Davide Castellani,
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Dear Workshop Organizers,

I am writing to express my interest in the NBER PhD Student Workshop on Climate Finance. I am currently a PhD candidate in Economics at Collegio Carlo Alberto, with an expected completion date of October 31, 2025, and a planned dissertation defense in March 2026. My next academic appointment is a postdoctoral fellowship at the University of Amsterdam from September. Professor Paul Smeets at the University of Amsterdam strongly encouraged me to apply for this workshop. For a reference, please feel free to contact Professor Giovanni Mastrobuoni, my PhD supervisor at Collegio Carlo Alberto, who is closely familiar with my research and academic trajectory.

My research is at the intersection of environmental economics, financial markets, and policy evaluation. My job market paper, "The Long-Run Effects of Tropical Cyclones on the U.S. Housing Market," examines the persistent effects of extreme weather on property values. Using a newly constructed cyclone exposure measure based on meteorological data, I find that housing markets experience a sustained decline in value—averaging 15% over eight years—following cyclone exposure, with the most pronounced effects in areas with historically lower storm activity.

The paper I intend to present at the workshop is titled "The Impact of Flooding on Credit Risk: Evidence from a Global Financial Institution." It uses firm-level credit rating data from the International Finance Corporation to examine how flood exposure affects creditworthiness. The results show that flooding significantly deteriorates credit ratings and increases default risk, particularly for clients hit by only one event.

Looking ahead, my future research agenda will explore how climate-related credit risk affects energy access, especially in developing economies. During my upcoming fellowship at the University of Amsterdam's Department of Finance—which has strong research clusters in insurance and housing—I intend to examine whether financial and insurance markets can serve as effective tools for climate adaptation and drivers of sustainable energy investment in developing countries.

Given the more advanced stage of development of my job market paper, I believe it would be more appropriate to present my paper titled "The Impact of Flooding on Credit Risk: Evidence from a Global Financial Institution." However, please feel free to reach out if you think presenting my job market paper would be more suitable. In any case, I see the NBER Workshop as an excellent opportunity to informally share both projects, engage with leading researchers in climate finance, and further strengthen the policy relevance and analytical rigor of my work.

Thank you for your time and considering my application.

Sincerely,

Davide Castellani

Davide Castellani

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Next Academic Appointment

University of Amsterdam, Netherlands
Postdoctoral Researcher — September 2025

Education

Collegio Carlo Alberto, Italy
PhD in Economics. Supervisors: Giovanni Mastrobuoni, Elena Esposito — 2021-2025

University of Bologna, Italy
MSc in Economics. Supervisor: Alessandro Tavoni — 2019 – 2021

University of Bologna, Italy
BA in Economics — 2016 – 2019

References

Prof. Giovanni Mastrobuoni
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Collegio Carlo Alberto
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Prof. Solomon Hsiang
School of Sustainability
Stanford University
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Prof. Elena Esposito
Dept. of Economics
Collegio Carlo Alberto
✉ e.esposito@unito.it

Prof. Paolo D'Odorico
Dept. of Environmental Science
University of California, Berkeley
✉ paolododo@berkeley.edu

Research Fields

Topics: Applied Microeconomics, Environmental Economics, Urban Economics

Methods: Spatial Analysis, Reduced-Form

Working Papers

"The Long-Run Effects of Tropical Cyclones on the U.S. Housing Market" (*Job Market Paper*)

Housing is a major component of wealth in the United States. Despite tropical cyclones causing approximately $1.3 trillion in damages since 1980—more than any other weather disaster—there is limited empirical evidence on their long-term effects on the housing market. This paper examines the impact of tropical cyclones on housing values in the contiguous U.S. from 1988 to 2021. Using data from the National Hurricane Center and a radial wind-speed model, I construct a new cyclone exposure measure and provide the first plausibly causal estimates of the aggregate impact of all recorded cyclones at the county-year level. Despite a short-term rise, housing values decline by 15% over an eight-year horizon following cyclone exposure. Within coastal counties, areas with lower historical cyclone activity tend to have more housing development and higher property values, suggesting households may sort into seemingly safer locations. Strikingly, these less-experienced areas suffer the most persistent declines

"The Impact of Flooding on Credit Risk: Evidence from a Global Financial Institution"

In this study, I investigate the impact of flooding on firm-level credit risk using data from the International Finance Corporation (IFC), covering 3,243 clients from 1994 to 2023. I combine clients' credit ratings with flood exposure data from the Dartmouth Flood Observatory and the Global Flood Database. The results indicate that clients exposed to flooding experience a deterioration in credit ratings of 20% after 3-year period and face between 4-10% higher probability of default compared to unexposed clients. The negative effects are concentrated among more severe flooding events—those displacing over 8,000 people—and are most pronounced for firms with lower historical exposure to flooding. These findings offer new empirical evidence on how physical climate risk—specifically flooding—translates into financial vulnerability, highlighting the need for better integration of climate data into credit risk assessments.

Work in Progress

"The Effects of Wind Turbine Visibility on Touristic Flows: Evidence from Italy"
with G. Pinto (U. Sapienza)

"The Unintended Consequences of Transparency Laws: Evidence from the Italian Gasoline Market"
with Mastrobuoni (CCA), Pozzi (EIEF), Martin (DICE), Erdemli (U. of Barcelona), Nicolini (U. of Pavia)

"An empirical socio-economic indicator of country-level food security"
with Tavoni (U. of Bologna), D'Odorico (UC Berkeley)

Teaching & Research Experiences

Teaching Assistant:
Microeconomics, bachelor (University of Turin) 2023

Research Assistant:
principal investigator: Elena Esposito (University of Turin) 2024
principal investigator: Alessandro Tavoni (University of Bologna) 2020

Experiences

Temporary Consultant at IFC - World Bank (Washington DC) 2025
Visiting PhD student (UC Berkeley) 2023-2024
Erasmus+ (TU Dublin) 2018-2019

Conferences

ARE dept. and Global Policy Lab (UC Berkeley); SIEP conference (U. of Cagliari); ECCD Workshop (GSSI, L'Aquila) 2024
IBEO conference (U. of Sassari) 2023

Others

Languages: English (Fluent), Italian (Native), Spanish (Basic)
Softwares: LaTeX, Stata, Python, QGIS

Last update: July 2025

The Impact of Flooding on Credit Risk: Evidence from a Global Financial Institution*

Davide Castellani†

August 8, 2025

Abstract

In this study, I examine the impact of flooding on firm-level credit risk using proprietary data from the International Finance Corporation (IFC), covering 3,243 clients between 1994 and 2023. I link clients' credit ratings with flood exposure data from the Dartmouth Flood Observatory and the Global Flood Database. The findings show that exposure to a single flood event leads to a deterioration in credit ratings of approximately 20% over a three-year period. This effect is driven by flood events that displace more than 8,000 people. When considering repeated flood exposure, I find that firms experiencing two to five floods over the 30-year panel show a less pronounced decline in credit ratings, suggesting some degree of adaptation. However, the negative impact increases again for firms exposed to more than five floods, indicating potential limits to adaptive capacity. These results provide new empirical evidence on how physical climate risks—particularly flooding—translate into financial vulnerability, underscoring the importance of integrating climate risk data into credit risk assessments.

