a high probability of being hit. This helps us ensure that we only consider those companies directly impacted by floods as treated and thus improves the accuracy of our treatment variable compared to studies that assign treatment at regionally



(a) Flooded Area with DFO polygons (b) Flooded Area 1 km from river

Figure 3.1: Example of the area correction procedure for the July 2021 Floods in Germany.
Figure 3.1 shows the area correction procedure applied in identifying treated firms. The red dots indicate the location of SMEs in our sample. In Panel (3.1a), the blue-shaded area indicates the flood map according to the DFO polygons. In Panel (3.1b), the blue-shaded area indicates the corrected flooded areas. Firms located inside the blue-shaded areas are considered treated.

aggregated levels, such as the county, state, or country. To create overlap with the firm-level data, we only retain flood events that affected geographies in which firms in our sample were located.

Our final flood sample consists of 26 major flood events across Europe, affecting a total of 130,449 firms (Table 3.1). According to the DFO's severity class assessment, 8 of these events are categorised as severity class 1 (10-20 years estimated recurrence interval), 12 events as class 2 (20-100 years estimated recurrence interval and/or local recurrence interval of 10-20 years and affecting a geographic region > 5,000 sq. km), and 5 events as class 3 events (> 100 years estimated recurrence interval).[5]

We match firms to floods using the generated flood maps and SMEs' geocoded addresses. We geolocate SMEs using ArcGIS based on the address information provided in Bureau van Dijk's Orbis/Amadeus database. In this process, we only keep companies for which we find a matched geographical coordinate.[6] We consider companies treated (i.e., affected by a flood) if their main address is within a flood-affected area in the year of the flood.

[5]Refer to the DFO's Archive Notes for more details about the classification procedure (Brakenridge, 2021).

[6]We investigated the quality and correctness of the geolocational algorithm from ArcGIS in a large random sample, confirming our expectation of its high accuracy in European countries.

4 Empirical methodology

We start by quantifying the dynamic economic impacts of floods on SMEs along several dimensions: Employment growth, leverage growth, total assets and tangible fixed assets growth, turnover, and net income. Then, we assess the role of firms' pre-flood corporate financial structure in post-flood firm outcomes.

4.1 Dynamic Analysis of Flood Impacts on SMEs

Recent advances in the econometric literature suggest that conventional two-way fixed effects estimators may produce biased results under heterogeneous treatments (different treatment timings, sizes, or statuses over time). This bias may be serious if summands in the weighted sum of the average treatment effects (ATE) of each group and period receive negative weights. In extreme cases, this can reverse the sign of the estimated coefficient of the ATE, i.e., one would find a positive treatment effect although all group-/period-specific treatment effects are negative, simply because some of the latter receive negative weights in the aggregation to the average treatment effect (Goodman-Bacon, 2021; Sun and Abraham, 2021; Callaway and Sant'Anna, 2021; de Chaisemartin and D'Haultfœuille, 2020).

To investigate this potential bias in our setting, we assess the prevalence of negative weights attached to the TWFE regressions of model 1 (de Chaisemartin and D'Haultfœuille, 2020). We find that only a marginal fraction of ATEs receive negative weights ($< 0.01\%$), suggesting that the baseline regressions are relatively robust to heterogeneous treatment effects (Tables A.12-A.16). In addition, we compare the event study estimates of conventional TWFE and heterogeneity-robust estimators. We don't find significant differences in the results, which leads us to conclude that the potential biases don't appear to be large in our application. Nonetheless, out of a precautionary motive, we check and demonstrate the consistency of our results using heterogeneity-robust estimators throughout the paper (Sun and Abraham, 2021; de Chaisemartin and D'Haultfœuille, 2024).

It should be noted that our results face possible survivorship bias. We quantify the impacts on firm performance (the intensive margin) for firms that keep reporting balance sheet information after being hit by a flood. While this is common in the literature so far (e.g., Basker and Miranda, 2018), it is likely that floods also threaten firm survival (Cathcart et al., 2023; Clò et al., 2024). Hence, the overall economic impacts of floods on SMEs are likely larger than our estimates.

Our baseline specification, quantifying the dynamic economic impacts of floods on SMEs, is given by:

$$y_{i,t} = \beta_{-\underline{3}} D_{i,t}^{-\underline{3}} + \beta_{-2} D_{i,t}^{-2} + \sum_{l=0}^{2} \beta_l D_{i,t}^{l} + \beta_{\overline{3}} D_{i,t}^{\overline{3}} + \gamma X_{i,t-1} + \eta_i + \theta_{c,s,t} + \epsilon_{i,t} \tag{1}$$

where $y_{i,t}$ is the dependent variable (employment growth, leverage growth, total assets growth, tangible assets growth, turnover, or net income) of firm i in year t. The $D_{i,t}^{l}$ are a series of relative time indicators of whether firm i was affected by a flood in a particular year. To avoid multi-collinearity, we follow the convention of normalizing the pre-treatment coefficients ($l = -1$) to zero (Sun and Abraham, 2021; Miller, 2023). $D_{i,t}^{-\underline{3}}$ and $D_{i,t}^{\overline{3}}$ are binned indicators which take into account all observed past and future effects of the treatment beyond the endpoints, i.e., the third lead and lag (Schmidheiny and Siegloch, 2023).

We select a set of control variables and fixed effects based on previous literature in corporate finance and the economic impacts of natural hazard shocks to account for potential confounding factors (e.g., Leiter et al., 2009; Pelli et al., 2023; Benincasa et al., 2024). Specifically, $X_{i,t-1}$ is a vector of predetermined control variables, which includes the first lags of the firm's logarithmised total assets, share of tangible assets in total assets, share of current assets in total assets, and leverage. We use the pre-flood values of these variables to avoid "bad control" problems (Cinelli et al., 2022). Moreover, we include firm fixed effects η_i to account for time-invariant firm characteristics such as locational risk factors and resulting adaptation measures, as well as country-sector-year fixed effects $\theta_{c,s,t}$ to account for sector- and country-specific factors such as the capital intensity of an industry that may affect the way its production is affected by floods, differences in disaster aid that vary at the country level, or differences in insurance coverage and the insurance protection gap for natural catastrophes. As treatment is assigned to firms, we cluster standard errors at the firm level, allowing for errors to be correlated within firms over time (Pelli et al., 2023; Miller, 2023; Abadie et al., 2022).

Identification rests on the assumption that flood occurrence is orthogonal to the error term. In general, the timing, intensity and location of severe flood events are difficult to predict and hold the potential to cause substantial impacts on affected firms. Therefore, controlling for firm- and (country-industry-)time-specific factors that capture the climatic conditions and the associated underlying baseline risk, as well as other unobserved geographic and locational factors at the SME's location allows for a plausible causal interpretation of the coefficient on the flood indicators (Auffhammer et al., 2013; Dell et al., 2014; Pankratz and Schiller, 2023). In this setup, the treatment leads in our dynamic model allow us to test the implied assumptions of no anticipation and parallel trends (Pelli et al., 2023; Clò et al., 2024; de Chaisemartin and D'Haultfœuille, 2024).

An important consideration for the modeling of floods (and other types of natural hazard shocks) in a difference-and-difference setup is how to handle the fact that a specific flood is typically just a one-off event. It is in this case not per se clear whether the treatment should be considered binary (switching on and off) or staggered (units remain "treated" after the shock) and how to deal with multiple treatments, i.e. firms being affected by floods repeatedly (Pelli et al., 2023). In many cases, researchers treat these events as binary in the sense that the treatment indicator switches off again after one or several periods (e.g., Duqi et al., 2021; Pelli et al., 2023). Since our setup considers major flood events which are rather infrequent, not many firms (around 0.02%) receive multiple treatments within the time frame of our analysis. In our baseline estimation, we therefore assume an absorbing treatment within our sample period, in line with, for instance, Deryugina (2017), Pelli et al. (2023) and Clò et al. (2024). In additional robustness tests, we check our results using the more flexible approach of de Chaisemartin and D'Haultfœuille (2024) that estimates treatment effects based on switchers into treatment and switchers out of treatment, allowing for multiple changes in the treatment indicator.

4.2 Heterogeneity Analyses

To investigate how the impact of floods on SMEs' performance is shaped by their pre-shock financial structure, we employ two complementary strategies. First, we exploit the flexibility of conventional TWFE estimators and estimate a triple difference-in-difference specification that interacts flood indicators with pre-flood levels of firm leverage. This analysis gives us a consistent and comprehensive picture across the entire leverage distribution while preserving statistical power. Second, we explore heterogeneity by estimating our baseline model (equation 1) for subsamples of firms in the same leverage quintiles using the interaction-weighted estimator of Sun and Abraham (2021). This approach provides robustness to treatment effect heterogeneity and only compares firms with similar levels of leverage, but may suffer from less precise estimates due to the reduced number of observations in each subsample.

In this setup, we estimate

$$\begin{aligned} Employment\ Growth_{i,t} = &\sum_{l=0}^{3} \beta_l D_{i,t}^l + \mu Leverage_{i,t-1} + \sum_{l=0}^{3} \delta_l D_{i,t}^l * Leverage_{i,t-1} + \\ &\sum_{l=0}^{3} \zeta_l D_{i,t}^l * Leverage_{i,t-1}^2 + \gamma X_{i,t-1} + \eta_i + \theta_{c,s,t} + \epsilon_{i,t} \end{aligned} \quad (2)$$

where $Leverage_{i,t-1}$ represents the leverage of firm i at the end of year *t-1*, the year before the shock. In this part of the analysis, we focus on SME i's employment growth in year t (calculated as the year-over-year percentage change in employment from the end of year *t-1* to the end of year t) as the main variable of interest, for several reasons. First, employment is a key indicator of firm health and resilience. When firms are hit by external shocks like floods, maintaining or growing employment suggests resilience and the ability to recover and continue operations (Martin and Sunley, 2014). Due to labour market frictions (Eckstein and van den Berg, 2007), employment is a less volatile proxy of overall firm health in the face of disasters than turnover or profits. Moreover, employment has broader implications for the economy and society and SME employment is particularly crucial for local communities and social stability. Hence, SME employment is highly relevant from a policy perspective (e.g., Udell, 2020).

We select a set of covariates and fixed effects consistent with specification 1. The primary coefficients of interest in specification 2 are thus the δ_l and ζ_l coefficients on the interaction terms between flood impact and SME leverage (squared). In line with our first hypothesis (Section 2), we allow the relationship between leverage, floods, and employment growth to be non-linear. We start by considering SMEs' total level of pre-shock leverage. Then, to disentangle the effect of debt with different maturities, we use firms' short-term (maturity < 1 year) and long-term (≥ 1 year) levels of pre-shock leverage.[7]

In addition, we test whether our results hold when using sector-specific normalized and standardized levels of leverage. In this way, we mitigate concerns that our results are driven by firms in industries that have higher levels of leverage per se and are simultaneously more vulnerable to the impacts of floods due to some unobserved characteristics. We compute these measures as

$$\text{Normalized Leverage}_{i,s,t} = \frac{\text{Leverage}_{i,s,t}}{\text{Average Leverage}_{\text{s}}} \tag{3}$$

$$\text{Standardized Leverage}_{i,s,t} = \frac{\text{Leverage}_{i,s,t} - \text{Average Leverage}_{\text{s}}}{\text{Standard Deviation of Leverage}_{\text{s}}} \tag{4}$$

for total, short-term, and long-term leverage, where *Normalized Leverage*$_{i,s,t}$ is the normalized leverage of firm i in sector s in year t. *Average Leverage*$_{\text{s}}$ is the average leverage calculated over all firms in sector s and over all sample years. We use these measures both in the estimation of model 2 and for the definition of subsamples in the heterogeneity analysis

[7]The distinction between short-term and long-term at the cutoff of 1 year is common in corporate finance (see e.g., Kalemli-Özcan et al., 2022; Barbiero et al., 2020) and Bureau van Dijk provides the data accordingly.

of model 1. While the unadjusted reported leverage estimates are interpreted as the effect of a one-unit increase in the debt-to-assets ratio, estimates using equation 3 present the effect of leverage in percent deviation from the average sectoral leverage and equation 4 expresses the effect in units of industry leverage standard deviations.

