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Washed Away: Industrial Capital, Labor, and Floods

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Abstract

This study quantifies the dynamic impacts of floods on industrial capital and labor in India using a novel dataset combining geocoded flood events with firm facility-level data from 2000 to 2021. Employing a stacked difference-in-differences approach with carefully matched controls, we uncover persistent negative effects of floods on firms' assets and employment, with striking heterogeneity across sectors and regions. In the post-flood period, we estimate declines from mean values in total assets of 46.1% (16.68 billion INR $\approx$ 225 million USD), employment of 49.0% (8.20 thousand workers), and the wage bill of 74.5% (5.52 billion INR $\approx$ 74 million USD). The sectoral impacts are highly varied: the information technology and communication, manufacturing, and utilities sectors experience significant declines in assets, while the financial services sector exhibits growth. Mapping the spatial distribution of flood events and industrial facilities reveals pronounced regional heterogeneity in flood exposure and economic impacts. Adding nuance to the empirical investigation of the "creative destruction" hypothesis, we find limited evidence of systematic capital reallocation toward better-performing sectors, suggesting instead that floods generate sector-specific impacts with varying recovery patterns. These findings challenge assumptions of rapid post-disaster equilibration and have important implications for policymakers and firm managers in developing sector-specific strategies to mitigate the adverse impacts of floods in an increasingly climate-uncertain world.

Keywords: Natural Disasters, Floods, Industrial Impacts, India

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1 Introduction

Floods are the most frequent and devastating of all natural disasters, accounting for nearly half of all natural catastrophes and affecting over three-quarters of disaster-impacted populations globally (Guha-Sapir et al., 2004). Asia in particular bears a disproportionate burden, accounting for over 40% of flood disasters worldwide and over 90% of flood-related deaths (Guha-Sapir et al., 2004). As climate change intensifies, the economic losses associated with these events continue to rise, driven by the growing value of assets exposed to risk and the disproportionate impact on vulnerable populations and businesses (Kousky, 2014; Hsiang, 2016; Botzen et al., 2019; Hallegatte et al., 2016). Understanding the long-term effects of these disasters on industrial capital and labor is crucial for developing effective adaptation, mitigation, and resilience strategies

We investigate the long-run economic impact of extreme flood events on industrial capital and labor in India, a global hotspot for devastating floods (Pörtner et al., 2022; Brunner et al., 2021; Gandhi et al., 2022). We leverage a unique panel of industrial asset locations and construction data spanning 21 years (2000-2020) combined with geocoded flood event data. Our primary objectives are threefold: (1) to estimate the causal effects of floods on firm-level outcomes, including capital asset destruction, job losses, and wage depression; (2) to examine the dynamic nature of these impacts over time; and (3) to uncover heterogeneous effects across different industrial sectors.

We employ a quasi-experimental stacked difference-in-differences estimation approach that accounts for multiple flood events of varying intensities over time. By exploiting the quasi-random nature of flood events and constructing a carefully matched sample of industrial projects with identical ten-year flood histories, this approach allows us to isolate the causal effects of floods from confounding factors and unobserved heterogeneity. Our high-resolution geospatial data on flood events combined with a comprehensive panel of industrial assets enables us to study granular localized impacts up to ten years post-flood, offering insights that are often overlooked by studies relying on aggregate data.

Our study expands the frontiers of research on economic impacts of floods, providing novel insights into their long-term effects on industrial capital and labor in India. While previous studies have primarily focused on short-term impacts (Pelli et al., 2023) or specific sectors (Hossain, 2020), our comprehensive analysis reveals persistent and heterogeneous effects across multiple industries over a ten-year post-flooding period. Drawing on recent advances in the literature (Dube et al., 2023; Patel, 2024), we uncover significant heterogeneity in sector-specific responses to floods. Manufacturing and information technology experience substantial declines in capital and labor, while the financial sector shows positive effects, primarily reflecting increased loan portfolios for post-flood reconstruction. Unlike Pelli et al. (2023), who find evidence of systematic reallocation toward better-performing industries after cyclones, our results suggest that floods primarily drive sector-specific impacts with varying recovery patterns. These findings contribute to the ongoing debate on the "creative destruction" hypothesis (Leiter et al., 2009; Skidmore and Toya, 2002) and underscore the need for developing targeted adaptation strategies that account for industry-specific vulnerabilities.