JEL-Codes: Q54, G32

*The views expressed in this paper are solely those of the author and do not represent the views of the International Finance Corporation (IFC) or its affiliates. All credit rating and default statistics are based on publicly available information (International Finance Corporation, 2024a). I thank Aurèle M. Houngbédji for his continuous support throughout the development of this work. I also thank my colleagues of the Climate Risk Team at IFC for their invaluable support in the data collection process and for the collaborative environment that made this research possible.

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1 Introduction

In recent years, there has been a global increase in the frequency and intensity of extreme precipitation events, a trend that has become particularly pronounced over the last decade and is closely linked to human-induced climate change (IPCC, 2021). One of the most severe consequences of these changes is flooding, which remains the most frequent natural disaster worldwide. Approximately 1.81 billion people, or 23% of the global population, are directly exposed to 1-in-100-year flood events (Rentschler et al., 2022).

In response to these escalating risks, investors and regulators are increasingly relying on Environmental, Social, and Governance (ESG) indicators to inform financial decision-making. ESG metrics are now used not only to assess a firm's sustainability practices but also to gauge its resilience, long-term performance, and creditworthiness in the face of climate-related stresses. Within the realm of finance, climate-related risks are typically divided into two broad categories: physical risks, which include the direct impacts of extreme weather events such as floods, wildfires, and storms, and transition risks, which stem from the policy, technological, and market shifts required to transition to a low-carbon economy. Despite the growing attention to these risks, a significant empirical gap remains in understanding how specific physical risks—particularly flooding—translate into financial outcomes, such as credit risk.

In this study, I examine the impact of flooding on credit risk using a unique dataset from the International Finance Corporation (IFC), the private-sector development institution within the World Bank Group that supports investment and growth in emerging markets. The analysis relies on credit ratings for 3,243 IFC clients spanning from 1994 to 2023. I use these credit ratings as a direct measure of credit risk: ratings are recorded on a 15-point ordinal scale, where a higher value indicates greater credit risk, and a rating of 15 corresponds to default (International Finance Corporation, 2024a). Thus, increases in the credit rating reflect a deterioration in a firm's creditworthiness. To identify clients exposed to flooding, I link the IFC credit rating data with two complementary sources of flood information: the Dartmouth Flood Observatory, which compiles global flood events from news and official reports dating back to 1985, and the Global Flood Database, which provides satellite-based measurements for 192 major flood events worldwide between 2000 and 2017. While the Dartmouth dataset offers broader temporal coverage, the Global Flood Database provides much finer spatial resolution—up to 250 meters—allowing for more precise identification of localized flood exposure.

Despite the originality of the data, several key empirical challenges arise. First, project locations are often not co-located with firm headquarters, which I have georeferenced globally. This spatial disconnect complicates the assignment of flood exposure. Second, the repeated occurrence of floods in the same geographic areas makes it difficult to clearly distinguish between treated and control firms over

time. To overcome this challenge, I leverage the local projection estimator for Difference-in-Differences event studies recently developed by Jordà et al. (2023), which allows for flexible dynamic treatment effects while ensuring that control observations remain unaffected by treatment across the specified event window. I begin by comparing clients who have ever experienced flooding to those who have not. Then, I estimate the average effect of a single flooding event, excluding cases with overlapping or repeated exposures to isolate clean treatment units.

The analysis reveals that both the intensity and frequency of flood exposure have significant and lasting impacts on firm creditworthiness. Firms exposed to a single severe flood—defined as an event displacing more than 8,000 people—experience a deterioration in credit ratings of approximately 20% within three years, while no meaningful effect is observed for less intense events. Repeated exposure compounds these risks: clients affected by more than five flood events over the 30-year period exhibit outcomes comparable to those with only one, suggesting that while some degree of adaptation may occur with moderate exposure (two to four events), this resilience breaks down under sustained climate stress. Sectoral analysis shows that firms in commerce—such as retail and banking—suffer more persistent credit deterioration than those in industry, likely due to higher dependence on local infrastructure and short-term liquidity. These effects are particularly pronounced among clients in emerging markets, where the deterioration in creditworthiness is significantly larger than in high-income countries.

This paper contributes to a growing literature on the economic and financial implications of climate change. A broad body of work has documented the economic impacts of climate change (Dell et al., 2014; Carleton and Hsiang, 2016; Auffhammer, 2018). More recently, scholars have increasingly focused on the ways in which climate change affects financial markets. This growing literature explores how climate risks are capitalized into asset prices—ranging from housing markets to corporate valuations—and how they influence firm profitability, infrastructure investment, and broader patterns of asset reallocation (Bernstein et al., 2019; Addoum et al., 2023; Balboni, 2025; Giglio et al., 2021). While previous research has modeled climate risk in terms of stock market responses or risk premia (Venturini, 2022), few studies have directly examined causal effects of physical climate events on firm-level credit outcomes. This gap is especially pronounced in emerging markets, where exposure to climate shocks is high, and financial data is often scarce.

This paper shifts the focus from market perceptions to actual credit risk outcomes, an underexplored but critical dimension of climate finance. While equity prices, bond spreads, and CDS data reflect investor expectations and can capture rapid changes in perceived risk, they are often limited to publicly traded firms in advanced economies and are sensitive to noise or short-term sentiment. In contrast, credit ratings are based on in-depth financial and operational assessments, offering a more stable and forward-looking measure of a firm's ability to meet its debt obligations. Credit ratings play a

central role in determining firms' access to capital—particularly in emerging markets, where financial systems are less developed and firms depend more heavily on institutional lending. By analyzing how flooding affects changes in credit ratings and defaults, this study provides new insights into the financial consequences of climate shocks, especially in contexts where traditional market signals are limited or unavailable.

The rest of the paper proceed as follow. Section 2 describes the background and data. Section 3 introduces the research design to identify the impact of flooding on credit risk. Section 4 presents the results. Section 5 provides the conclusion, and Section 6 acknowledgments.

2 Background and Data

2.1 Physical risk

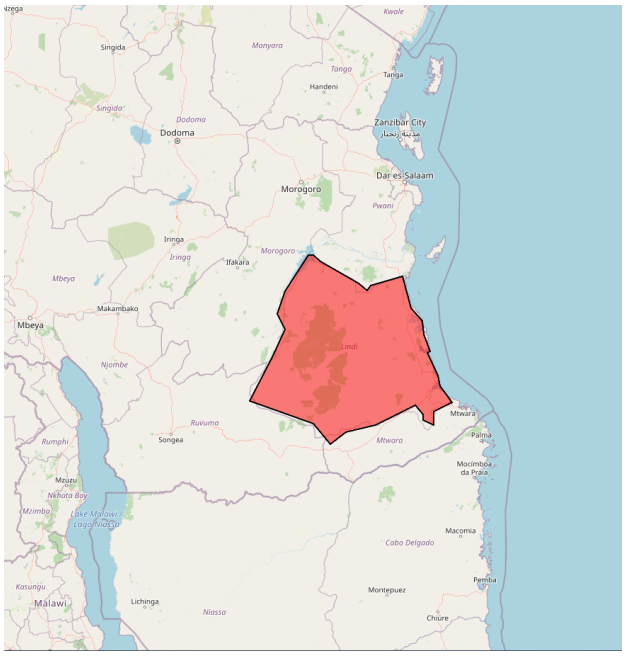
Physical risks—defined as the direct consequences of climate-related hazards such as floods, hurricanes, wildfires, and droughts—are increasingly recognized as material threats to financial stability. These risks can damage physical assets, disrupt business operations, and impair a firm's ability to meet financial obligations, ultimately influencing credit risk and valuation. Recent work has highlighted how such risks can affect asset prices, lending practices, and firm default probabilities, yet empirical evidence remains limited, particularly in emerging markets. In this study, I focus on one of the most common and damaging physical hazards—flooding—as a lens through which to examine how environmental shocks shape credit outcomes. By isolating the impact of flood exposure on firm-level credit ratings and default events, this approach provides a tractable and policy-relevant pathway for quantifying physical climate risk in financial markets.