5 Results

5.1 The Dynamic Impacts of Floods on SMEs

We start by discussing the baseline results of model 1, capturing the dynamic impact of floods on several firm-level outcomes: employment growth, leverage growth, total assets and tangible assets growth, turnover, and net income. Figure 5.1 presents event study plots for each outcome variable, estimated using a conventional TWFE estimator and the heterogeneity-robust approach of Sun and Abraham (2021). The corresponding regression results are compiled in Tables 5.1 and 5.2 respectively. The results of the different estimation methods are very similar, suggesting that the potential biases of the TWFE estimator discussed in Section 4 are not large in this application. Given this similarity, we focus on the discussion of the results of the heterogeneity-robust method.

In the three years after a flood event, affected SMEs experienced a statistically significant decline in employment growth (Figure 5.1, Panel a), leverage growth (Panel b), total asset growth (Panel c), tangible asset growth (Panel d), turnover (Panel e), and net income (Panel f). The average annual effect on employment growth (over years 0 to 2) is estimated to be 1.7 percentage points, representing 1/3 of the expected annual employment growth, and is statistically significant at the 99% level (Table 5.1). The negative effect increases up to 2.4 percentage points in the second year after the flood.

Back-of-the-envelope calculations demonstrate the economic significance of this result: An average SME in our sample with 15 employees would expect to hire three more workers over three regular years. Due to a flood, one of these jobs will be lost. If around 15% of SMEs are affected by floods each year (our sample: 14.13%, Table 3.1), and around 60 million workers are employed in SMEs in the countries included in our sample (Katsinis et al., 2024), around 1,800 jobs will be lost or not created each year due to floods.[8] Given the localised nature and the occurrence of major flood events, this represents considerable

[8] Assuming an expected annual employment growth of 6% (Table 3.2), which will be reduced by 1/3. Note that this estimate does not include the possibility of firms (temporarily) reducing the working hours/wages of workers to adjust labour costs in the aftermath of a flood. Moreover, our data does not allow us to disentangle hirings and separations as we only observe the total firm-level employment and compute the growth rate based on year-to-year changes.

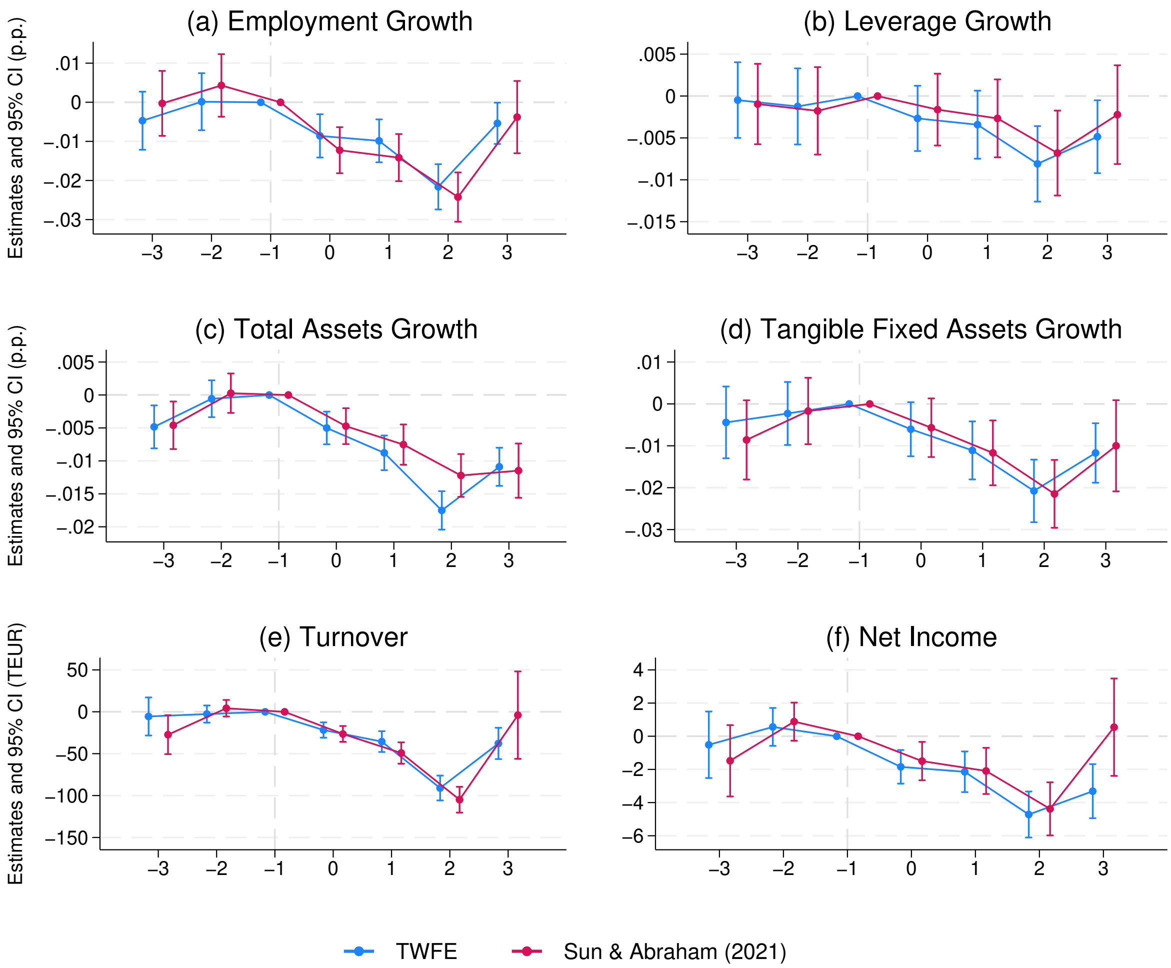


Figure 5.1: Dynamic impacts of floods on SME outcomes.

Figure 5.1 shows the dynamic impacts of floods on various SME outcomes. The y-axis shows the estimated point coefficients of the leads and lags of the flood indicator including 95%-level confidence intervals. In each Panel, the blue line depicts estimation results using a conventional TWFE estimator and the red line depicts results using the heterogeneity-robust approach of Sun and Abraham (2021). In Panel (5.1a), the dependent variable is employment growth.

Table 5.1: Dynamic impacts of floods on firm outcomes: Sun & Abraham (2021).

	Employment growth	Leverage growth	Total assets growth	Tangible assets growth	Turnover	Net Income
Flood [l ≤ -3]	-0.000	-0.001	-0.005**	-0.009*	-27.298**	-0.583
	(0.004)	(0.002)	(0.002)	(0.005)	(11.866)	(1.972)
Flood [l = -2]	0.004	-0.002	0.000	-0.002	4.249	1.089
	(0.004)	(0.003)	(0.002)	(0.004)	(5.043)	(1.087)
Flood [l = 0]	-0.012***	-0.002	-0.005***	-0.006	-26.432***	-1.367
	(0.003)	(0.002)	(0.001)	(0.004)	(4.813)	(1.099)
Flood [l = 1]	-0.014***	-0.003	-0.008***	-0.012***	-49.169***	-1.830
	(0.003)	(0.002)	(0.002)	(0.004)	(6.490)	(1.296)
Flood [l = 2]	-0.024***	-0.007***	-0.012***	-0.021***	-104.878***	-4.410***
	(0.003)	(0.003)	(0.002)	(0.004)	(7.850)	(1.564)
Flood [l ≥ 3]	-0.004	-0.002	-0.011***	-0.010*	-3.959	1.200
	(0.005)	(0.003)	(0.002)	(0.006)	(26.615)	(2.834)
Observations	3,088,552	4,383,838	4,575,141	4,062,628	3,958,083	3,949,320
Firms	633,449	836,703	865,126	778,859	765,020	750,887
R-squared	0.220	0.334	0.501	0.294	0.961	0.691
Avg. effect	-0.017***	-0.004*	-0.008***	-0.013***	-60.159***	-2.536**
Joint Sig. Pretrend	0.546	0.782	0.028	0.200	0.011	0.419
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-country-year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 5.1 presents the results of the dynamic impacts of floods on six different firm outcomes: employment growth, leverage growth, total assets growth, tangible assets growth, turnover, and net income. The Flood indicator is one for SMEs located in a flooded area in the respective year. Standard errors in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Results in this table are estimated using the interaction-weighted estimator of Sun and Abraham (2021). The average cumulative effect is calculated over periods 0 to 2. Joint Sig. Pretrend is the p-value of an F-test on the joint nullity of the pre-flood coefficients.

Table 5.2: Dynamic impacts of floods on firm outcomes: TWFE.

	Employment growth	Leverage growth	Total assets growth	Tangible assets growth	Turnover	Net Income
Flood [l ≤ -3]	-0.005	-0.000	-0.005***	-0.004	-5.555	0.177
	(0.004)	(0.002)	(0.002)	(0.004)	(11.582)	(1.869)
Flood [l = -2]	0.000	-0.001	-0.001	-0.002	-2.673	0.599
	(0.004)	(0.002)	(0.001)	(0.004)	(5.210)	(1.053)
Flood [l = 0]	-0.009***	-0.003	-0.005***	-0.006*	-21.710***	-1.926*
	(0.003)	(0.002)	(0.001)	(0.003)	(4.658)	(1.010)
Flood [l = 1]	-0.010***	-0.003*	-0.009***	-0.011***	-35.531***	-2.159*
	(0.003)	(0.002)	(0.001)	(0.004)	(6.343)	(1.161)
Flood [l = 2]	-0.022***	-0.008***	-0.018***	-0.021***	-90.949***	-5.110***
	(0.003)	(0.002)	(0.001)	(0.004)	(7.567)	(1.363)
Flood [l ≥ 3]	-0.005**	-0.005**	-0.011***	-0.012***	-37.748***	-4.471***
	(0.003)	(0.002)	(0.001)	(0.004)	(9.533)	(1.559)
Observations	3,088,552	4,383,838	4,575,141	4,062,628	3,958,083	3,949,320
Firms	633,449	836,703	865,126	778,859	765,020	750,887
R-squared	0.221	0.334	0.497	0.294	0.961	0.691
Avg. effect	-0.013***	-0.005***	-0.010***	-0.013***	-49.396***	-3.065***
Joint Sig. Pretrend	0.397	0.865	0.009	0.590	0.845	0.837
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-country-year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 5.2 presents the results of the dynamic impacts of floods on six different firm outcomes: employment growth, leverage growth, total assets growth, tangible assets growth, turnover, and net income. The Flood indicator is one for SMEs located in a flooded area in the respective year. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. Results in this table are estimated using a conventional TWFE estimator. The average cumulative effect is calculated over periods 0 to 2. Joint Sig. Pretrend is the p-value of an F-test on the joint nullity of the pre-flood coefficients.

harm to affected communities.