The remainder of this paper is structured as follows. Section 2 provides an overview of the existing literature on the economic impacts of floods. Section 3 describes the unique dataset we have developed by combining geo-coded flood event data with industrial asset locations and construction data. Section 4 presents our quasi-experimental stacked difference-in-differences estimation strategy and the construction of a matched sample of industrial projects with similar flood histories. Section 5 discusses our main findings, including the overall impacts of floods on firm capital and labor, the dynamic effects over time, and the heterogeneous impacts across sectors. We conclude in Section 6 with implications for adaptation and mitigation scholarship and policy.

2 Existing Literature

The economic impacts of natural disasters, particularly floods, have received increasing attention as climate change intensifies their frequency and severity (Kousky, 2014; Hsiang, 2016; Botzen et al., 2019). These events cause immediate destruction of physical capital and infrastructure, with impacts distributed unequally across rich and poor economies (Grames et al., 2016; Hallegatte et al., 2016).

Recent sectoral studies have documented substantial heterogeneity in how industries respond to flood events (Hu et al., 2019). This heterogeneity is particularly relevant for India, where climate change is exacerbating flooding frequency and severity (Pörtner et al., 2022; Brunner et al., 2021; Gandhi et al., 2022). Firm-level analyses reveal significant reductions in output, capital, and employment among manufacturing establishments, particularly affecting low-productivity firms (Hossain, 2020).[1] Most recently, Pelli et al. (2023) find that tropical cyclones lead to temporary destruction of fixed assets and decreased sales, with evidence of capital reallocation toward better-performing industries.

The long-term impacts of floods on capital and labor vary significantly across sectors. While firms impacted by hydrogeological events show higher market exit rates and revenue declines (Clò et al., 2024), some studies document positive short-run effects on firm growth and employment, particularly for companies with larger shares of intangible assets (Leiter et al., 2009). Even when floods negatively impact manufacturing and retail sectors, they can stimulate growth in construction (Ashizawa et al., 2022).

Recent methodological advances using satellite remote sensing and geospatial data have enabled more precise mapping of flood impacts on industrial assets (Chang and Zheng, 2022; Rabano and Rosas, 2023). Moreover, studies emphasize how natural disasters propagate through supply chain networks, potentially generating indirect effects that exceed direct damages (Inoue and Todo, 2019; Kashiwagi et al., 2021). For example, the indirect supply chain effects of the 2011 Great East Japan earthquake (10.6% of GDP) substantially exceeded direct effects (0.5%), highlighting the importance of network effects in disaster impact assessment. Similarly, Hayakawa et al. (2015) showed that floods in Thailand significantly disrupted procurement patterns, particularly affecting small firms' local sourcing capabilities. Input-output frameworks have emerged as powerful tools for capturing these complex propagation effects (Galbusera and Giannopoulos, 2018; Di Noia et al., 2024).

3 Flood and Firm Data

3.1 India Flood Data

Our analysis employs the India Flood Inventory (IFI), the most comprehensive database of flooding events in India, which integrates and standardizes data from multiple sources spanning 1967-2019 (see Appendix A.2 for detailed data description). The IFI's key advantage is its geospatial format, providing flood event centroids that enable precise matching with firm facility locations. Each flood event record includes standardized attributes such as a unique identifier, temporal span, and coordinates of the centroids of affected areas. We additionally

[1] Similar impacts have been documented elsewhere, including in China (Pan and Qiu, 2022).

obtain the geo-coded flood vulnerability index for pan-India from the National Database for Emergency Management (NDEM, 2024).

Figure 1 illustrates the spatial distribution of flood risk and events: panel (A) maps India's flood vulnerability index (NDEM, 2024), panel (B) plots the locations of flood events from the IFI dataset, and panel (C) shows the time series of flood-affected firm facilities in our sample. While the IFI represents a significant improvement over previously available flood data for India, we acknowledge certain limitations in historical coverage and spatial precision (detailed in Appendix A.2), which we address through our empirical strategy.