2.1.1 Flooding exposure

To operationalize exposure to physical risk, I focus on flooding, the most frequent and economically costly natural disaster worldwide. This analysis draws on two complementary data sources: the Dartmouth Flood Observatory (DFO) and the Global Flood Database (GFD). The DFO provides a comprehensive global record of flood events since 1985, compiled through media reports, government sources, and satellite imagery. It offers broad temporal and geographic coverage, making it particularly useful for long-run event analysis. In contrast, the GFD, developed using satellite-based remote sensing, includes 192 major flood events between 2000 and 2017 and offers high-resolution spatial data (250-meter resolution). While the GFD captures fewer events, its precision enables more accurate identification of firm-level exposure to flooding. By combining these datasets, I am able to capture both the long-term frequency and the fine-grained geography of flood events, allowing for a robust examination of their effects on corporate credit risk.

Figure 1 illustrates examples of flood polygons constructed by the Dartmouth Flood Observatory (DFO). These polygons represent the estimated geographic extent of each flood event, based on a combination of satellite imagery and information collected from news reports and official sources.

Figure 1: Examples of flooding extent from DFO



(a) Example 1

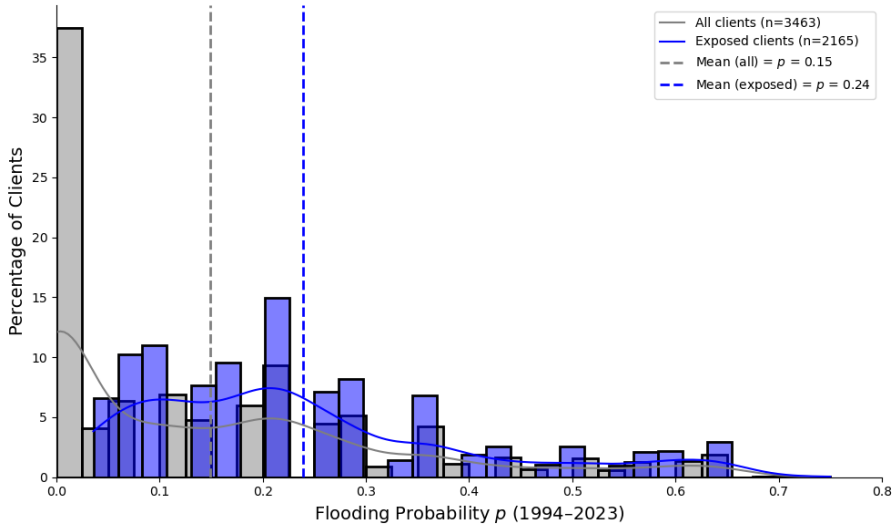


(b) Example 2

To assess client exposure, I spatially matched the DFO flood polygons with the geographic coordinates of the IFC client headquarters. For each year, I identified whether a client was located within a flood-affected area. I find that 2,165 out of 3,463 IFC clients, over 60%, experienced at least one flood event during the sample period.

To analyze how the likelihood of experiencing a flood varies across clients, I calculate, for each client, the share of years since 1994 during which their headquarters were located within a flooded area. This frequency serves as a proxy for the probability of flood exposure, denoted by p. Figure 2 presents the distribution of p across all clients, as well as the subset of clients who experienced at least one flood during the sample period.

Figure 2: Probability of Receiving Flooding from 1994 to 2024

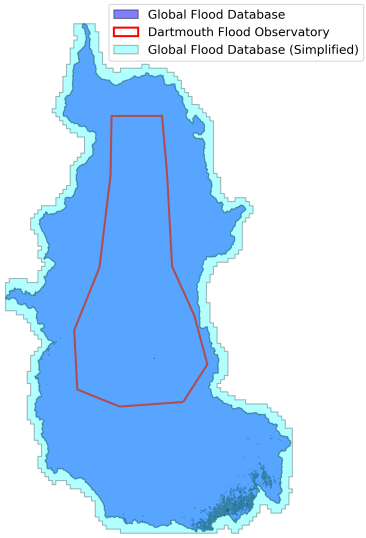


The average probability of experiencing at least one flood event over the 30-year period is 0.24, indicating that affected areas face a flood approximately once every four years. In Table 1, I use this probability as a benchmark to compare how credit risk varies depending on whether a region is above or below this average. Additionally, I conduct subsample analyses in the empirical section to examine how the impact of flooding differs across varying probabilities of occurrence, providing insights into potential adaptation to these events.

In addition to geographic information, the DFO dataset includes qualitative details for each flood event, such as the number of displaced people, fatalities, and infrastructure damage, which I use to report descriptive statistics in Table 1.

While the DFO provides broad coverage over time, the delineated flood polygons tend to underestimate the true spatial extent of flooding. This becomes evident when comparing DFO polygons to those from the Global Flood Database (GFD), which is based on satellite-detected surface water changes at a much finer resolution (250 meters). Figure 3 illustrates this comparison for a representative event: the red polygon (DFO) lies entirely within the broader blue-shaded area derived from the GFD. To manage the high granularity of the GFD—comprising millions of pixels—I generate simplified flood boundaries by extracting only the outermost pixels, which I refer to as "GFD simplified" in the figure.

Figure 3: Comparison of flood extent: DFO vs. GFD



This pattern holds across multiple events (additional examples are provided in the Appendix A.1), and the discrepancy between datasets has quantitative implications: despite covering only 192 events between 2000 and 2017, the GFD identifies flood exposure in approximately 18% of firm-year observations—higher than the DFO's estimate. This comparison highlights the importance of spatial resolution in measuring physical climate risk and motivates the use of both datasets in the analysis. While the DFO provides longer historical coverage, with data dating back to 1994, the GFD offers more spatially granular information but is only available from 2000 onward—illustrating a trade-off between historical coverage and spatial precision.

2.2 Credit risk

Credit risk refers to the possibility that a borrower will fail to meet its financial obligations, potentially resulting in financial losses for the lender. In this study, I use firm-level internal credit ratings and default events as proxies for credit risk, consistent with established practices in the finance literature (Altman, 1968; Merton, 1974; Duffie and Lando, 2001). Credit ratings offer an assessment of a firm's creditworthiness, incorporating both quantitative financial indicators and qualitative assessments of business risk. Default, in turn, represents the most severe manifestation of credit risk. Together, these measures provide complementary views on a firm's evolving financial health and exposure to adverse shocks—such as those induced by natural disasters.