The growth of total assets declines on average by 0.8 percentage points per year over the three years after a flood (11% of average total asset growth). This reduction is demonstrably due to the reduction in the growth of tangible assets, which, compared to intangible assets, are directly exposed to the risk of physical destruction. The average flood effect on tangible asset growth is 1.3 percentage points (40% of annual mean) and, again, most pronounced in the second year after the shock. Furthermore, over the years 0 to 2, the average firm sees an annual reduction of 60 TEUR, or 2.4%, in its turnover and of 2.5 TEUR, or 2.8%, in its net income. Average leverage growth is less significantly affected, with a negative average effect of 0.4 percentage points (40% of annual mean).

Figure 5.1 backs the assumptions of no anticipation and parallel pre-shock trends across the different model setups. F-tests on the joint nullity of treatment leads further confirm this assessment ("Joint Sig. Pretrend" presents corresponding p-values in Tables 5.1 and 5.2). A potential exception is total asset growth (Panel c), where both specifications record a rather small but statistically significant coefficient on the third lead.

Overall, these findings are in line with the recent evidence (Fatica et al., 2022; Clò et al., 2024).[9] Floods are a considerable threat to the health of European SMEs, with persistent negative effects over several years and potentially large repercussions for affected regions and communities. This evidence emphasises the need for firms, policymakers, and economies at large to increase their efforts to adapt to these threats, identify vulnerabilities, and enhance resilience, particularly in the face of unabated climate change (Berkhout, 2011; Grover and Kahn, 2024).

5.2 The Role of Pre-Flood Leverage and Debt Maturity

The corporate financial structure of SMEs may be an important source of vulnerability or resilience to physical climate shocks, but there is little empirical evidence investigating this aspect. We employ two different strategies to assess the role of pre-shock leverage in European SMEs' resilience to floods. We expect a non-linear, negative relationship between leverage and economic resilience. All else equal, high leverage creates vulnerabilities that are more likely to be exposed in critical periods such as floods, while low levels of leverage per se should not (negatively) affect the resilience of SMEs. Some leverage may in fact be beneficial, insofar as it reflects access to external sources of financing that firms can draw on

[9]Our results are at odds with some of the earlier studies considering European firms, particularly studies where treatment status is assigned at more aggregated regional levels (Leiter et al., 2009; Noth and Rehbein, 2019). This emphasizes the need for spatial precision when investigating the direct economic impacts of natural hazard shocks.

in times of crisis (Section 2)

In the first setup, we exploit the flexibility of the conventional TWFE estimator to estimate model 1. As the results presented in Section 5.1 show, TWFE and heterogeneity-robust methods produce highly similar results in our application, indicating that the potential issues with TWFE estimators discussed in Section 4 are unlikely to create significant bias. We take this as reassurance that our estimates are not biased by treatment effect heterogeneity.

To capture the hypothesised functional form, we interact the Flood indicators with continuous variables measuring firms' pre-flood leverage in linear and polynomial forms (Model 2). This allows us to investigate heterogeneity in the firm-level consequences of floods across the entire leverage distribution. In this setup, we combine firms with different levels of leverage into one control group. To address the potential concern that these firms differ systematically in their employment growth, we retain pre-shock leverage (squared) as a stand-alone control variable.

To illustrate the differential effect of leverage on the dynamic impacts of floods over time, we use the estimates of model 2 to predict the employment growth of affected and unaffected SMEs depending on their pre-period leverage. Figure 5.2 collects the estimated marginal effects of total, short-term, and long-term leverage for years 0, 1, and 2 using unadjusted firm leverage. Figure 5.3 presents the estimates using the standardized measure. The columns in both figures show the the effects in years 0, 1, and 2 respectively, while the rows divide the results in total, short-term, and long-term leverage. Table 5.3 presents the corresponding OLS estimates for the unadjusted (columns 1-3) and standardized (columns 4-6) measures of total, short-term, and long-term leverage.[10]

First, it stands out that both figures present very similar pictures across all panels, suggesting the underlying results are not driven by industry-specific patterns in leverage and vulnerability to floods. SMEs affected by floods register lower predicted employment growth on average over the years 0 to 2. However, the first row of panels suggests that the negative impacts are concentrated in firms with very high levels of total leverage. In all three years, predicted outcomes are very similar for affected and unaffected low-leverage firms, but a wedge is driven between the groups as leverage increases. In the first two years, expected employment growth in high-leverage firms is around 3 percentage points lower compared to unaffected firms with similar leverage. In year two, this difference increases to up to 5 percentage points. The second row of panels demonstrates this effect is largely driven by firms' short-term leverage. Again, this effect seems to become even larger over

[10]For the sake of brevity, we added results using the normalized leverage to the robustness checks (Section 5.3) Using the normalized leverage produces very similar results compared to the unadjusted and standardized measures.

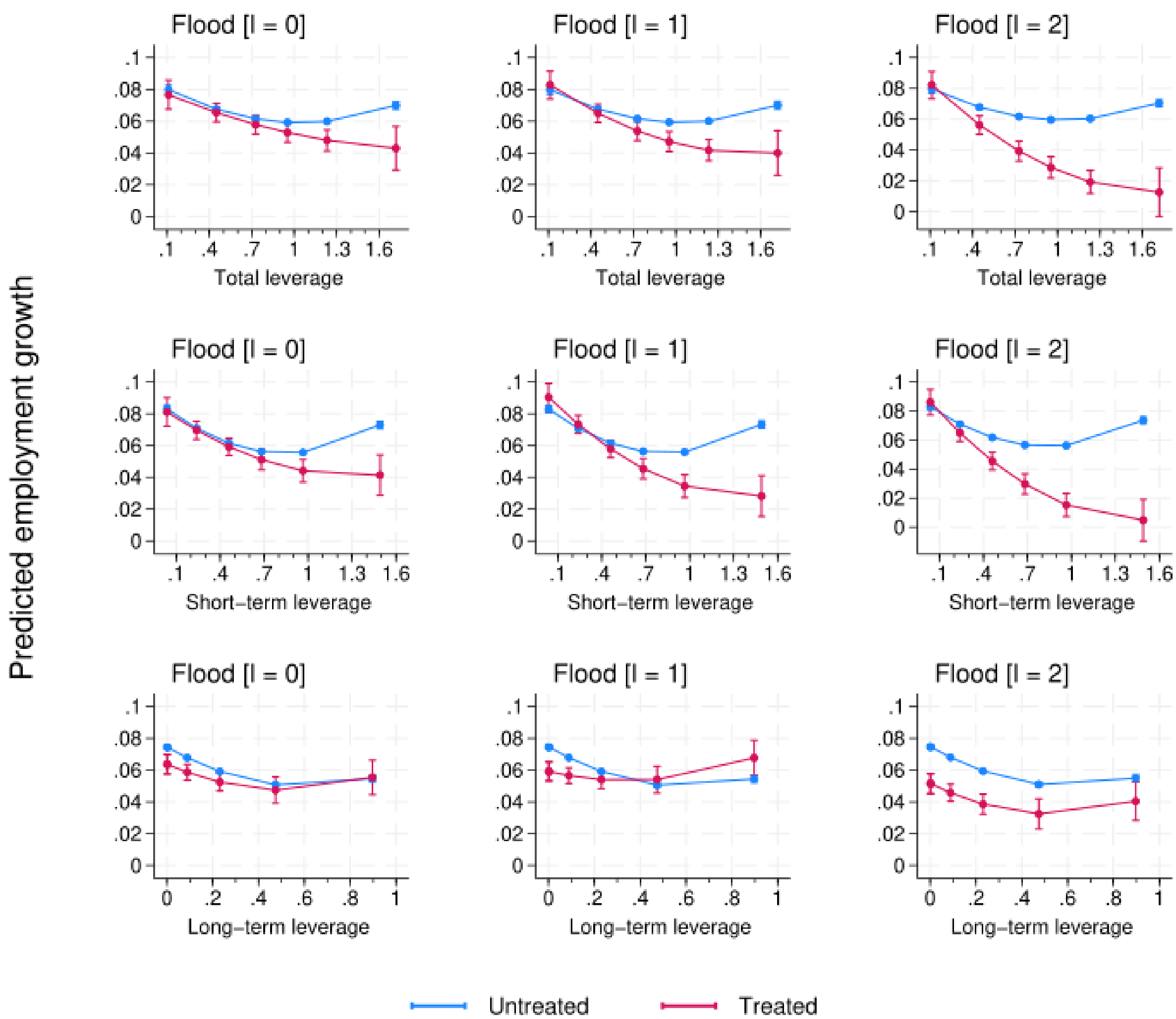


Figure 5.2: Predictive margins of floods on employment growth across the distribution of leverage.

Figure 5.2 shows the predictive margins of floods on employment growth across the distribution of leverage and its components. In the 3x3, the rows represent different leverage components, total leverage, short-term leverage, and long-term leverage, while the columns represent different time lags after the flood, l=0, l=1, and l=2. The red line shows the predicted employment growth of treated SMEs.

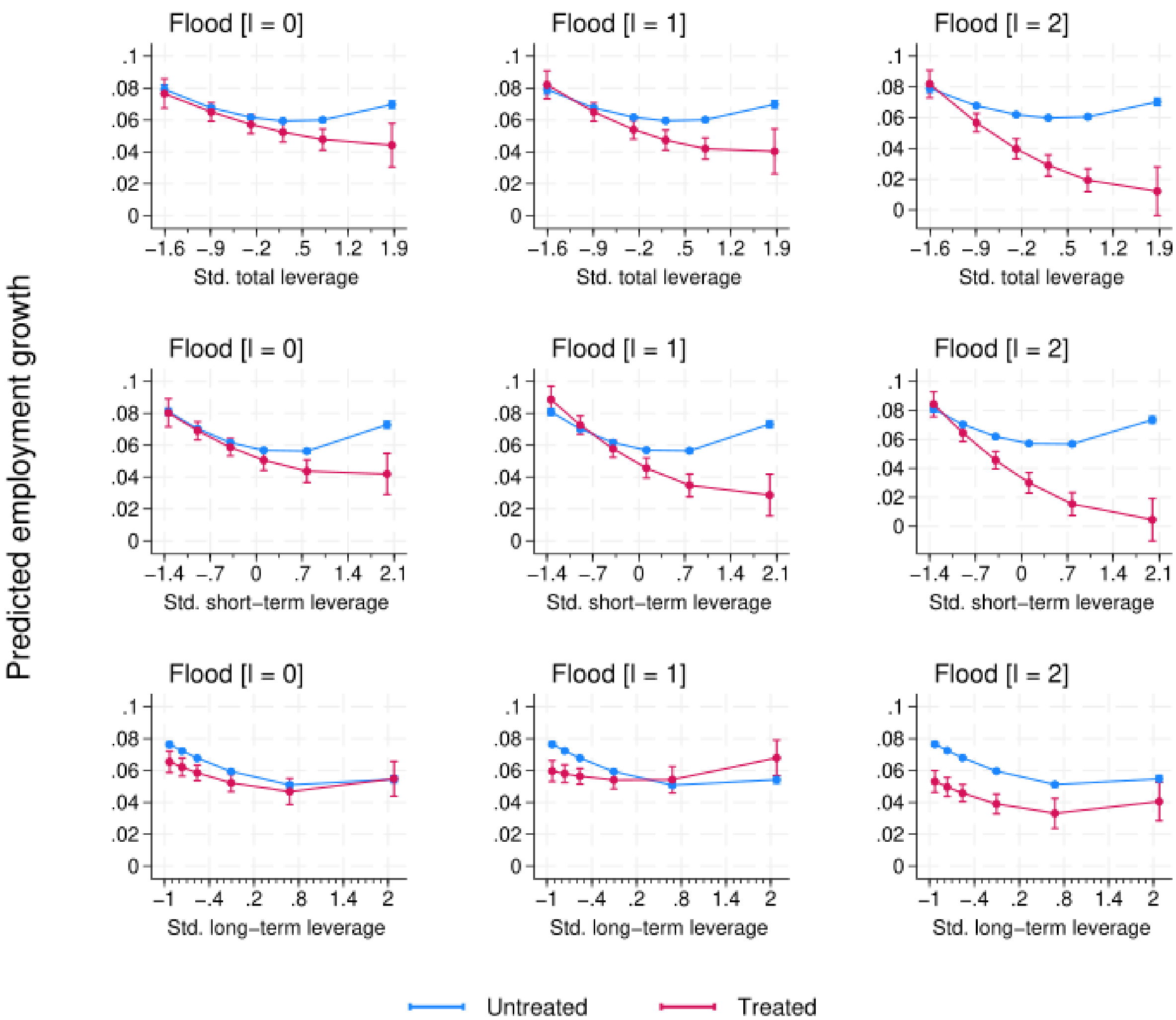


Figure 5.3: Predictive margins of floods on employment growth across the distribution of standardized leverage.