3.2 Firm Data

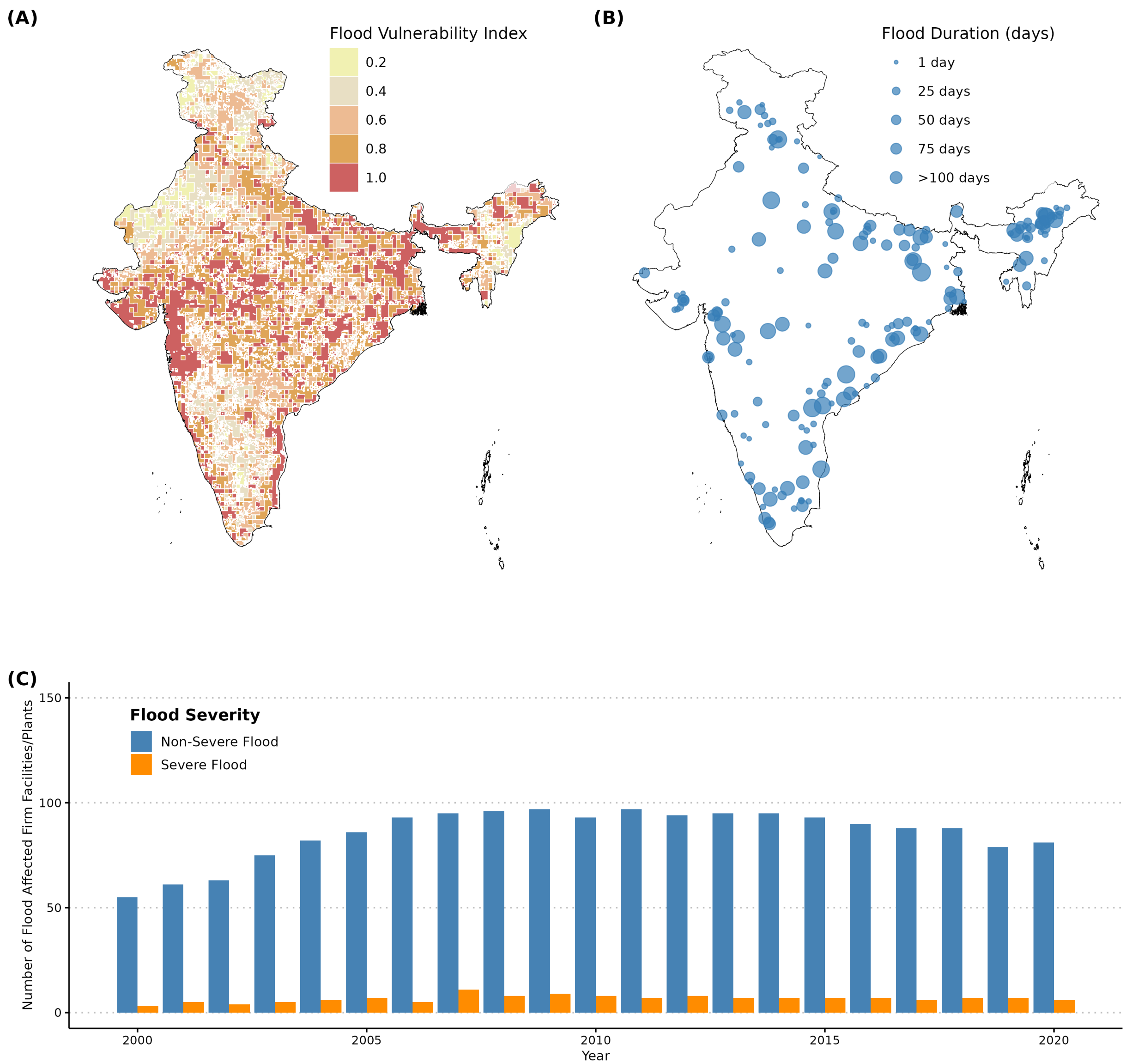
Our firm-level data come from two databases provided by the Centre for Monitoring Indian Economy (CMIE): Prowess$_{dx}$ and CapEx. Prowess$_{dx}$ provides comprehensive financial data including total assets, fixed assets, intangible assets, employment, and wages for over 40,000 Indian companies. CapEx offers detailed location information for capital investment projects, allowing us to map multiple facilities to each firm.

We cleaned and extracted data on 45,145 completed capital asset investment projects with latitude and longitude data from 2000 to 2021 from CapEx and mapped these to respective firm-level financial data from Prowess$_{dx}$. Our data preparation involved selecting privately owned firms, winsorizing data at the 0.5% level on key financial metrics, and dropping National Industrial Classification (NIC) industry divisions with fewer than 100 companies in each fiscal year. We further excluded NIC 4-digit industry codes with fewer than 30 companies in each fiscal year. The final sample of treated firm facilities matched with the "clean controls" in a ± 10 years window around the flood event consists of 57,426 firm-year observations spanning 2000 to 2021. Our final sample includes 166 flood events intersecting with firm facilities using a 10km distance criterion.