2.2.1 International Finance Corporation

The International Finance Corporation (IFC) is a member of the World Bank Group and the largest global development institution dedicated to the private sector in emerging and developing markets.

Founded in 1956, IFC plays a critical role in promoting inclusive and sustainable economic growth by providing investment, advisory, and asset management services. Its mission is to encourage private sector development as a means to reduce poverty and improve lives. IFC works with businesses, financial institutions, and governments to unlock private investment, foster innovation, and build markets that are resilient and environmentally sustainable. With a strong focus on sectors such as infrastructure, manufacturing, agribusiness, financial services, and climate solutions, IFC helps mobilize capital, create jobs, and expand access to services in regions that need it most.

The IFC's disbursed investment portfolio consists of loans (57.0%), equity investments (29.0%), and debt securities (14.0%), with broad diversification across countries, regions, industries, and project types (International Finance Corporation, 2024b). For the purposes of this analysis, I restrict the sample to IFC clients that received loan-based financing. This focus reflects both empirical and conceptual considerations: loans provide a more direct and interpretable link between climate shocks and credit risk. In contrast, equity positions introduce valuation complexities and strategic interactions that obscure causal identification. Moreover, credit ratings and repayment performance are more consistently defined and observed in the loan portfolio, facilitating a cleaner analysis of climate-related credit dynamics.

2.2.2 Credit ratings

To assess credit risk, this study begins by examining credit ratings. I use firm-level credit rating data from the International Finance Corporation (IFC). While IFC investments are targeted toward projects in developing countries, credit ratings are based on financial performance of the client and the headquarters can be in a different location with respect to the projects. [1]

Each observation in the dataset corresponds to a unique client-year pair, enabling a panel-level analysis of credit ratings over time. The dataset includes annual credit ratings from 1994 to 2023 for 3,463 institutions, totaling 21,595 observations, and is further complemented with monthly data from 2017 onward.

According to International Finance Corporation (2024a), ratings are reviewed at least once annually and reflect a broad spectrum of credit events. The IFC's internal credit rating system assesses clients on a 15-point ordinal scale, where 1 denotes the best credit risk and 15 indicates a default. A counterparty is considered to have defaulted if either of the following occurred: (i) it was assigned non-accrual status or (ii) a portion or all the loan balance was written-off.

When considering the number of unique clients that have ever defaulted, I found that 570 out of 3,463 clients (approximately 16%) experienced at least one default event from 1994. This is comparable

[1] Notably, approximately 60% of IFC clients are headquartered in developing markets.

to IFC's published statistics, which report 784 defaults out of 3,680 clients since 1986 (International Finance Corporation, 2024a).

The methodology used by IFC to compute defaults is broadly aligned with the approaches adopted by major credit rating agencies, such as Moody's and Standard & Poor's. This alignment enables meaningful benchmarking of empirical default rates and rating transitions. For details on the mapping between IFC's internal credit ratings and S&P classifications, see International Finance Corporation (2024a).

3 Descriptive statistics

Table 1 presents descriptive statistics for clients grouped by their historical exposure to flooding. The grouping is based on the share of years between 1994 and the end of the sample period in which a client's headquarters fell within a flooded area. I classify clients into three categories: those with no exposure ($p = 0$), those with occasional exposure ($p < 0.24$), and those with repeated exposure ($p > 0.24$), where 0.24 represents the average flood exposure probability across exposed clients (Figure 2.

Table 1: Means of Key Variables by Flood Exposure

	No Exposure ($p = 0$)	**Occasional Exposure** ($p < 0.24$)	**Repeated Exposure** ($p > 0.24$)
# of Clients	1,823	782	702
Observations	8,551	7,225	4,308
Default (0/1)	0.078	0.136	0.103
Credit Rating (1–15)	8.830	9.047	8.788
Displacements	0	200,04	456,883

Interestingly, the default rate is highest among clients with occasional exposure to flooding, while it is slightly lower for those with repeated exposure, suggesting a potential adaptation or resilience effect. Credit ratings are relatively stable across groups, with a slight dip for repeatedly exposed clients. The average number of displacements—used as a proxy for flood severity—increases markedly with exposure probability. This likely reflects the greater chance of encountering a severe event due to more frequent exposure.

While Table 1 provides a long-run view of clients' historical exposure to flooding, it is also important to examine the nature of the flood events themselves in terms of both their intensity and their frequency. This complementary perspective links the probability-based exposure groups to the actual characteristics of the shocks they face. To this end, I draw on event-level data from the Dartmouth

Flood Observatory. Among the available indicators, the most consistent and viable measure of *intensity* is the number of people displaced due to flooding events. The left panel of Table 2 presents summary statistics for this variable. Given the highly skewed nature of displacement (with extreme right-tail values), I use the median displacement value of 8,000 people to split the sample into low- and high-intensity events. This threshold allows for a meaningful comparison in downstream analysis while mitigating the influence of extreme outliers.

In addition to intensity, I examine the frequency of flood exposure per client over the observation window. The right panel of Table 2 reports the number of observations by event frequency and the corresponding number of unique clients exposed at each level. Approximately 41% of the observations pertain to clients who were never affected by any flood, while another 9% were affected only once. A significant share of the dataset—over 50% of the observations—involves clients exposed to multiple flood events. This distribution is central to the research design. The variation in treatment frequency supports a two-pronged analytical strategy. First, I evaluate the causal effect of a single flooding event on outcomes using a difference-in-differences design comparing clients with and without exposure before and after the event. Second, I extend the analysis to account for multiple treatments—a more complex but realistic setting given the recurrence of flooding in many regions. The frequency table helps highlight the importance of considering repeated exposures: many clients are exposed multiple times across the panel.

Frequency of Flooding Events

Events	Freq.	Percent	Cum.	Clients
Never treated	12,925	40.83	40.83	1,274
Single event	2,858	9.03	49.86	125
2	2,518	7.95	57.82	199
3	2,170	6.86	64.67	212
4	1,676	5.29	69.97	156
5	2,099	6.63	76.60	194
6	837	2.64	79.24	292
7	1,365	4.31	83.55	144
8	674	2.13	85.68	165
9	1,277	4.03	89.72	27
10	209	0.66	90.38	136
11	53	0.17	90.54	37
12	139	0.44	90.98	54
13	585	1.85	92.83	20
14	319	1.01	93.84	46
15	421	1.33	95.17	20
16	1,488	4.70	99.87	40
17	41	0.13	100.00	57
Total	31,654	100.00		3,248

Intensity of Flooding Events
(Displacements from Flooding)

Statistic	Value
Observations	2,810
Mean	397,842
Std. Deviation	2,384,811
Percentiles	
1st	0
5th	0
10th	0
25th	180
50th (Median)	**8,000**
75th	81,600
90th	452,000
95th	1,166,000
99th	9,500,000
Maximum	40,000,000
Minimum	0