Figure 5.3 shows the predictive margins of floods on employment growth across the distribution of leverage and its components. In this figure, we use a standardized measure of leverage following equation 4. In the 3x3, the rows represent different leverage components, total leverage, short-term leverage, and long-term leverage, while the columns represent different time lags after the flood, l=0, l=1, and l=2. The red line shows the predicted employment growth of treated SMEs.

Table 5.3: SME Flood Outcomes and the Role of Leverage and Debt Maturity.

	Leverage			Standardized Leverage		
	Total	Short-term	Long-term	Total	Short-term	Long-term
Flood [l = 0]	-0.004	-0.002	-0.011***	-0.006*	-0.005*	-0.007**
	(0.006)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)
Flood [l = 0] x L.Leverage	0.011	0.009	0.019	-0.006***	-0.007***	0.004
	(0.015)	(0.015)	(0.017)	(0.002)	(0.002)	(0.003)
Flood [l = 0] x L.Leverage^2	-0.014*	-0.019**	-0.007	-0.002	-0.003	-0.000
	(0.008)	(0.010)	(0.014)	(0.002)	(0.002)	(0.001)
Flood [l = 1]	0.005	0.008*	-0.015***	-0.010***	-0.010***	-0.004
	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)
Flood [l = 1] x L.Leverage	-0.015	-0.021	0.048***	-0.009***	-0.015***	0.012***
	(0.014)	(0.015)	(0.017)	(0.002)	(0.002)	(0.003)
Flood [l = 1] x L.Leverage^2	-0.003	-0.010	-0.018	-0.001	-0.001	-0.002
	(0.008)	(0.010)	(0.013)	(0.002)	(0.002)	(0.001)
Flood [l = 2]	0.007	0.005	-0.023***	-0.027***	-0.025***	-0.020***
	(0.005)	(0.005)	(0.003)	(0.003)	(0.004)	(0.003)
Flood [l = 2] x L.Leverage	-0.043***	-0.044***	0.010	-0.018***	-0.021***	0.003
	(0.015)	(0.016)	(0.018)	(0.002)	(0.003)	(0.004)
Flood [l = 2] x L.Leverage^2	0.003	-0.004	-0.000	0.001	-0.000	-0.000
	(0.009)	(0.010)	(0.014)	(0.002)	(0.002)	(0.001)
Flood [l $\geq$ 3]	0.014***	0.014***	-0.007**	-0.008**	-0.008***	-0.007**
	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Flood [l $\geq$ 3] x L.Leverage	-0.016	-0.031**	-0.008	-0.016***	-0.017***	0.001
	(0.012)	(0.013)	(0.014)	(0.002)	(0.002)	(0.003)
Flood [l $\geq$ 3] x L.Leverage^2	-0.011	-0.006	0.019*	-0.002	-0.001	0.002*
	(0.007)	(0.008)	(0.011)	(0.001)	(0.001)	(0.001)
Observations	3,088,552	3,088,552	3,223,073	3,088,552	3,088,552	3,223,073
Firms	633,449	633,449	673,928	633,449	633,449	673,928
R-squared	0.221	0.221	0.223	0.221	0.221	0.223
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-country-year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 5.3 presents the results of regressions estimating equation 2, interacting the flood indicators with different components (and measures) of pre-shock leverage. Columns (1)-(3) use leverage as defined in Table A.1, while columns (4)-(6) use standardized leverage as defined in equation 4. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. Results in this table are estimated using a conventional TWFE estimator.

time. Particularly high levels of short-term leverage seem to exacerbate the negative effects of floods.

The third row of panels considers firms' long-term leverage. Here we find a different pattern. Over all years, firms with very low levels of long-term leverage experience consistently lower employment growth when affected by floods, with a difference of 1-2 percentage points. The predicted employment growth of firms with high levels of long-term leverage is similar to unaffected firms in year 0, slightly higher in year 1, and slightly lower in year 2, but not significantly different. Relatively high levels of long-term leverage thus do not appear to weaken the resilience of SMEs. We take this result as an indication of the importance of access to long-term finance for the resilience of SMEs. Financially constrained SMEs that are unable to secure long-term financing for their projects may have to rely on short-term debt instruments like bank overdrafts or lines of credit, resulting in higher short-term leverage and greater vulnerability to unexpected shocks. SMEs able to secure a stable level of long-term financing seem to be able to convert this into resilient performance in the aftermath of shocks.

We combine these results with evidence from a complementary estimation strategy, where we split the sample into groups with different levels of leverage and estimate the impact of floods on treated and control firms within these subsamples using our baseline model 1, i.e., the specification without the leverage interaction effects. This allows us to directly compare the effects of floods using affected and unaffected SMEs with similar leverage (instead of having a combined control group). We hence expect some differences in the coefficient estimates, yet overall consistent results. We estimate these models using the heterogeneity-robust estimator of Sun and Abraham (2021).[11]

Table 5.4 collects the average effects of floods estimated for different leverage subsamples over the years 0 to 2. To create the subsamples, we divide the sample into leverage quintiles. In addition, we extract the subsamples of firms above the 90^{th} and 95^{th} percentile, i.e., firms with very high levels of leverage.[12]

Again, using unadjusted or industry-standardized levels of firm leverage does not make a substantial difference in the overall picture. Considering total leverage, firms in the first, second and fifth quintiles register significant negative impacts of floods of around 1.5-2.1 percentage points. Meanwhile, the flood coefficients of the third and fourth quintile samples are negative, but around 50% smaller and statistically insignificant. What stands out are the coefficients of the Top-5% subsamples, with negative estimated average impacts of 3.5

[11]For the sake of brevity, results using the estimator of (de Chaisemartin and D'Haultfœuille, 2024) can be found in Section 5.3.

[12]Full regression results can be found in Tables A.5 to A.9.

Table 5.4: Average impacts of floods on firm outcomes in different leverage subsamples.

Measure	Component	Q1	Q2	Q3	Q4	Q5	P90	P95
Leverage (unadjusted)	Total	-0.021***	-0.016***	-0.008	-0.011	-0.015*	-0.014	-0.035
		(0.004)	(0.005)	(0.007)	(0.007)	(0.008)	(0.015)	(0.025)
		N=637,262	N=575,608	N=591,213	N=635,022	N=648,680	N=277,938	N=131,309
	Short-term	-0.021***	-0.017***	-0.012*	-0.016**	-0.013	-0.038**	-0.054**
		(0.004)	(0.006)	(0.007)	(0.008)	(0.009)	(0.015)	(0.024)
		N=603,387	N=612,001	N=621,507	N=635,926	N=614,987	N=242,964	N=108,707
	Long-term	-0.023***	-0.026***	-0.011	-0.007	0.001	-0.011	-0.020
		(0.004)	(0.006)	(0.007)	(0.008)	(0.008)	(0.013)	(0.015)
		N=620,853	N=629,891	N=695,678	N=690,642	N=585,133	N=212,429	N=105,417
Standardized Leverage	Total	-0.021***	-0.019***	-0.004	-0.013	-0.015**	-0.029	-0.041*
		(0.004)	(0.006)	(0.007)	(0.008)	(0.009)	(0.018)	(0.023)
		N=637,856	N=577,169	N=590,806	N=635,810	N=646,103	N=164,689	N=153,021
	Short-term	-0.020***	-0.015**	-0.016**	-0.010	-0.018**	-0.017	-0.054**
		(0.004)	(0.006)	(0.007)	(0.008)	(0.009)	(0.017)	(0.022)
		N=605,102	N=612,128	N=618,772	N=635,054	N=616,757	N=156,102	N=142,178
	Long-term	-0.025***	-0.014***	-0.012	-0.004	-0.004	0.018	0.003
		(0.004)	(0.006)	(0.007)	(0.008)	(0.008)	(0.017)	(0.014)
		N=636,096	N=623,252	N=690,160	N=689,756	N=582,876	N=136,993	N=134,938

Table 5.4 presents the average cumulative effects of floods on employment growth, based on regressions estimating equation 1 and using the heterogeneity-robust estimator of Sun and Abraham (2021) on subsamples of SMEs in different leverage quintiles and above the $90^{th}/95^{th}$ percentile, respectively. The rows entail results for the different leverage components and measures. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. The average cumulative effects are calculated over periods 0 to 2. Full regression results in the Appendix, Tables A.5 to A.9.

(unadjusted) and 4.1 (standardized) percentage points compared to the respective control groups. While these estimates are less precisely estimated due to the much smaller sample sizes, the effect is statistically significant at the 10% level in the standardized leverage sample.

Consistent with the previous analysis, the negative effects of high leverage (Top-5% subsamples) seem driven by short-term debt. With -5.4 percentage points, firms in this leverage category show a significant reduction in employment growth relative to other firms in their leverage category which is 3 to 5 times larger than for firms in the third leverage quintile. Interestingly, these results also suggest that firms in the lower short-term leverage quintiles suffer more than firms in the third and fourth quintiles, although the estimated relative impact is only around 0.5-1 percentage points.

Very high levels of long-term leverage don't seem to have a strong amplifying effect of flood impacts. The estimated coefficients for the high-leverage subsamples are not statistically different from zero and don't differ in magnitude from the median quintiles. However, with 1.4-2.5 percentage points, SMEs with very little long-term debt seem to lose about 2 to 3 times more employment growth relative to their respective control groups than firms in the median quintiles. These results confirm the findings presented in the previous section.

The combined evidence of the different estimation strategies provides a nuanced picture of the role of leverage in SME resilience to floods. Overall, there seems to be a non-linear relationship between leverage and resilience. SMEs with very low levels of leverage, which may indicate financial constraints, and SMEs with very high levels of leverage, with high rollover risks, are statistically and economically less resilient to these shocks. "Too little" leverage seems to be particularly critical in terms of long-term debt, supporting the notion that access to stable long-term financing helps in stabilising firms and allowing them to make investments that decrease their vulnerability to exogenous shocks. The effects of "too high" leverage are primarily driven by short-term debt, consistent with tightening lending standards in flood-affected regions (Correa et al., 2022; Barbaglia et al., 2024).