Figure 2 maps the geographical distribution of firm facilities color-coded by NIC industry division codes, and Table 1 presents summary statistics along key variable definitions.

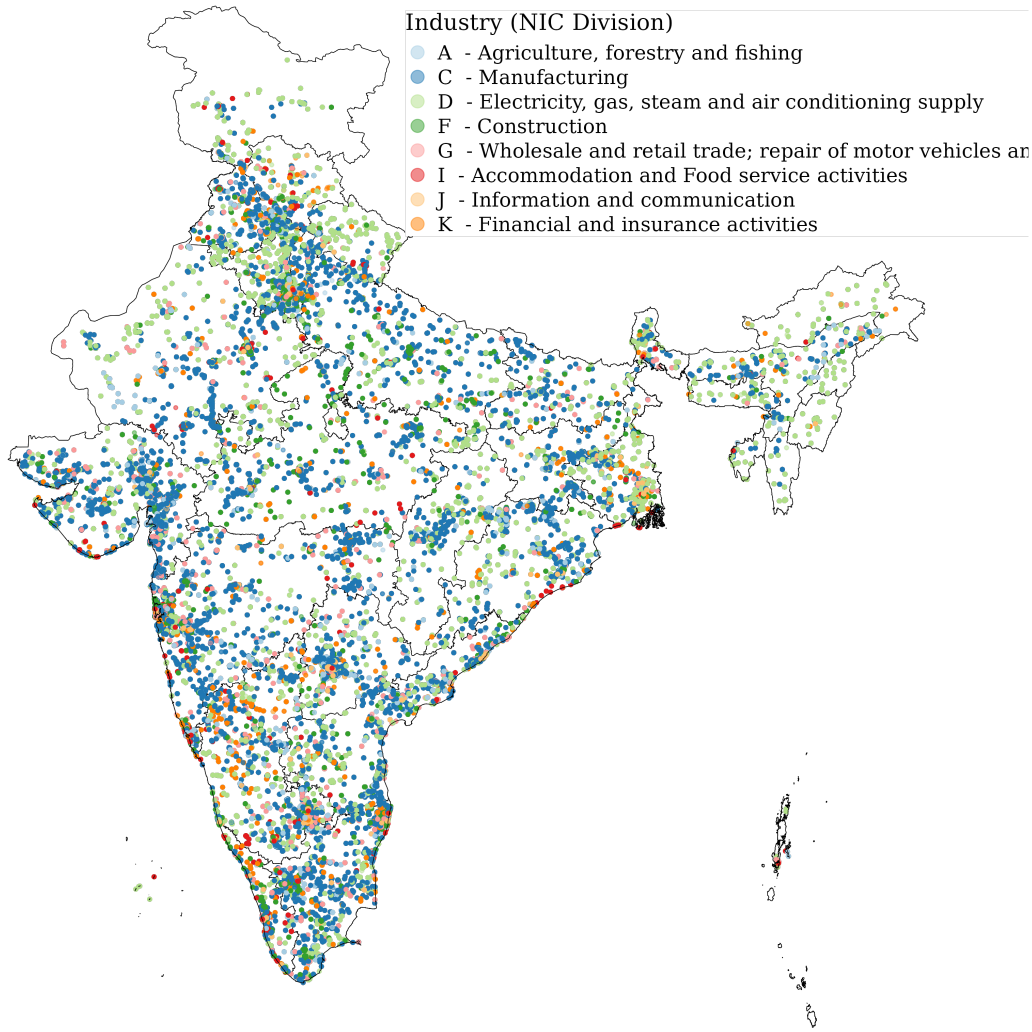
While the CMIE datasets provide rich and detailed information, they primarily cover formal sector firms and may exhibit some size bias towards larger firms. These limitations and additional caveats are discussed in detail in Appendix A.1.3.

Figure 1: Flood Vulnerability and Spatio-Temporal Distribution of Floods in India (2000-2020)



Note: Panel A shows the flood vulnerability index from the National Database for Emergency Management, with darker red indicating higher vulnerability (scale 0-1.0). Panel B maps flood events from the India Flood Inventory (IFI) database, with circle size proportional to flood duration (ranging from 1 to $>$ 100 days). Panel C presents the annual time series of flood events, distinguishing between severe floods (orange) and non-severe floods (blue) based on the Dartmouth Flood Observatory severity classification. We classify DFO severity class = 2 as a severe flood. The panels jointly illustrate the spatial variation in flood risk, the geographical distribution of actual flood events, and their temporal evolution over the study period.