Table 2: Summary Statistics: Frequency and Intensity of Flood Exposure

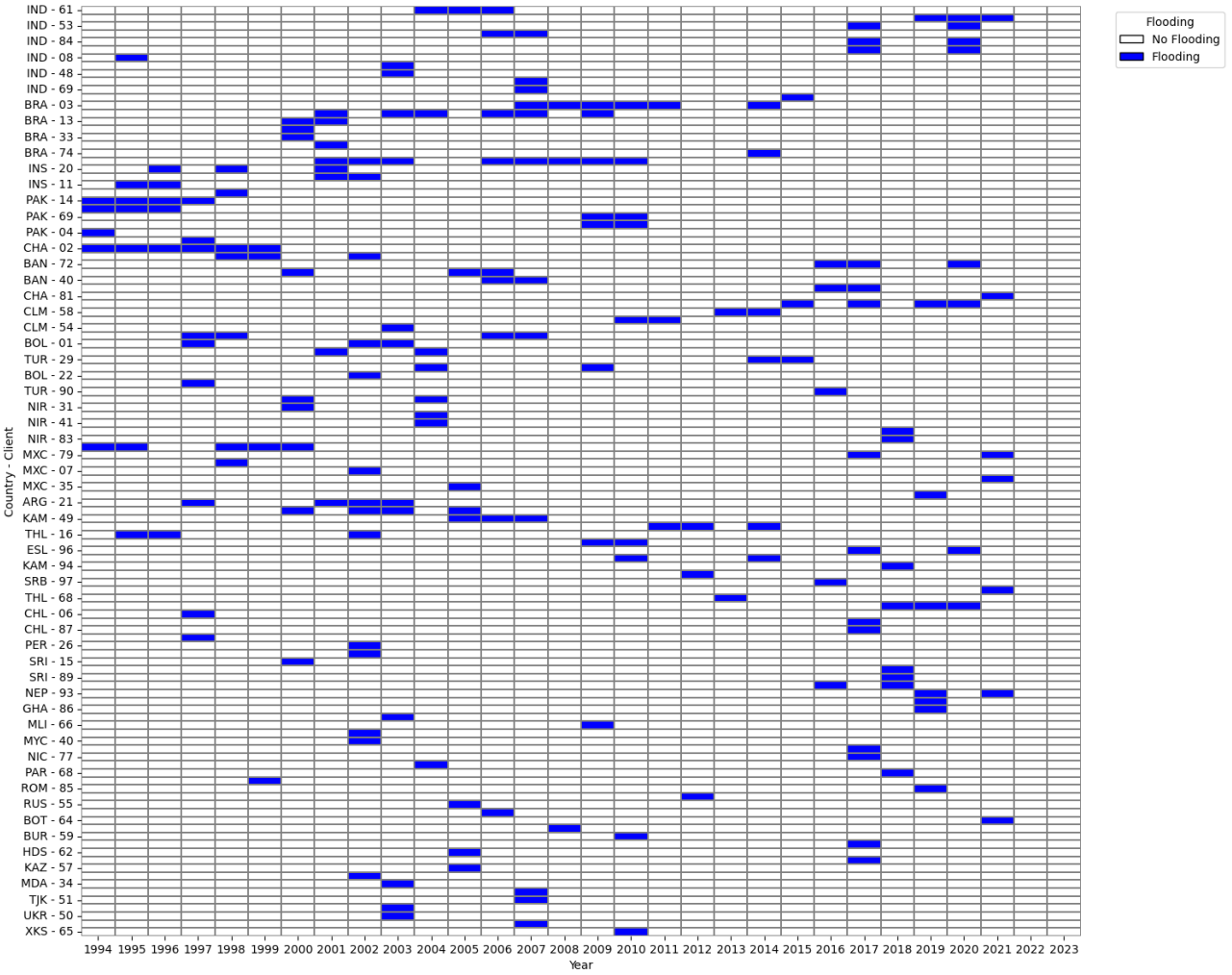
4 Research design

To estimate the impact of flooding on the creditworthiness of private-sector borrowers, I exploit the quasi-random timing and location of flood events across the globe. The dataset comprises client-level data from the International Finance Corporation (IFC), spanning multiple countries and years. This diverse, multinational setting offers a unique opportunity to study climate risk in emerging and developing markets, where credit infrastructure and resilience may vary substantially.

Flood events are matched to clients based on geolocation and year. Conditional on client and year fixed effects, the incidence of flooding in the client's location can be considered as-good-as random, enabling a natural experiment framework for causal inference.

To better understand the impact of flooding on clients, I construct a treatment variation plot. I randomly select 100 clients who experienced at least one flooding event and track their exposure over time. For each client-year, the plot indicates whether the client was affected by flooding. The y-axis is ordered by country, with countries experiencing more frequent flooding events appearing at the top.

Figure 4: Flood exposure across 100 random clients



Note: The heatmap displays flood exposure for 100 random clients over time with at least one flooding event. Countries are ordered by total flood exposure (top = more frequent flooding). Blue indicates exposure in year t; white indicates no exposure.

As shown in Figure 4, some clients remain unaffected by flooding for multiple consecutive years, while others experience repeated exposure over time. This heterogeneity in treatment patterns complicates identification, as it introduces challenges in clearly distinguishing between treated and control groups.

Because the likelihood of flooding is not uniform across countries, I apply Inverse Probability Weighting (IPW) to correct for differential treatment propensities. For each client, I compute the historical flood probability p based on the share of flood years. Weights are then assigned as follows:

- $1/p$ for treated clients (those exposed to floods in year t),
- $1/(1-p)$ for untreated clients (in years without flood exposure).

Impact of flooding on Credit Ratings

To estimate the average treatment effect on the treated (ATT) of flooding exposure on municipal credit ratings, I adopt the Local Projection Difference-in-Differences (LP-DiD) estimator proposed by Jordà

et al. (2023):

$$\Delta^h y_{i,t} = \delta_t^h + \beta_h^{LP-DID} \Delta D_{i,t} + e_{i,t}^h \tag{1}$$

In Equation 1, $\Delta^h y_{i,t}$ denotes the change in credit ratings from year $t-1$ to $t+h$, while $\Delta D_{i,t}$ captures the change in flooding exposure. The coefficient β_h^{LP-DID} measures the dynamic impact of a flood occurring at time t on credit ratings h years later.

The LP-DiD framework is particularly well-suited for this context, where treatment exposure is intermittent, and units are treated at varying times—often more than once. It avoids the "contamination effects" that bias traditional fixed-effects models in the presence of overlapping treatments and dynamic responses. To ensure unbiased estimation, I follow the conditions proposed by Jordà et al. (2023):

1. 'clean control condition': Control units must be untreated throughout the interval from $t-K$ to $t+h$.

2. Treated units must not have experienced flooding in the K years prior to treatment and must remain treated for the h years following it.

I set the stabilization window to $K^* = 3$ in the baseline specification, meaning units must be flood-free for at least 3 consecutive years to entering the control group. I confirm robustness by extending this window and find that the results remain stable, suggesting the estimates are not sensitive to the choice of K^* and the control group is sufficiently clean.

One challenge with the second condition is the possibility of overlapping flood events within the h years following treatment. To address this, I isolate a subset of treated units that experienced only a single flooding event. I then conduct a sensitivity analysis by varying the restriction on K for treated units as well—requiring a minimum number of flood-free years before a unit can be treated again ('clean treatment condition'). This approach allows me to estimate the average treatment effect of a flooding event on credit ratings more accurately, eliminating potential confounding from repeated or overlapping events.

To further strengthen identification, I employ inverse probability weighting (IPW) to improve covariate balance between treated and control units. Placebo tests examining pre-flood trends support the no-anticipation assumption, confirming that treated and control groups were on similar trajectories before exposure.