Our results are consistent with the results of Fatica et al. (2022) who find European manufacturing firms with a debt-to-assets ratio in the top quartile of their sample distribution to be more negatively affected by floods. However, our results provide a much more nuanced picture by demonstrating that this effect is concentrated in the top 5-10% of the (our) sample leverage distribution and that the relationship between leverage and resilience is likely non-linear, consistent with a trade-off between economic growth and efficiency on the one hand and economic resilience on the other (Peters et al., 2023). Moreover, our results are consistent with studies investigating the link between leverage and firm performance in the context of other types of crises, such as the Global Financial Crisis (Cathcart et al., 2020; Kalemli-Özcan et al., 2022).

5.3 Robustness

We conduct a variety of targeted checks to assess the robustness and sensitivity of our results.

In addition to the heterogeneity-robust estimator of Sun and Abraham (2021), we check the consistency of our results using the recent estimator proposed by de Chaisemartin and D'Haultfœuille (2024) which allows for settings in which treatment status is non-absorbing. As discussed in Section 4, it is conceptually unclear whether flood events should (econometrically) be treated as one-off binary (treatment switching from 0 to 1 and back again) or as absorbing events (treatment switching from 0 to 1 once and never back). While the estimator of Sun and Abraham (2021) builds on the latter treatment definition, de Chaisemartin and D'Haultfœuille (2024) allow units to switch in and out of treatment multiple times. We repeat the estimation of our baseline model 1 and the heterogeneity analysis of Section 5.2 with this estimator.

As Figure A.1 in the Appendix shows, the estimated dynamic impacts of floods on SME outcomes are very similar to the baseline results.[13] For instance, the estimated average effect of floods on employment growth over years 0 to 2 is -1.9 percentage points, as compared to -1.7 percentage points in our baseline setup. Some differences occur in the estimation of total assets growth, where the estimator of de Chaisemartin and D'Haultfœuille (2024) detects a negative coefficient on the second lead and henceforth small and marginally significant positive effects in years 0 and 1 before the coefficients drop to estimates similar to baseline setup. Except for this, all estimates show quantitatively and qualitatively similar results. We take this as additional assurance that our baseline regressions are not distorted by treatment effect heterogeneity.

An important concern regarding the role of firm leverage is that industry-specific differences in the use of leverage that correlate with structural differences in firm vulnerability to floods may drive our results. In addition to using standardized firm leverage in Section 5.2, we test a normalized measure of leverage to assess whether our results are sensitive to these issues. Table A.4 in the Appendix presents the results of regression 2 using normalized leverage as an explanatory variable. Figure A.2 illustrates the results, comparing the predicted employment growth of affected and unaffected SMEs across the leverage distribution. The results are quantitatively and qualitatively in line with our previous findings, strengthening the view that the results are not driven by industry differences.

We further repeat the heterogeneity analysis, splitting the sample by leverage, using the estimator proposed by de Chaisemartin and D'Haultfœuille (2024). We show these results in Table A.11 in the Appendix. For almost all quintile and leverage component combinations,

[13]Detailed estimation results can be found in Table A.3 in the Appendix.

the results are quantitatively very similar. For the smaller subsamples, considering SMEs above the 90^{th} and 95^{th} leverage percentiles and thus reducing the sample size further, the estimates of the de Chaisemartin and D'Haultfœuille (2024) estimator seem more conservative, albeit showing a qualitatively consistent picture.[14]

6 Discussion and Conclusion

Floods are the most prevalent and destructive natural hazard in Europe and smaller- and medium-sized enterprises are particularly vulnerable to their impacts. Increasing the resilience of SMEs to these shocks is an important issue for policymakers, business owners, financiers, and societies at large. Combining a spatially granular dataset on major European floods with detailed firm-level balance sheet data over the period 2012-2020, we shed light on the role of the corporate financial structure of SMEs in their resilience to physical climate shocks.

First, we provide evidence for the negative consequences of floods on SME performance. We find employment growth, asset growth, turnover and income to be stunted for several years after a flood event. Then, our results reveal an inverted U-shaped relationship between SME resilience and leverage, in which the maturity structure of debt plays a crucial role. Highly leveraged SMEs are particularly at risk of suffering from flood impacts and this effect is driven by the short-term component of leverage. When the rollover risk and limited access to additional funding associated with high short-term debt coincide with unexpected disruptions to cash flows and a need to repair or replace destroyed assets, SMEs cut back employment. At the same time, firms that are more likely financially constrained, particularly lacking access to long-term financing, appear less resilient to the impacts of floods. Hence there appears to be a "sweet spot" of leverage that balances the needs of SMEs to access external sources of funding to smooth operations during shocks and invest in (long-term) defensive adaptation measures with the risks of overly high levels of (short-term) leverage. Our results are robust to various tests and additional analyses, including alternative identification strategies, alternative treatment definitions, and the use of alternative estimators.

Some limitations should be considered when interpreting our results. Ideally, we would like to capture SMEs' "choice of leverage" and assess its consequences for flood resilience, but, of course, leverage is a function of various demand and supply factors as well as the institutional environment that we cannot entirely control for (so far). While these factors certainly influence SME leverage, they are outside of the realm of the firms' decision space.

[14]Some emerging evidence suggests that the latter point may be due to the limited power of modern difference-in-difference estimators with small samples (Weiss, 2024).

On the other hand, however, these factors do present a set of main levers that policymakers could consider to improve the resilience of the SME sector and we come back to this point below.

Similarly, we cannot assess the extent to which firms already use leverage for resilience-enhancing investments. However, if such investments are of a more long-term nature, as suggested by Benincasa et al. (2024), this would corroborate our findings with respect to the benefits of access to long-term financing. Moreover, the costs and benefits of different levels of SME leverage may differ depending on the source of the debt. A large literature investigates the importance of bank-firm relationships and the associated consequences for firms during crisis- and non-crisis-times (e.g., Belke et al., 2016; Bolton et al., 2016; Langford and Feldman, 2022; Levine et al., 2024; Peters et al., 2024). Banks with different types of business models, ownership structures, or capitalization behave differently, which may have consequences for flood-affected SMEs sourcing their debt from certain types of lenders. While we do not address this aspect in this paper, it provides a promising avenue for future research in the European context.

In assessing the impact of floods and leverage on the post-shock performance of firms, our analysis focuses on businesses that remain active after the event (i.e., the intensive margin). Our results are thus conditional on firm survival and likely present a lower bound of the total economic impact of floods on firms. Recent evidence suggests that physical climate shocks in Europe also increase the default risk of affected firms (i.e., the extensive margin; Fatica et al., 2022; Cathcart et al., 2023; Clò et al., 2024). Building on our work, future research should incorporate heterogeneity in the pre-shock financial structure of firms as an important explanatory factor of post-shock default and recovery patterns of firms, particularly SMEs.

Besides the leverage aspects of the paper, the analysis comes with limitations related to the identification of floods common to this literature. First, while we believe that our granular mapping of flooded areas provides a good approximation of which firms were indeed affected and is an improvement over previous studies, we cannot rule out the existence of measurement error in our treatment assignment. An alternative to our approach is firm-level data of self-reported (and ideally independently confirmed) flood damages (Koetter et al., 2020; Benincasa et al., 2024), but such data is currently not available to us. In addition, we share the common shortcoming with other papers in this line of research that detailed data on governmental aid in response to floods remains unavailable (Deryugina, 2022; Clò et al., 2024). In our setting, the extent of government involvement may vary by country, which we try to account for using high-dimensional fixed effects.

Our results give rise to several relevant policy considerations. In light of increasing physical climate risks, policymakers interested in enhancing SME resilience need to focus on striking a balance in SME leverage that addresses both the challenges of under-leveraged and over-leveraged firms. Hence, it needs incentives and institutional conditions that make firms less reliant on high levels of short-term debt and better able to access long-term sources of financing. This could be achieved via the demand side, e.g., by reducing biases in firms' capital structure decisions stemming from distortive corporate tax systems in which debt receives a preferential treatment (see e.g., Fan et al., 2011; Cao and Whyte, 2022), or the supply side, e.g., by incentivising banks to provide more access for SMEs to longer-term credit and to vet corporate borrowers more thoroughly concerning their physical climate risks (see e.g., Ginglinger and Moreau, 2023).

Our results may also have implications for government aid programs during and after disasters. Major floods frequently trigger government aid programs and some studies show evidence supportive of their positive impacts (Davlasheridze and Geylani, 2017). Policy measures could use our results to target government assistance more effectively to firms that struggle to access traditional lending, ideally combined with a mandate to improve risk management and disaster preparedness measures while maintaining leverage in a healthy range. An idea to address rollover risks exacerbated by flood-induced disruptions might be for government aid programs to facilitate the rolling over of debt (into longer maturities) through temporary guarantees.

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A Appendix

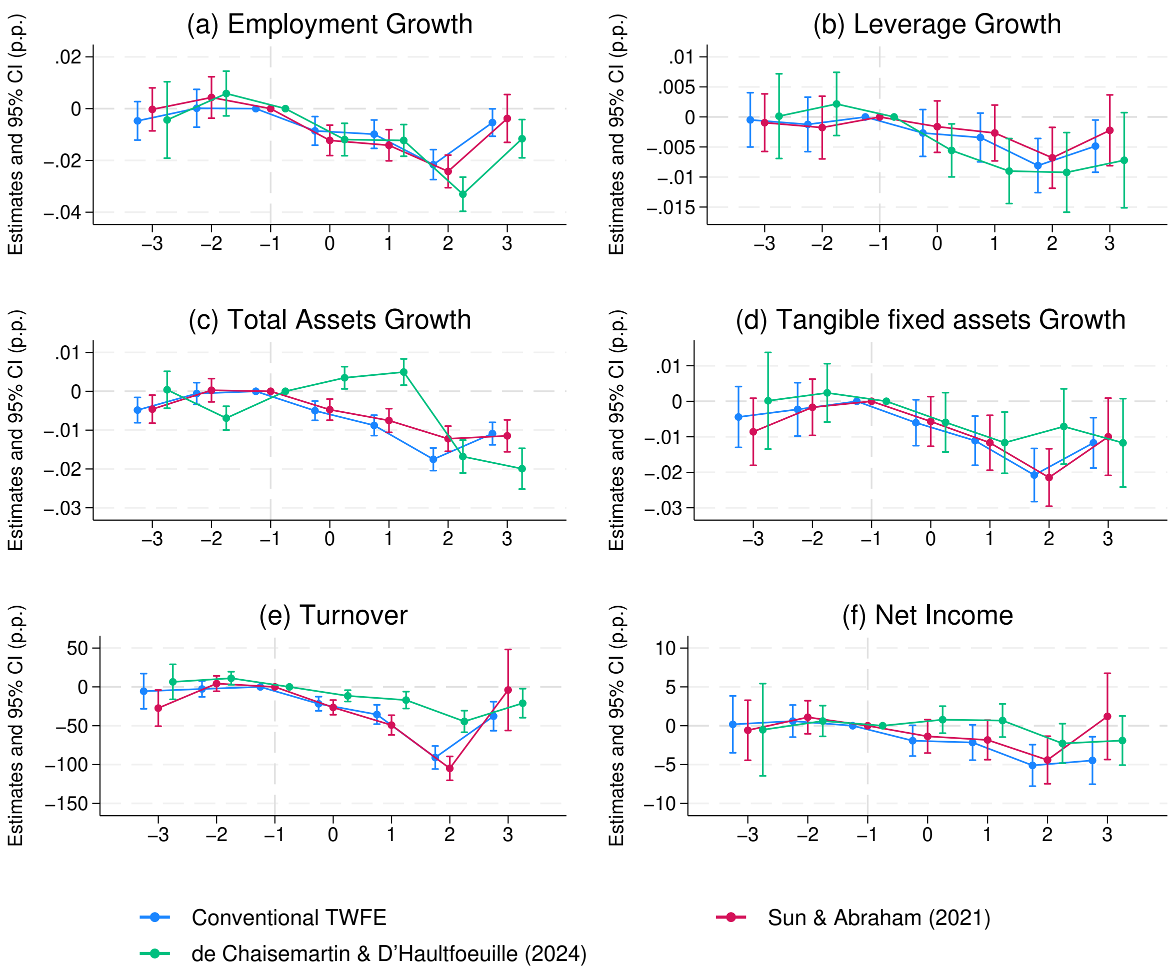

Figure A.1: Dynamic impacts of floods on SME outcomes: Additional estimators.