Figure 2: Spatial Distribution of Industrial Assets in India (2000-2021)



Note: The map shows the geographical distribution of firm facilities in our sample, color-coded by National Industrial Classification (NIC) division codes. Each point represents a facility location from the CMIE CapEx database. The eight industry divisions shown reflect those with sufficient observations for statistical inference in our final sample: Agriculture, forestry and fishing (A), Manufacturing (C), Electricity, gas, steam and air conditioning supply (D), Construction (F), Wholesale and retail trade (G), Accommodation and food service activities (I), Information and communication (J), and Financial and insurance activities (K). The spatial pattern reveals significant clustering in major industrial regions while also showing broad geographical coverage across India.

Table 1: Summary Statistics of Key Variables

	N	Mean	SD	Units
Flood (Treatment)	57426	0.03	0.18	Dummy {0,1}
Flood Severity	57426	0.10	0.30	Dummy {0,1}
Total Assets	57426	29.67	98.25	INR billion
Fixed Assets	57253	6.59	28.52	INR billion
Intangible Assets	33620	0.45	3.78	INR billion
Num. of Employees	22078	15.74	36.66	Number Thousand
Total Wages	57033	7.98	37.76	INR billion
Total Executive Wages	34593	37.49	224.00	INR million
Total Sales	57426	23.24	83.53	INR billion
Debt to Equity Ratio	57426	1.34	3.59	Ratio
Cash Slack	57278	0.05	0.09	INR million
R&D to Sales	57426	0.00	0.03	Ratio
Advertising to Sales	57426	0.01	0.60	Ratio
Water Area	56865	5.98	9.19	Sq Km
Distance from River	56865	0.20	0.19	Km
Distance from Coast	56865	0.05	0.07	Km
Elevation	56865	372.87	346.33	Meters
Slope	56865	1.09	1.21	Degrees
Ruggedness	56865	19.76	20.70	Index
Geographical Area	57350	5040.61	5926.82	Sq Km
Flood Vulnerability Index	57402	0.60	0.26	Index

Note: Firm data is for the period 2000-2021. All financial variables are defined as per the accounting standards issued by the Institute of Chartered Accountants of India.

1. Total Assets : The sum of all current and non-current assets held by a company as on the last day of an accounting period.

2. Fixed Assets : Net value of the fixed assets of a company after cumulative depreciation on gross fixed assets.

3. Intangible Assets : An identifiable non-monetary asset, without physical substance, held for use in the production or supply of goods or services, usually includes the gross value of goodwill, and software systems. Some examples computer software, intellectual property,licenses, market access rights, brands, etc.

4. Total Wages: The total compensation to employees, reflects the total remuneration in cash or in kind paid by a company to or on behalf of all its employees. Compensation to employees comprises of salaries and wages and social security contributions.

5. Total Executive Wages: Remuneration paid to the company's executive directors. It forms a part of the total amount of compensation paid to employees.

6. Geographical variables like water area, distances to river and coast, elevation, slope, ruggedness, and geogrpahical area; corresponds to the disitrict in which the respective firm facility is located.

7. Flood Vulnerability Index: is obtained from the National Database for Emergency Management (NDEM, 2024).

8. Flood Severity: The three point classification (1, 1.5, 2) is obtained from the Dartmouth Flood Observatory, with valid observations for about 10% of sample. Dummy variable set to severe (1) for category 2 floods. Missing data also classified as non severe.

4 Estimation Strategy

We employ a stacked difference-in-differences (DiD) approach with carefully matched controls to overcome the limitations of traditional estimators when analyzing multiple flood events of varying intensities. By constructing event-specific cohorts of treated and control units, we avoid the bias that arises in traditional TWFE estimators when treatment timing varies and effects are heterogeneous. This is crucial for our setting where facilities face multiple flood events of varying intensities over time.

Following recent advances in the literature (Patel, 2024; Dube et al., 2023), our approach provides more credible estimates of flood impacts by explicitly accounting for treatment effect dynamics and heterogeneity, addressing key methodological challenges in the flood impact literature. This approach allows us to combine multiple flood events occurring at different times and locations into a unified and computationally efficient framework.