Impact of flooding on probability of default

To identify the causal effect of flooding exposure on the likelihood that an IFC client defaults, I estimate logistic regression models with and without fixed effects. Since the outcome variable is binary—equal

to 1 if an IFC client is in default in a given year and 0 otherwise—a logistic model is appropriate for this setting.

The baseline specification is a pooled logit model of the form:

$$\Pr(\text{Default}_{i,t} = 1) = \Lambda\left(\beta_1 \cdot \text{Flood}_{i,t} + \mathbf{X}'_{i,t}\boldsymbol{\gamma}\right) \tag{2}$$

where $\Lambda(z) = \frac{e^z}{1+e^z}$ is the logistic function, $\text{Default}_{i,t}$ is a binary indicator for default of client i in year t, $\text{Flood}_{i,t}$ is a binary indicator equal to 1 if the client was exposed to a flood event in year t, and $\mathbf{X}_{i,t}$ is a vector of time-varying controls.

To account for unobserved heterogeneity across IFC clients or institutions—such as differences in risk profiles, sectors, or geographic exposures—I estimate a fixed-effects logistic regression model:

$$\Pr(\text{Default}i, t = 1) = \Lambda\left(\alpha_i + \alpha_t + \beta_1 \cdot \text{Flood}i, t + \mathbf{X}'_{i,t}\boldsymbol{\gamma}\right) \tag{3}$$

where α_i represents time-invariant fixed effects at the client level and α_t represents year fixed effects. The identification assumption in both specifications is that, conditional on observables (and fixed effects, where included), flood exposure is exogenous to other unobserved shocks that may influence default. The fixed-effects specification strengthens this assumption by controlling for all time-invariant unobserved heterogeneity. However, it comes with the trade-off that clients with no variation in the outcome (i.e., always in default or never in default) are excluded from the estimation sample.

5 Results

Impact of Flooding on Credit Rating (CR)

Here, I assess the dynamic impact of flooding events on firms' creditworthiness. Following Local Projections Difference-in-Differences (LP-DiD) presented in equation 1, I estimate how credit ratings evolve relative to the year prior to a flood event. .

To estimate the average treatment effect (ATE) of a single severe flooding event, I restrict the analysis to clients who experienced exactly one flood over the entire 30-year panel. This allows for a clean comparison between treated and untreated firms, free from confounding effects related to repeated or overlapping events. While this is the most restrictive sample, it offers the clearest identification strategy by comparing firms with one isolated event to firms that were never treated. To explore heterogeneity in treatment intensity, I further divide the treatment group based on the median value of displacement (8,000 people), as shown in Table 2. This results in two subgroups: clients experiencing a single flood that displaced more than 8,000 people, and those exposed to a single flood with fewer than 8,000 displacements.

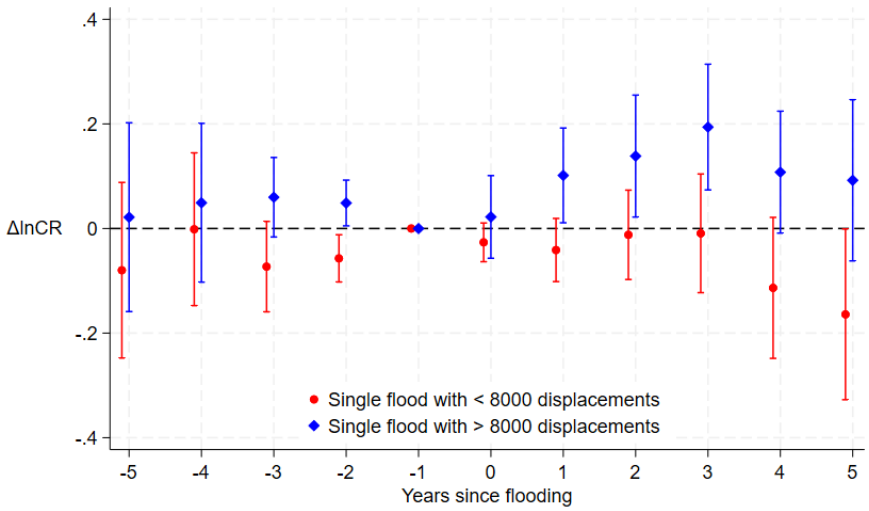
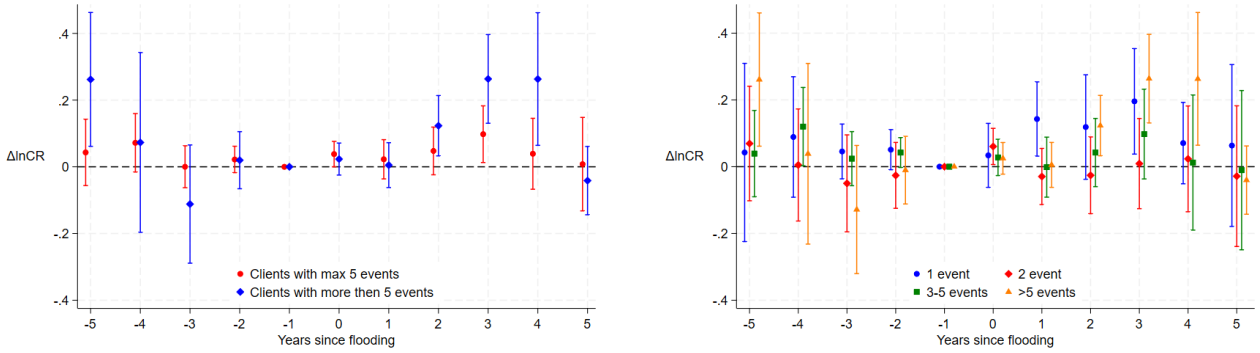


Figure 5: ATE of flooding on credit rating (single-event sample)

Figure 5 shows that credit ratings deteriorate significantly following a severe flood (i.e., more than 8,000 displacements), with an average increase of 20% in credit rating values observed three years after the event. In contrast, no significant effect is found for floods below the median displacement threshold. These findings are robust to alternative difference-in-differences estimators such as Callaway and Sant'Anna (2021) and de Chaisemartin et al. (2025) (Appendix B).

While this restrictive sample improves causal identification, it limits statistical power due to the small number of treated units, as reflected in the wider confidence intervals. To address the trade-off between bias and efficiency, I extend the analysis to include clients with multiple flood exposures. Appendix B presents a sensitivity analysis using varying exclusion windows to define "clean" treatment episodes. Specifically, I consider values of K ranging from 1 to 5, where K indicates the number of years before and after the focal event during which no other flood is allowed. For example, $K = 3$ requires that a client not experience another flood three years before or after the event. Results under this relaxed definition closely resemble the baseline estimates from the single-event sample, supporting the robustness of the main findings. This broader sample allows me to incorporate clients who were exposed to multiple floods and examine how the number of events affects outcomes.

Figure 6: Heterogeneous effects by number of flood events



(a) Split by median number of events, 5

(b) Further breakdown by number of events

Figure 6 presents heterogeneous effects based on the number of flood events experienced. In panel (a), I split the sample at the median number of flood events (five). Clients exposed to more than five events over the 30-year panel suffer larger negative impacts on credit ratings compared to those with fewer than five events.