Figure A.1 shows the dynamic impacts of floods on various SME outcomes. The y-axis shows the estimated point coefficients of the leads and lags of the flood indicator including 95%-level confidence intervals. In each Panel, the blue line depicts estimation results using a conventional TWFE estimator, the red line depicts results using the heterogeneity-robust approach of Sun and Abraham (2021), and the green line depicts results using the estimator of de Chaisemartin and D'Haultfœuille (2024). In Panel (a), the dependent variable is employment growth.

Table A.1: Variable descriptions.

Variable	Description	Sources
Outcome variables		
Employment growth	Year-over-year percentage change in employment.	Orbis/Amadeus
Leverage growth	Year-over-year percentage change in leverage.	Orbis/Amadeus
Asset growth	Year-over-year percentage change in total assets.	Orbis/Amadeus
Tangible fixed asset growth	Year-over-year percentage change in tangible fixed assets.	Orbis/Amadeus
Turnover	Annual operating revenue (in 1,000 EUR).	Orbis/Amadeus
Net income	Profit/loss in reporting period (in 1,000 EUR).	Orbis/Amadeus
Treatment variables		
Flood indicator	Firm's main address inside flood area in year t.	EM-DAT, DFO, own mapping.
SME Financial Structure		
Leverage	Total debt-to-assets ratio.	Orbis/Amadeus
Short-term leverage	Current liabilities-to-assets ratio. Current liabilities comprise all loans, trade credits, and other current liabilities with residual maturities of up to one year.	Orbis/Amadeus
Long-term leverage	Non-current liabilities-to-assets ratio. Non-current liabilities comprise all loans and bonds with residual maturities above one year.	Orbis/Amadeus
Normalized leverage	Leverage normalized by average leverage of NACE-2 sector: Equation 3 in Section 4.2 (same for short-/long-term leverage).	Own calculation.
Standardized leverage	The difference of firm-specific leverage and the sector-average leverage divided by the standard deviation of the sector-average leverage: Equation 4 in Section 4.2 (same for short-/long-term leverage).	Own calculation.
Other firm-level variables		
Firm age	Year t - year of incorporation.	Orbis/Amadeus
Firm size	Log of total assets.	Orbis/Amadeus
Tangible share	Tangible fixed assets / total assets.	Orbis/Amadeus
Current share	Current assets / total assets.	Orbis/Amadeus

Table A.1 presents detailed descriptions of all variables used in the analyses. EM-DAT = Emergency Events Database of the Centre for Research on the Epidemiology of Disasters (2021), DFO = Dartmouth Flood Observatory (Brakenridge, 2021). Normalization and standardization of leverage are specified in equations 3 and 4 in Section 4.2.

Table A.2: Descriptive statistics for treated and untreated firms.

Variables	Untreated (a)	Treated (b)	Diff. (a - b)	SE
Employees	15.00	14.73	0.27***	(0.04)
Employment Growth	0.07	0.06	0.01***	(0.00)
Firm Age	17.15	17.59	-0.44***	(0.02)
Turnover	2612.01	1995.89	616.12***	(6.89)
Net income	90.33	84.97	5.36***	(0.45)
Total Assets	2032.77	1583.43	449.34***	(4.38)
Total Assets Growth	0.07	0.07	0.00	(0.00)
Tangible Assets	496.23	353.89	142.34***	(1.66)
Tangible Assets Growth	0.03	0.01	0.02***	(0.00)
Tangble / Total Assets	0.21	0.17	0.04***	(0.00)
Current / Total Assets	0.72	0.75	-0.03***	(0.00)
Total Liabilities	1168.00	854.96	313.04***	(2.66)
Current Liabilities	765.34	495.46	269.88***	(1.96)
Non-current Liabilities	402.66	359.50	43.16***	(1.26)
Leverage Ratio	0.88	0.72	0.16***	(0.00)
Short-term Leverage Ratio	0.65	0.54	0.11***	(0.00)
Long-term Leverage Ratio	0.27	0.23	0.03***	(0.00)
Leverage Ratio (Normalized)	1.03	0.84	0.19***	(0.00)
Short-term Leverage (Norm.)	1.03	0.85	0.17***	(0.00)
Long-term Leverage (Norm.)	1.02	0.90	0.12***	(0.00)
Leverage Ratio (Standardized)	0.05	-0.29	0.35***	(0.00)
Short-term Leverage (Std.)	0.04	-0.21	0.25***	(0.00)
Long-term Leverage (Std.)	0.02	-0.08	0.10***	(0.00)
Leverage Growth	0.01	-0.00	0.01***	(0.00)
Share Micro Firms	61.76	63.85	-2.09	
Share Small Firms	31.81	29.94	1.87	
Share Medium Firms	6.43	6.22	0.21	
Share Industry C	30.25	28.98	1.27	
Share Industry G	57.56	58.79	-1.23	
Share Industry I	12.18	12.22	-0.04	

Table A.2 presents descriptive statistics for untreated (a) and treated (b) firms. Column 4 entails the mean difference between a and b and indicates its statistical significance (with * $p<0.10$, ** $p<0.05$, *** $p<0.01$). Column 5 shows the corresponding standard errors. Monetary values are expressed in 1,000s of Euros and 2015 values. Growth rates and asset ratios are winsorized at the 1% and 99% level. Normalization and standardization of leverage as specified in equations 3 and 4 in Section 4.2.

Table A.3: Dynamic impacts of floods on firm outcomes: de Chaisemartin and D'Haultfœuille (2024).

	Employment growth	Leverage growth	Total assets growth	Tangible assets growth	Turnover	Net Income
Flood [l = -3]	-0.004	0.000	0.000	0.000	6.495	-0.518
	(0.008)	(0.004)	(0.002)	(0.007)	(11.486)	(3.032)
Flood [l = -2]	0.006	0.002	-0.007***	0.002	11.124***	0.607
	(0.004)	(0.003)	(0.002)	(0.004)	(4.284)	(1.011)
Flood [l = 0]	-0.012***	-0.006**	0.003**	-0.006	-11.520***	0.780
	(0.003)	(0.002)	(0.001)	(0.004)	(3.721)	(0.887)
Flood [l = 1]	-0.012***	-0.009***	0.005***	-0.012***	-16.978***	0.670
	(0.003)	(0.003)	(0.002)	(0.004)	(5.543)	(1.088)
Flood [l = 2]	-0.033***	-0.009***	-0.017***	-0.007	-44.490***	-2.279*
	(0.003)	(0.003)	(0.002)	(0.005)	(7.104)	(1.298)
Flood [l = 3]	-0.012***	-0.007*	-0.020***	-0.012*	-20.993**	-1.907
	(0.004)	(0.004)	(0.003)	(0.006)	(9.543)	(1.613)
Avg. effect	-0.039***	-0.018***	-0.013***	-0.021**	-52.048***	-1.056
Joint Sig. Placebo	0.324	0.716	0.000	0.843	0.031	0.767
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-country-year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A.3 presents the results of the dynamic impacts of floods on six different firm outcomes: employment growth, leverage growth, total assets growth, tangible assets growth, turnover, and net income. The Flood indicator is one for SMEs located in a flooded area in the respective year. Standard errors in parantheses. * p<0.10, ** p<0.05, *** p<0.01. Results in this table are estimated using the heterogeneity-robust estimator of de Chaisemartin and D'Haultfœuille (2024). The average cumulative effect is calculated over periods 0 to 3.

Table A.4: SME Flood Outcomes and the Role of Leverage and Debt Maturity: Normalized Leverage Measure.

	Normalized Leverage		
	Total	Short-term	Long-term
Flood [l = 0]	-0.004	-0.002	-0.011***
	(0.006)	(0.005)	(0.003)
Flood [l = 0] x L.Leverage	0.011	0.009	0.019
	(0.015)	(0.015)	(0.017)
Flood [l = 0] x L.Leverage^2	-0.014*	-0.019**	-0.007
	(0.008)	(0.010)	(0.014)
Flood [l = 1]	0.005	0.008*	-0.015***
	(0.005)	(0.005)	(0.003)
Flood [l = 1] x L.Leverage	-0.015	-0.021	0.048***
	(0.014)	(0.015)	(0.017)
Flood [l = 1] x L.Leverage^2	-0.003	-0.010	-0.018
	(0.008)	(0.010)	(0.013)
Flood [l = 2]	0.007	0.005	-0.023***
	(0.005)	(0.005)	(0.003)
Flood [l = 2] x L.Leverage	-0.043***	-0.044***	0.010
	(0.015)	(0.016)	(0.018)
Flood [l = 2] x L.Leverage^2	0.003	-0.004	-0.000
	(0.009)	(0.010)	(0.014)
Flood [l ≥ 3]	0.014***	0.014***	-0.007**
	(0.005)	(0.004)	(0.003)
Flood [l ≥ 3] x L.Leverage	-0.016	-0.031**	-0.008
	(0.012)	(0.013)	(0.014)
Flood [l ≥ 3] x L.Leverage^2	-0.011	-0.006	0.019*
	(0.007)	(0.008)	(0.011)
Observations	3,088,552	3,088,552	3,223,073
Firms	633,449	633,449	673,928
R-squared	0.221	0.221	0.223
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Industry-country-year FE	Yes	Yes	Yes

Table A.4 presents the results of regressions estimating equation 2, interacting the flood indicators with different components of pre-shock normalized leverage as defined in equation 4 in Section 4.2. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. Results in this table are estimated using a conventional TWFE estimator.