Let i index firms, j index individual facilities (a firm i can have multiple facilities), and t index time periods (years). The "treatment" variable $Flood_{j,t}$ equals 1 if facility j experienced a flood in period t and 0 otherwise. The outcome variable $Y_{i,t+\tau}$ denotes the firm-level outcome for firm i in period $t+\tau$, where τ traces out the impulse response function. The treatment status for a firm is defined as:

$$Flood_{j,t} = \begin{cases} 1 & \text{if facility } j \text{ experienced at least one flood in period } t \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

$$Flood_{i,t} = \max(Flood_{j,t}) \quad \text{for all } j \in J_i \tag{2}$$

where J_i is the set of all facilities belonging to firm i. A firm is considered treated if at least one of its facilities experiences a flood during a given period. A facility j is recorded as having experienced a flood if the centroid of a flood event intersects with a 10-kilometer radius[2] centered at the facility within the same period t (fiscal year). If a facility is exposed to multiple flood events in a given year, these events are treated as a single occurrence for the purpose of our analysis.

The traditional two-way fixed effects (TWFE) difference-in-differences estimator can suffer from negative weighting issues in settings with dynamic and heterogeneous treatment

[2] We additionally consider definitions of treatment based on circles of 20km, 30km, and 50km radial distances from the facility for robustness.

effects (de Chaisemartin and D'Haultfœuille, 2020; Goodman-Bacon, 2021). To address this concern, we follow the approach of Patel (2024) and construct a matched "clean control" stacked panel in the spirit of the local projection difference-in-differences (LP-DiD) estimator (Dube et al., 2023).

Corresponding to every treated facility, we construct a group of "clean controls" from a starting pool of untreated facilities in each period. To mitigate geographic spillovers, any control firm with a facility within 10 kilometers of a treated facility is excluded. Control facilities are matched to treated facilities based on identical flood history for the previous ten years ($Flood^{pre}_{i,t-1}$), ensuring that dynamic impacts from previous flooding exposure do not influence the results[3]. Control facilities are further restricted to those with similar expected flood risk as treated facilities by matching on the corresponding long-term flood vulnerability index of the location of the respective facilities. As an additional robustness check, we check the sensitivity of the estimates at varying flood definition distances of 5km, 10km, 20km, and 30km (Appendix A.4).

The causal effect of interest in our study is the average treatment effect on the treated (ATT), which captures the impact of experiencing a flood on firm-level outcomes over a range of τ from -10 to 10 years. The relevant firm-level outcomes include capital variables such as total assets, fixed assets, and intangible assets, as well as labor variables like total employment, employee wages, and executive wages. The ATT is given by the following equation:

$$\text{ATT}^{\tau} = \sum_{t} w_t \left(\mathbb{E}\left[Y^{T}_{i,t+\tau} - Y^{C}_{i,t+\tau} \,\middle|\, \text{Flood}_{i,t} = 1 \right] \right) \tag{3}$$

where $Y^{T}_{i,t+\tau}$ denotes the observed outcome for firm i at time $t+\tau$ if the firm is treated, and $Y^{C}_{i,t+\tau}$ denotes the counterfactual outcome if the firm is not treated. The weights w_t are proportional to group size and treatment variance, ensuring that larger and more variable cohorts have a greater influence on the estimated ATT. This approach allows us to capture the marginal impact of an additional flood irrespective of past inundation exposure. We estimate the causal effect of flood exposure on firm-level outcomes using the following empirical

[3] We use a circle of radius 100km from every facility in the sample to detect floods for the purpose of flood history construction. We create a flood history of ten years assuming no dynamic effects beyond this time window.

specification:

$$Y_{(i,t+\tau,y)} = \alpha + \sum_{\tau=-10}^{10} \beta_\tau \cdot Flood_{(i,t+\tau,y)} + \phi_i + \theta_{(s(i,y),t)} + \mathbf{X}(i,t) \cdot \lambda + \varepsilon(i,t+\tau,y) \tag{4}$$

where $Y_{(i,t+\tau,y)}$ represents firm-level outcomes, $Flood_{(i,t+\tau,y)}$ is the treatment indicator equal to 1 if firm i experiences a flood τ years from t (where $t = 0$ corresponds to year y), α is the constant term, ϕ_i represents firm fixed effects, $\theta_{(s(i,y),t)}$ represents stratum cohort by relative time fixed effects, $\mathbf{X}(i,t)$ represents a vector of firm-level control variables, and $\varepsilon(i,t+\tau,y)$ is the error term. The coefficients of interest, β_τ, represent the treatment effect of experiencing a flood τ years after the event. To estimate the cumulative impact of floods, we replace the individual horizon terms β_τ with an indicator for observations occurring after the treatment event ($\tau \geq 0$). This allows us to capture the overall impact of flood exposure over the post-flood period.