Panel (b) further decomposes the sample by number of events. Interestingly, clients exposed to two or three floods experience smaller impacts than those exposed to only a single event, suggesting some degree of adaptation. However, the protective effect appears to diminish with more repeated exposure. Clients with more than five events exhibit similar outcomes compared to those with only a single exposure. This suggests that while some resilience may emerge with moderate exposure, it eventually breaks down under repeated stress.

In addition to the overall treatment effects, I conduct a sector-level analysis to examine whether certain industries are more vulnerable to flood-related credit deterioration.

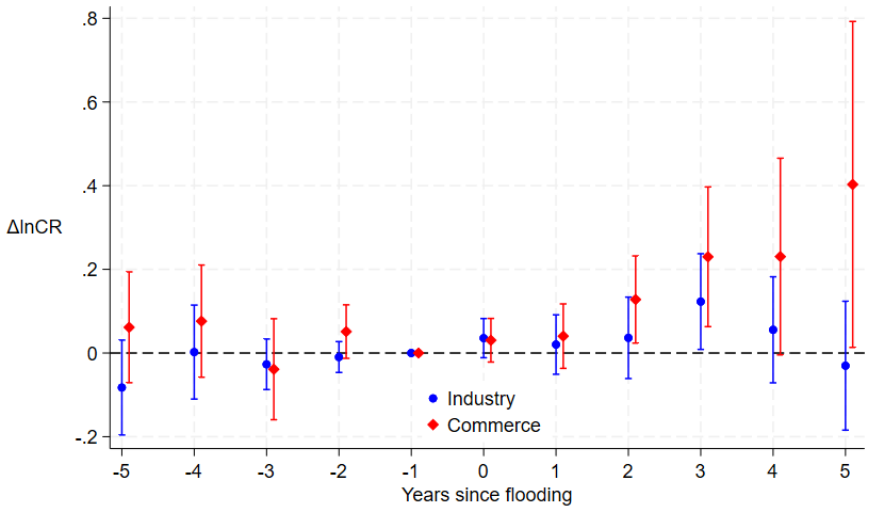


Figure 7: sector analuyss

Figure 7 illustrates that the commerce sector (e.g., retail and banking services) experiences signif-

icantly greater declines in credit ratings following flooding events compared to the industrial sector. Moreover, the negative effects in commerce persist for a longer duration—up to five years after the event—whereas impacts on industrial clients tend to be more transitory. This differential vulnerability may be attributed to several factors. Commercial firms are more likely to rely on localized infrastructure (e.g., storefronts, customer foot traffic, and physical banking branches), which can be severely disrupted by floods. In contrast, industrial firms may be better equipped to absorb or mitigate flood shocks due to stronger asset bases, diversified supply chains, or the ability to temporarily suspend operations without losing customer relationships. Additionally, firms in commerce may have tighter cash flows and greater dependency on short-term revenue, making them more financially fragile when physical disruptions occur. These findings suggest that credit risk assessments in the face of climate shocks should not only consider the intensity and frequency of exposure, but also sectoral heterogeneity in vulnerability and recovery capacity.

Impact of Flooding on the Probability of Default (PD)

This section examines whether exposure to flooding significantly affects a firm's probability of default. Assessing this outcome provides a more direct measure of financial distress than credit ratings alone. I estimate binary response models using both standard logit and fixed effects (FE) logit specifications, where the dependent variable is a binary indicator equal to one if the firm is in default in a given year. The primary independent variable is an indicator for whether the firm's location was affected by a flood event in that year.

To ensure robustness, I rely on two distinct flood datasets: the Dartmouth Flood Observatory, which documents major riverine flood events globally based on media and governmental sources, and the Global Flood Database (GFD), which uses satellite imagery to detect flood extents at high spatial resolution. Table 3 reports the results using both sources.

Table 3: Impact of Flood Exposure on Probability of Default (PD)

	Dartmouth Flood Observatory		**Global Flood Database**	
	Logit	FE Logit	Logit	FE Logit
Log-odds Coefficient	0.121	0.158	0.226	0.395
Standard Error	0.060	0.095	0.055	0.096
p-value	0.045	0.099	0.000	0.000
Marginal Effect (dy/dx)	1.14%	3.94%	2.12%	9.79%
Observations	21,606	4,940	21,606	4,940
Number of Groups	–	570	–	570

The findings indicate that flooding significantly increases the likelihood of default. According to the logit estimates using the Dartmouth dataset, firms in flood-affected areas are 1.14 percentage points more likely to default, with the effect rising to 3.94 percentage points in the fixed-effects specification.

However, the stronger effects are observed when using the Global Flood Database: the probability of default increases by 2.12 percentage points in the standard logit model and nearly 9.8 percentage points when accounting for institution fixed effects.

Notably, these results are obtained in a context where approximately 10% of observations in the full sample are in default, underscoring the economic relevance of the estimated effects. In the fixed-effects models, roughly 2,893 clients (16,655 observations) are omitted due to a lack of variation in the dependent variable.

Taken together, these findings reinforce the view that flooding significantly compromises firms' financial health. The stronger effects observed with the Global Flood Database also underscore the importance of high-resolution, remotely sensed data in disaster impact assessments. These results align with and complement the credit rating analysis, providing consistent evidence that flood exposure leads to a meaningful deterioration in firms' creditworthiness and repayment capacity.

6 Conclusion

This study provides novel empirical evidence on the impact of physical climate risk—specifically, flooding—on firm-level financial outcomes in emerging markets. By combining geospatial data on flood events from the Dartmouth Flood Observatory with a unique panel of microfinance client credit histories, I examine how both the intensity and frequency of exposure to flooding shape firms' financial vulnerability over time.

The results highlight two key dimensions of climate risk. First, in terms of intensity, I find that only severe flood events—defined as those displacing more than 8,000 people—have a statistically significant negative effect on credit ratings. Firms affected by such events experience an average 20% increase in their credit rating value (indicating deterioration in creditworthiness) within three years post-event, whereas firms affected by less intense floods show no measurable impact. This finding underscores the importance of distinguishing between low-impact and high-impact climate shocks when assessing firm-level risk.

Second, the analysis of treatment frequency reveals a more complex dynamic. While firms exposed to only one flood event suffer significant deterioration in credit ratings, those exposed to two or three events show smaller effects—suggesting possible adaptation or improved preparedness. However, this resilience appears to erode under repeated stress: clients experiencing more than five flood events over the panel period show negative financial outcomes comparable to, or worse than, those affected by only one. This non-linear relationship implies that adaptive capacity may be present at lower levels of exposure but becomes insufficient when climate shocks are frequent and prolonged.

These results are robust to alternative difference-in-differences estimators (such as Callaway and Sant'Anna, and Charles-Matin), and persist across multiple definitions of treatment windows that

allow for varying levels of event overlap. Even when relaxing the design to include clients with multiple exposures—using exclusion windows up to three years—the negative impact of severe flooding remains consistent, reinforcing the credibility of the findings.

Finally, the sector-level analysis reveals important heterogeneity in vulnerability to flood shocks. Firms in the commerce sector suffer greater and more persistent credit deterioration than those in industry, with effects lasting up to five years post-event. This suggests that credit risk linked to climate exposure is not evenly distributed across the economy, and that sectoral characteristics—such as dependence on local infrastructure and liquidity constraints—play a key role in shaping financial resilience. These insights underscore the need for sector-sensitive risk management frameworks in the context of climate-related hazards.