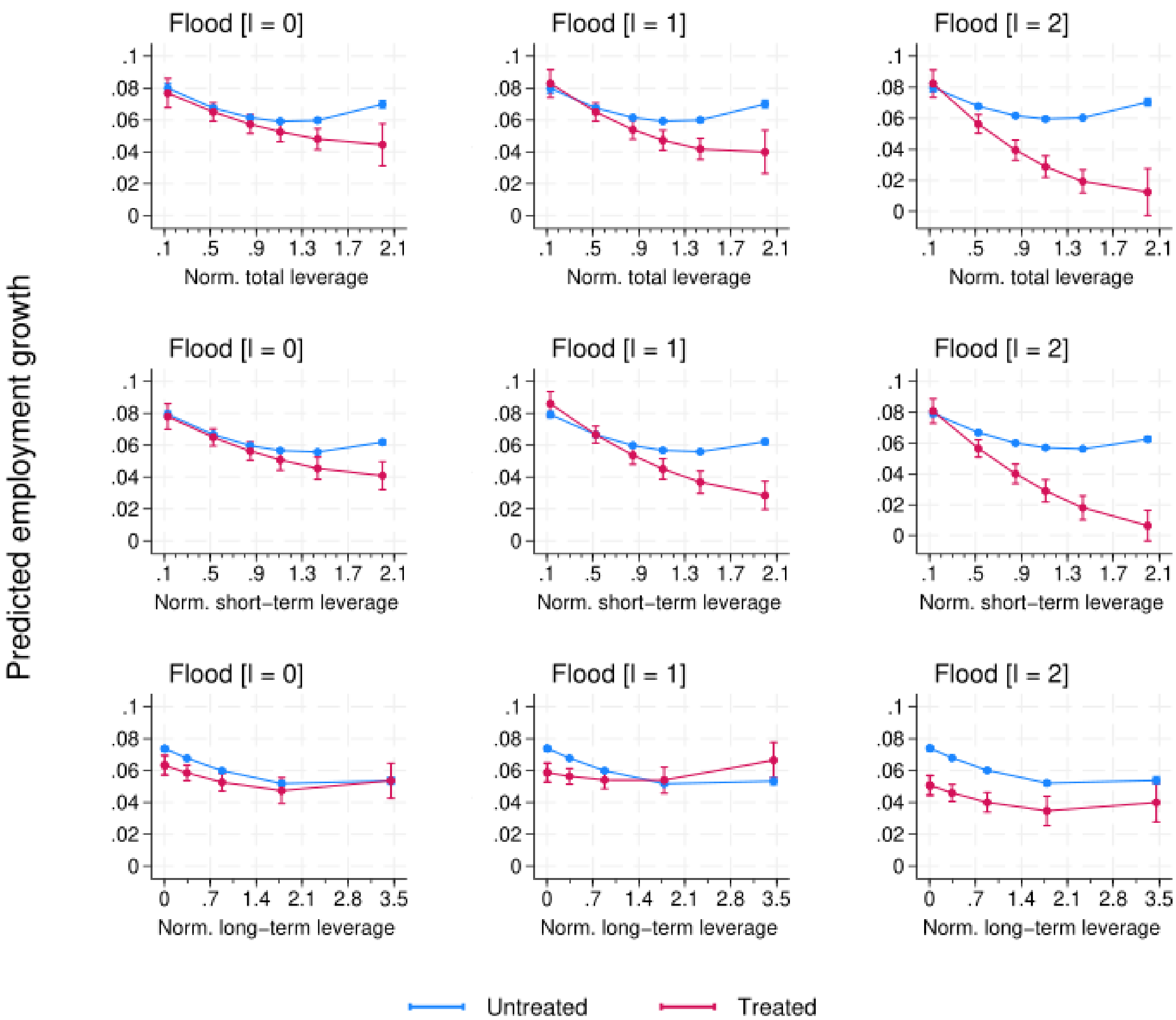

Figure A.2: Predictive margins of floods on employment growth across the distribution of normalised leverage.

Figure A.2 shows the predictive margins of floods on employment growth across the distribution of leverage and its components. In this figure, we use the normalized measure of leverage as defined in equation 3 in Section 4.2. In the 3x3, the rows represent different leverage components, total leverage, short-term leverage, and long-term leverage, while the columns represent different time lags after the flood, l=0, l=1, and l=2. The red line shows the predicted employment growth of treated SMEs.

Table A.5: Firm leverage and flood outcomes: Unadjusted total leverage.

	Q1	Q2	Q3	Q4	Q5	P90	P95
Flood [l $\leq$ -3]	-0.002	-0.009	-0.004	-0.020**	0.030***	0.032*	0.058**
	(0.010)	(0.009)	(0.009)	(0.009)	(0.011)	(0.018)	(0.029)
Flood [l = -2]	0.002	-0.000	0.013	-0.003	0.015	-0.001	0.046
	(0.007)	(0.009)	(0.010)	(0.011)	(0.012)	(0.018)	(0.030)
Flood [l = 0]	-0.021***	-0.014**	0.005	-0.012	-0.001	-0.002	-0.015
	(0.005)	(0.007)	(0.008)	(0.008)	(0.009)	(0.015)	(0.023)
Flood [l = 1]	-0.020***	-0.010	-0.008	-0.006	-0.011	-0.016	-0.037
	(0.005)	(0.007)	(0.008)	(0.009)	(0.010)	(0.017)	(0.027)
Flood [l = 2]	-0.023***	-0.024***	-0.022***	-0.017*	-0.033***	-0.024	-0.051
	(0.005)	(0.007)	(0.008)	(0.010)	(0.011)	(0.020)	(0.033)
Flood [l $\geq$ 3]	-0.009	-0.004	0.013	-0.009	0.003	-0.121	-0.282*
	(0.006)	(0.008)	(0.011)	(0.013)	(0.028)	(0.090)	(0.153)
Obs.	637,262	575,608	591,213	635,022	648,680	277,938	131,309
Firms	121,845	115,071	119,799	131,881	144,695	82,291	41,339
R^2	0.181	0.213	0.226	0.236	0.244	0.312	0.335
Avg. effect	-0.021***	-0.016***	-0.008	-0.011	-0.015*	-0.014	-0.035
Joint Sig. Pretrend	0.908	0.565	0.277	0.100	0.017	0.181	0.076
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-country-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A.5 contains detailed regression results for row (2) of Table 5.4, (unadjusted) total leverage. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. Results in this table are estimated using the interaction-weighted estimator of Sun and Abraham (2021). The average cumulative effect is calculated over periods 0 to 2. Q1-Q5 group SMEs by their respective leverage quintiles. P90 and P95 are SMEs above the 90^{th} and 95^{th} percentile of the leverage distribution.

Table A.6: SME leverage and flood outcomes: Unadjusted short-term leverage.

	Q1	Q2	Q3	Q4	Q5	P90	P95
Flood [$l \leq -3$]	-0.006	-0.001	0.004	-0.016*	0.018*	0.027	-0.004
	(0.011)	(0.009)	(0.008)	(0.009)	(0.011)	(0.020)	(0.034)
Flood [$l = -2$]	0.005	-0.010	0.010	-0.001	0.022*	0.015	0.014
	(0.007)	(0.009)	(0.009)	(0.010)	(0.012)	(0.019)	(0.029)
Flood [$l = 0$]	-0.025***	-0.009	-0.005	-0.001	-0.004	-0.021	-0.040*
	(0.005)	(0.007)	(0.007)	(0.008)	(0.009)	(0.015)	(0.023)
Flood [$l = 1$]	-0.013***	-0.018***	-0.007	-0.021**	-0.006	-0.038**	-0.050*
	(0.005)	(0.007)	(0.007)	(0.009)	(0.010)	(0.017)	(0.027)
Flood [$l = 2$]	-0.023***	-0.024***	-0.023***	-0.024***	-0.027**	-0.054***	-0.071**
	(0.005)	(0.007)	(0.008)	(0.009)	(0.011)	(0.019)	(0.030)
Flood [$l \geq 3$]	-0.016**	-0.013	0.014	0.001	0.011	-0.084	-0.467**
	(0.007)	(0.008)	(0.010)	(0.012)	(0.029)	(0.083)	(0.205)
Obs.	603,387	612,001	621,507	635,926	614,987	242,964	108,707
Firms	118,185	120,691	123,008	129,573	141,856	76,446	36,575
R^2	0.18	0.21	0.22	0.23	0.25	0.33	0.35
Avg. effect	-0.021***	-0.017***	-0.012*	-0.016**	-0.013	-0.038**	-0.054**
Joint Sig. Pretrend	0.597	0.542	0.518	0.171	0.071	0.346	0.871
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A.6 contains detailed regression results for row (3) of Table 5.4, (unadjusted) short-term leverage. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. Results in this table are estimated using the interaction-weighted estimator of Sun and Abraham (2021). The average cumulative effects are calculated over periods 0 to 2. Q1-Q5 group SMEs by their respective leverage quintiles. P90 and P95 are SMEs above the 90th and 95th percentile of the leverage distribution.

Table A.7: SME leverage and flood outcomes: Unadjusted long-term leverage.

	Q1	Q2	Q3	Q4	Q5	P90	P95
Flood $[l \leq -3]$	-0.011	-0.019**	0.001	0.031***	-0.003	0.006	0.000
	(0.009)	(0.009)	(0.009)	(0.009)	(0.012)	(0.022)	(0.030)
Flood $[l = -2]$	0.004	-0.002	0.010	0.015	-0.001	-0.016	-0.032
	(0.007)	(0.009)	(0.010)	(0.011)	(0.012)	(0.017)	(0.022)
Flood $[l = 0]$	-0.019***	-0.017**	-0.006	0.001	-0.002	-0.009	-0.013
	(0.005)	(0.007)	(0.007)	(0.008)	(0.008)	(0.012)	(0.015)
Flood $[l = 1]$	-0.020***	-0.027***	-0.010	-0.003	0.012	0.002	-0.001
	(0.005)	(0.007)	(0.008)	(0.009)	(0.009)	(0.014)	(0.017)
Flood $[l = 2]$	-0.029***	-0.033***	-0.016*	-0.020**	-0.007	-0.027	-0.046**
	(0.005)	(0.008)	(0.009)	(0.010)	(0.009)	(0.017)	(0.020)
Flood $[l \geq 3]$	-0.000	-0.029*	-0.005	0.017	0.007	-0.016	-0.106
	(0.005)	(0.016)	(0.012)	(0.012)	(0.018)	(0.048)	(0.073)
Obs.	620,853	629,891	695,678	690,642	585,133	212,429	105,417
Firms	129,989	129,039	137,239	141,022	136,489	64,608	32,336
R^2	0.215	0.224	0.224	0.227	0.238	0.301	0.305
Avg. effect	-0.023***	-0.026***	-0.011	-0.007	0.001	-0.011	-0.020
Joint Sig. Pretrend	0.378	0.100	0.598	0.004	0.964	0.581	0.348
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A.7 contains detailed regression results for row (4) of Table 5.4, (unadjusted) long-term leverage. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. Results in this table are estimated using the interaction-weighted estimator of Sun and Abraham (2021). The average cumulative effects are calculated over periods 0 to 2. Q1-Q5 group SMEs by their respective leverage quintiles. P90 and P95 are SMEs above the 90^{th} and 95^{th} percentile of the leverage distribution.

Table A.8: SME leverage and flood outcomes: Standardized total leverage.

	Q1	Q2	Q3	Q4	Q5	P90	P95
Flood [$l \leq -3$]	-0.003	-0.014	0.006	-0.025***	0.032***	0.019	0.044*
	(0.010)	(0.009)	(0.009)	(0.010)	(0.011)	(0.022)	(0.023)
Flood [$l = -2$]	-0.000	0.001	0.017*	-0.002	0.014	-0.019	0.056**
	(0.007)	(0.009)	(0.010)	(0.011)	(0.012)	(0.024)	(0.025)
Flood [$l = 0$]	-0.022***	-0.014**	0.007	-0.011	-0.001	-0.014	-0.017
	(0.005)	(0.007)	(0.008)	(0.008)	(0.009)	(0.019)	(0.021)
Flood [$l = 1$]	-0.020***	-0.013**	-0.001	-0.009	-0.012	-0.039*	-0.030
	(0.005)	(0.007)	(0.008)	(0.009)	(0.010)	(0.020)	(0.024)
Flood [$l = 2$]	-0.022***	-0.029***	-0.018**	-0.019*	-0.032***	-0.035	-0.077***
	(0.005)	(0.007)	(0.008)	(0.010)	(0.011)	(0.023)	(0.029)
Flood [$l \geq 3$]	-0.010**	-0.005	0.013	0.005	-0.014	0.016	-0.244*
	(0.005)	(0.009)	(0.011)	(0.015)	(0.026)	(0.022)	(0.146)
Obs.	637,856	577,169	590,806	635,810	646,103	164,689	153,021
Firms	121,967	115,383	119,975	131,997	143,959	36,262	37,880
R^2	0.181	0.214	0.227	0.234	0.244	0.241	0.276
Avg. effect	-0.021***	-0.019***	-0.004	-0.013	-0.015*	-0.029	-0.041*
Joint Sig. Pretrend	0.956	0.260	0.199	0.026	0.010	0.378	0.029
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A.8 contains detailed regression results for row (5) of Table 5.4, standardized total leverage. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. Results in this table are estimated using the interaction-weighted estimator of Sun and Abraham (2021). The average cumulative effects are calculated over periods 0 to 2. Q1-Q5 group SMEs by their respective leverage quintiles. P90 and P95 are SMEs above the 90$^{\text{th}}$ and 95$^{\text{th}}$ percentile of the leverage distribution.