We further restructure the dynamic specification to estimate the average impact of floods on firm outcomes by categorizing $\tau < 0$ as the pre-flood period and $\tau \geq 0$ as the post-flood period:

$$\begin{aligned} Y_{(i,t)} = \alpha &+ \gamma_1 \cdot Post_{(i,t)} + \gamma_2 \cdot Flood_{(i,t)} + \gamma_3 \cdot (Post_{(i,t)} \times Flood_{(i,t)}) \\ &+ \phi_i + \theta_{(s(i,t))} + \mathbf{X}(i,t) \cdot \lambda + \varepsilon(i,t) \end{aligned} \tag{5}$$

Here, $Post_{(i,t)}$ is a binary variable equal to 1 if $\tau \geq 0$ and 0 if $\tau < 0$. The interaction term $Post_{(i,t)} \times Flood_{(i,t)}$ captures the differential impact of floods in the post-flood period. γ_1 measures the average difference in outcomes in the post-flood period for non-flooded firms, γ_2 measures the average difference in outcomes for flooded firms irrespective of timing, and γ_3 measures the average treatment effect of experiencing a flood in the post-flood period. Standard errors are clustered at the facility level to account for potential serial correlation and common shocks.

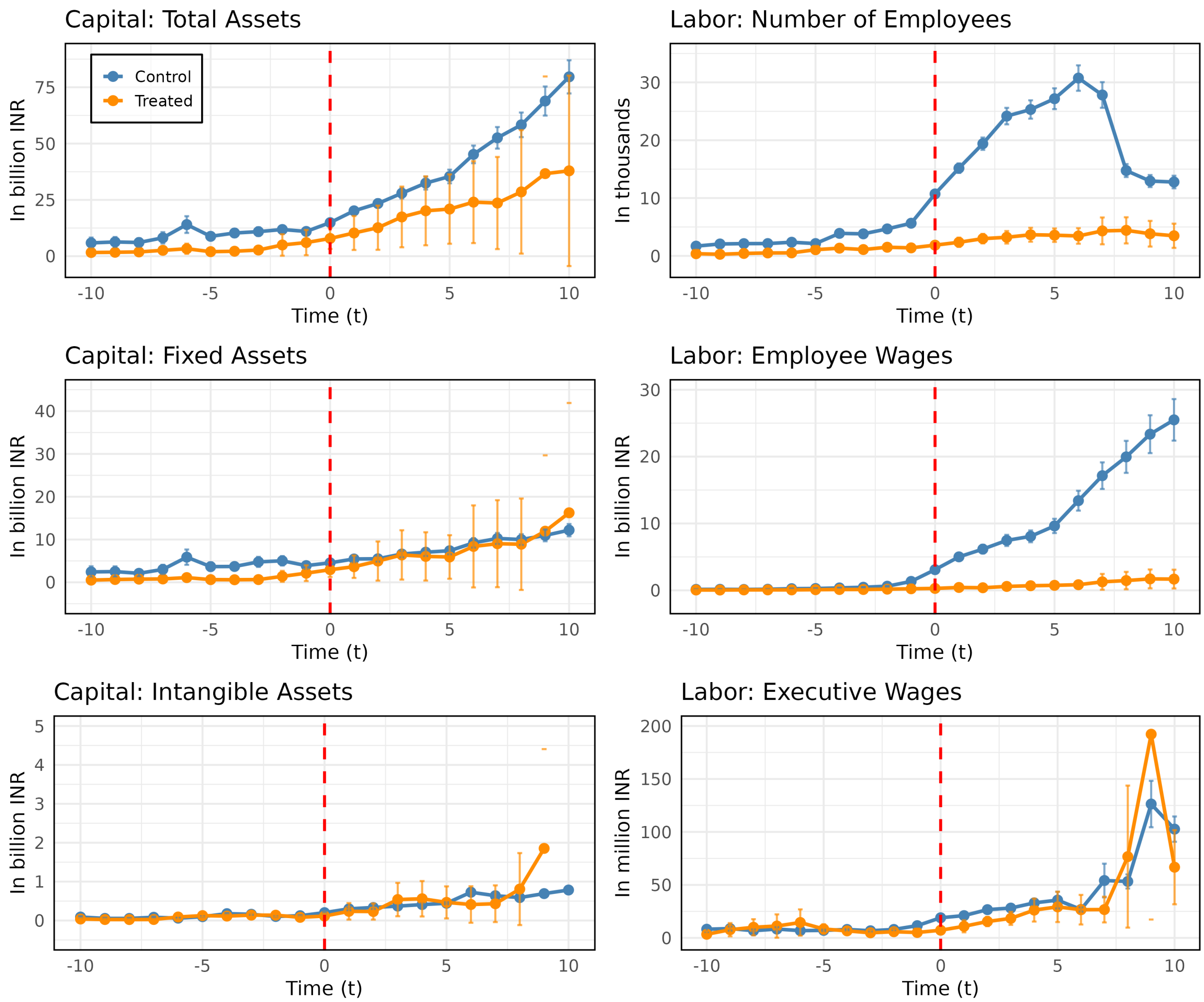
Our empirical strategy rests on two key assumptions: no anticipation and parallel trends. We employ a stacked difference-in-differences approach with "clean controls" to comply with these assumptions. While floods are generally unpredictable, firms in flood-prone areas might engage in anticipatory behavior like investing in flood defenses or diversifying assets geographically—a limitation we consider in our interpretation. For detailed methodology, see Appendix Sections A.1.1 and A.1.2.