For institutions such as the International Finance Corporation (IFC), multilateral banks, and long-term private investors, these results underscore the importance of integrating physical climate risk into credit evaluation and investment frameworks. With the increasing availability of high-resolution climate and geospatial exposure data, incorporating physical risk assessments into loan pricing, credit scoring, and capital allocation strategies is not only feasible, but essential. Proactively embedding climate risk into financial decision-making will be critical to enhancing the resilience of capital flows and supporting sustainable development in the face of a changing climate.

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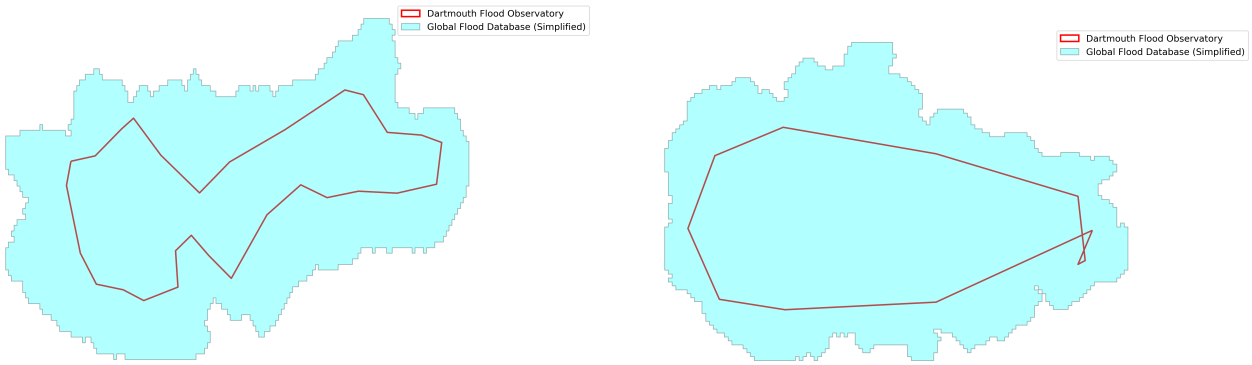
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A Flooding maps

Figure A.1: Examples of comparisons between GFD and DFO

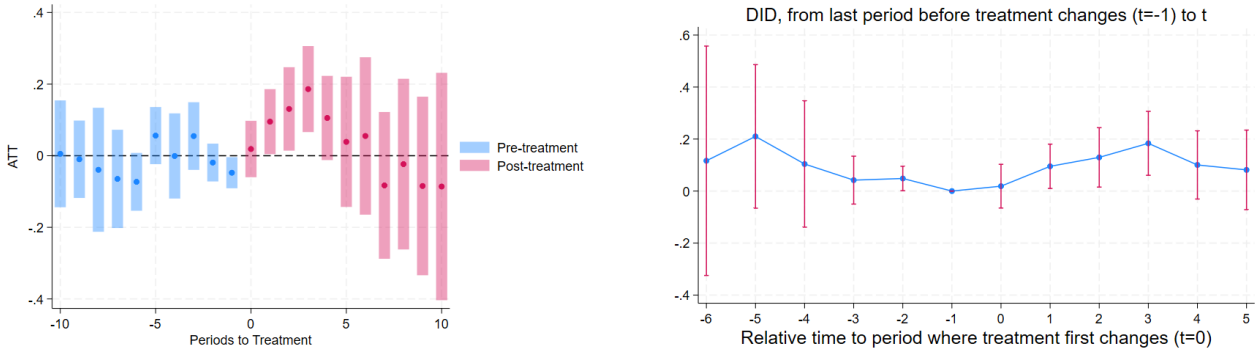


(a) Example 1 (b) Example 2

B Robustness of the main result

Results from other difference in difference literature

Figure B.1: Results from csdid and multipleg



(a) Example 1 (b) Example 2

Trade-off between bias and efficiency

To estimate the effect of flooding on credit ratings, I rely on different assumptions about the "cleanliness" of the treatment group—specifically, how isolated a flooding event must be from others. I define a parameter K to indicate how many years before and after the treatment window a client must remain flood-free to be included. For example, $K = 1$ excludes treated units that experience another flood in the year immediately following the initial event. At the other extreme, I consider only clients hit by a single flood over the entire 30-year panel (as shown in Figure 5).

Figure B.2: Comparing different clean treatment conditions

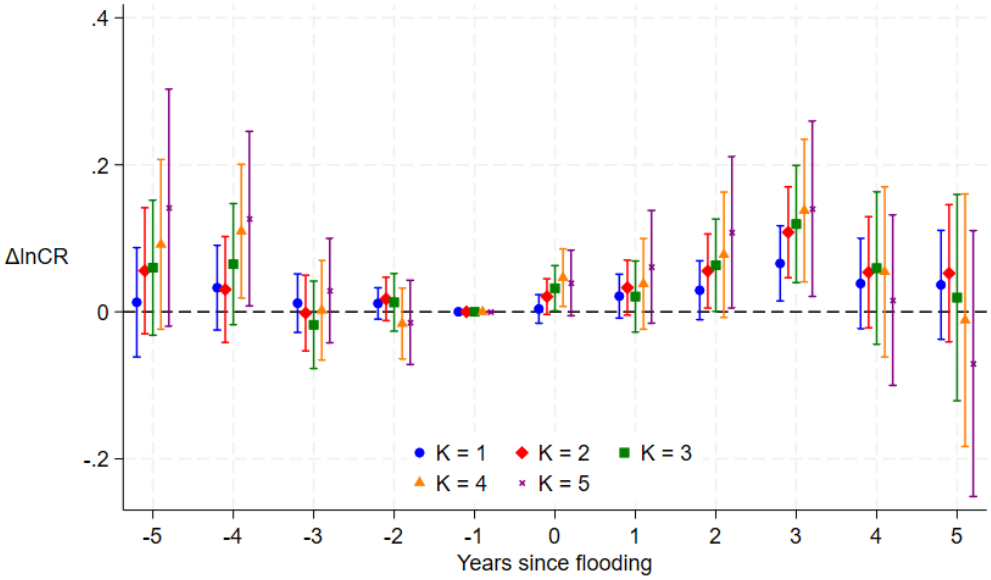


Figure B.2 illustrates how treatment effect estimates vary across different values of K (from 1 to 5). While the point estimates are broadly consistent, increasing K reduces the sample size and increases the variance of the estimates, reflecting a classic trade-off between bias and efficiency.

When $K = 1$, the treatment group is larger, resulting in tighter confidence intervals and better balance in pre-trends. However, this specification includes clients affected by overlapping flood events, which may attenuate the estimated effect of a single flood. In contrast, higher values of K (e.g., $K = 5$) produce cleaner comparisons by removing clients exposed to repeated events, thereby isolating the impact of a standalone flood. These cleaner estimates show a more immediate increase in credit risk following the event—an effect that is less visible in more inclusive samples. Because all the specification point out a significant effect after 3 year,and then insignificant reuslts, I have used K=3 in the main specification (Figure 5)