Table A.9: SME leverage and flood outcomes: Standardized short-term leverage.

	Q1	Q2	Q3	Q4	Q5	P90	P95
Flood $[l \leq -3]$	-0.003	-0.010	0.006	-0.012	0.016	0.023	0.030
	(0.011)	(0.009)	(0.008)	(0.009)	(0.010)	(0.021)	(0.026)
Flood $[l = -2]$	0.009	-0.018**	0.009	0.006	0.017	0.016	0.043*
	(0.007)	(0.009)	(0.009)	(0.010)	(0.012)	(0.023)	(0.026)
Flood $[l = 0]$	-0.025***	-0.008	-0.008	0.003	-0.008	-0.000	-0.029
	(0.005)	(0.006)	(0.007)	(0.008)	(0.009)	(0.018)	(0.022)
Flood $[l = 1]$	-0.013***	-0.014**	-0.012	-0.016*	-0.012	-0.017	-0.057**
	(0.005)	(0.007)	(0.008)	(0.009)	(0.010)	(0.019)	(0.024)
Flood $[l = 2]$	-0.023***	-0.022***	-0.028***	-0.018*	-0.033***	-0.034	-0.076***
	(0.005)	(0.007)	(0.008)	(0.009)	(0.011)	(0.021)	(0.027)
Flood $[l \geq 3]$	-0.020***	-0.006	0.006	0.012	0.008	0.023	-0.192
	(0.006)	(0.008)	(0.010)	(0.013)	(0.029)	(0.023)	(0.158)
Obs.	605,102	612,128	618,772	635,054	616,757	156,102	142,178
Firms	118,510	120,606	122,707	129,671	141,820	35,667	36,928
R^2	0.184	0.207	0.219	0.229	0.252	0.250	0.283
Avg. effect	-0.020***	-0.015**	-0.016**	-0.010	-0.018**	-0.017	-0.054**
Joint Sig. Pretrend	0.413	0.105	0.551	0.259	0.175	0.527	0.194
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A.9 contains detailed regression results for row (6) of Table 5.4, standardized short-term leverage. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. Results in this table are estimated using the interaction-weighted estimator of Sun and Abraham (2021). The average cumulative effects are calculated over periods 0 to 2. Q1-Q5 group SMEs by their respective leverage quintiles. P90 and P95 are SMEs above the 90^{th} and 95^{th} percentile of the leverage distribution.

Table A.10: SME leverage and flood outcomes: Standardized long-term leverage.

	Q1	Q2	Q3	Q4	Q5	P90	P95
Flood $[l \leq -3]$	-0.010	-0.019**	0.003	0.027***	-0.005	0.028	-0.015
	(0.009)	(0.009)	(0.009)	(0.009)	(0.012)	(0.027)	(0.024)
Flood $[l = -2]$	0.005	0.004	0.005	0.020*	-0.007	-0.017	-0.007
	(0.007)	(0.008)	(0.010)	(0.011)	(0.012)	(0.027)	(0.022)
Flood $[l = 0]$	-0.021***	-0.006	-0.006	-0.000	-0.005	0.018	0.005
	(0.005)	(0.007)	(0.008)	(0.008)	(0.008)	(0.019)	(0.015)
Flood $[l = 1]$	-0.024***	-0.013**	-0.013	0.003	0.007	0.032*	0.020
	(0.005)	(0.007)	(0.008)	(0.009)	(0.009)	(0.019)	(0.016)
Flood $[l = 2]$	-0.031***	-0.024***	-0.017*	-0.015	-0.014	0.003	-0.016
	(0.005)	(0.007)	(0.009)	(0.010)	(0.009)	(0.021)	(0.018)
Flood $[l \geq 3]$	-0.003	-0.015*	-0.001	0.019	0.003	0.003	-0.037
	(0.007)	(0.008)	(0.013)	(0.012)	(0.017)	(0.039)	(0.059)
Obs.	636,096	623,252	690,160	689,756	582,876	136,993	134,938
Firms	132,144	128,018	136,547	140,909	136,134	33,494	32,857
R^2	0.216	0.226	0.223	0.226	0.238	0.248	0.242
Avg. effect	-0.025***	-0.014**	-0.012	-0.004	-0.004	0.018	0.003
Joint Sig. Pretrend	0.385	0.054	0.883	0.007	0.812	0.406	0.803
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A.10 contains detailed regression results for row (7) of Table 5.4, standardized long-term leverage. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. Results in this table are estimated using the interaction-weighted estimator of Sun and Abraham (2021). The average cumulative effects are calculated over periods 0 to 2. Q1-Q5 group SMEs by their respective leverage quintiles. P90 and P95 are SMEs above the 90^{th} and 95^{th} percentile of the leverage distribution.

Table A.11: Average impacts of floods on firm outcomes in different leverage subsamples: de Chaisemartin and D'Haultfœuille (2024).

Measure	Component	Q1	Q2	Q3	Q4	Q5	P90	P95
Leverage (unadjusted)	Total	-0.026*** (0.004)	-0.011* (0.006)	-0.007 (0.007)	-0.007 (0.008)	-0.006 (0.008)	0.016 (0.019)	-0.007 (0.030)
	Short-term	-0.020*** (0.004)	-0.014** (0.006)	-0.006 (0.007)	-0.010 (0.008)	-0.006 (0.008)	-0.126* (0.066)	-0.091 (0.083)
	Long-term	-0.021*** (0.004)	-0.022*** (0.006)	-0.012** (0.007)	-0.013 (0.008)	-0.002 (0.008)	-0.026 (0.016)	0.003 (0.013)
Normalized Leverage	Total	-0.024*** (0.004)	-0.013*** (0.006)	-0.003 (0.007)	-0.009 (0.008)	-0.006 (0.008)	-0.019 (0.017)	0.006 (0.016)
	Short-term	-0.017*** (0.004)	-0.017*** (0.006)	-0.009 (0.007)	-0.000 (0.007)	-0.014* (0.00)	-0.034** (0.016)	-0.009 (0.016)
	Long-term	-0.023*** (0.004)	-0.014** (0.006)	-0.020 (0.007)	-0.005 (0.008)	-0.008 (0.008)	0.005 (0.018)	0.004 (0.013)
Standardized Leverage	Total	-0.023*** (0.004)	-0.014** (0.006)	0.014 (0.007)	-0.013 (0.008)	-0.004 (0.008)	-0.035** (0.017)	0.014 (0.017)
	Short-term	-0.013*** (0.004)	-0.016*** (0.005)	-0.006 (0.007)	-0.004 (0.007)	-0.013 (0.008)	-0.005 (0.016)	-0.027 (0.017)
	Long-term	-0.024*** (0.004)	-0.015** (0.006)	-0.018 (0.007)	-0.008 (0.008)	-0.006 (0.008)	0.022 (0.018)	0.010 (0.013)

Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. Results in this table are estimated using the heterogeneity-robust estimator of de Chaisemartin and D'Haultfœuille (2024). The average cumulative effects are calculated over periods 0 to 2 (consistent with previous analyses). Full regression results are omitted for brevity but are available from the authors.

Table A.12: Two-way fixed effects weights estimated using de Chaisemartin and D'Haultfœuille (2020). Dependent variable: Employment growth.

	N. ATTs	Sum weights
Positive weights	87,448	1
Negative weights	20	-.0000354
Total	87,468	1

Summary Measures:
TWFE coefficient ($\beta_f e$) = -0.0031
min $\sigma(\Delta)$ compatible with $\beta_f e$ and $\Delta_T R = 0$: 0.0107
min $\sigma(\Delta)$ compatible with treatment effect of opposite sign than $\beta_f e$ in all (g,t) cells: 1.1122

Table A.13: Two-way fixed effects weights estimated using de Chaisemartin and D'Haultfœuille (2020). Dependent variable: Leverage growth.

	N. ATTs	Sum weights
Positive weights	124,272	1
Negative weights	26	-.0000345
Total	124,298	1

Summary Measures:
TWFE coefficient ($\beta_f e$) = -0.0014
min $\sigma(\Delta)$ compatible with $\beta_f e$ and $\Delta_T R = 0$: 0.0054
min $\sigma(\Delta)$ compatible with treatment effect of opposite sign than $\beta_f e$ in all (g,t) cells: 0.5287

Table A.14: Two-way fixed effects weights estimated using de Chaisemartin and D'Haultfœuille (2020). Dependent variable: Tangible fixed assets growth.

	N. ATTs	Sum weights
Positive weights	135,025	1
Negative weights	9	-.0000109
Total	135,034	1

Summary Measures:
TWFE coefficient ($\beta_f e$) = -0.0011
min $\sigma(\Delta)$ compatible with $\beta_f e$ and $\Delta_T R = 0$: 0.0046
min $\sigma(\Delta)$ compatible with treatment effect of opposite sign than $\beta_f e$ in all (g,t) cells: 0.7213

Table A.15: Two-way fixed effects weights estimated using de Chaisemartin and D'Haultfœuille (2020). Dependent variable: Turnover.

	N. ATTs	Sum weights
Positive weights	99,723	1
Negative weights	13	-.0000169
Total	99,736	1

Summary Measures:
TWFE coefficient ($\beta_f e$) = -0.0014
min $\sigma(\Delta)$ compatible with $\beta_f e$ and $\Delta_T R = 0$: 0.0053
min $\sigma(\Delta)$ compatible with treatment effect of opposite sign than $\beta_f e$ in all (g,t) cells: 0.7589

Table A.16: Two-way fixed effects weights estimated using de Chaisemartin and D'Haultfœuille (2020). Dependent variable: Net income.

	N. ATTs	Sum weights
Positive weights	118,776	1
Negative weights	10	-.000014
Total	118,786	1

Summary Measures:
TWFE coefficient ($\beta_f e$) = -0.9078
min $\sigma(\Delta)$ compatible with $\beta_f e$ and $\Delta_T R = 0$: 3.3666
min $\sigma(\Delta)$ compatible with treatment effect of opposite sign than $\beta_f e$ in all (g,t) cells: 504.4679

Table A.17: Two-way fixed effects weights estimated using de Chaisemartin and D'Haultfœuille (2020). Dependent variable: Total assets growth.

	N. ATTs	Sum weights
Positive weights	119,838	1
Negative weights	10	-.0000139
Total	119,848	1

Summary Measures:
TWFE coefficient ($\beta_f e$) = -0.0163
min $\sigma(\Delta)$ compatible with $\beta_f e$ and $\Delta_T R = 0$: 0.0612
min $\sigma(\Delta)$ compatible with treatment effect of opposite sign than $\beta_f e$ in all (g,t) cells: 9.1015

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