The parallel trends assumption implies that flood-affected firms would have followed similar trajectories as unaffected firms absent treatment. This is supported by the quasi-random nature of floods (Dell et al., 2014; Patel, 2024), which affect firms based on geographic and meteorological factors rather than firm characteristics. Our matching on flood history and vulnerability substantially strengthens this assumption.

Figure 3 demonstrates our approach's effectiveness, showing aligned pre-treatment trends for treated and control firms across capital and labor outcomes. The close trend alignment before the flood event ($t = 0$) provides visual evidence, while a formal pre-treatment placebo test (Table A1) offers statistical support through insignificant 'Flooded (Placebo)' coefficients.

Despite the potential for any residual unobserved factors affecting flood likelihood and firm outcomes, our approach with "clean controls" and firm-level controls provides a robust framework for estimating causal impacts. This enhanced DiD method enables confident estimation of Average Treatment Effect on the Treated (ATT), contributing to the literature on causal inference with staggered treatment adoption.

Figure 3: Parallel Trends: Flooded (Treated) and Non-Flood (Control) Firms



Note: The figure plots mean outcomes for treated (orange) and control (blue) firms from 10 years before to 10 years after flood events (t=0, marked by vertical red dashed line). Error bars represent 95% confidence intervals. Capital outcomes (left panels) show trends in total assets, fixed assets, and intangible assets (in billion INR). Labor outcomes (right panels) show trends in employment (thousands), employee wages (billion INR), and executive wages (million INR). The parallel pre-trends between treated and control groups support the identification assumption of our difference-in-differences design. Control firms are matched on flood history and vulnerability within 100km radius but outside 10km of treated facilities.

5 Results: Flood Impacts on Firm Capital, Labor, and Sectoral Heterogeneity

5.1 Impact on Capital

5.1.1 Overall Impact

Our stacked difference-in-differences estimation reveals substantial negative impacts of flooding on firm capital (Table 2), with flooded firms experiencing an average annual decline in total assets of 16.68 billion INR ($\approx$ US$ 225 million at 2021 market exchange rate; $p < 0.01$) over the post-flood period—a 46.1% reduction relative to the sample mean. [4] Figure 5 Panel (A) strikingly illustrates this divergence, showing how treated firms' capital steadily declines post-flood while control firms continue their upward trajectory, with the gap widening to nearly 20 billion INR by $t + 10$. While the fixed assets impact aligns with previous findings on natural disasters (Pelli et al., 2023), the longer-lasting flood impacts likely reflect higher reconstruction costs and prolonged interruptions (Hallegatte et al., 2016).

5.1.2 Dynamic Effects

The effect on total assets intensifies gradually, becoming significant four years post-flood (-10.25 billion INR; $p < 0.05$) and reaching -14.58 billion INR ($p < 0.01$) by year six (Table A3). This persistent impact suggests compounding factors including reduced reinvestment capacity and heightened risk perceptions (Hsiang, 2016). Fixed assets show a lagged decline, significant four years post-flood (-3.08 billion INR; $p < 0.15$), reflecting gradual deterioration (Kreibich and Thieken, 2009). Intangible assets response remains volatile and statistically non-significant, possibly due to their potential for redeployment (Leiter et al., 2009). Figure 5 (Panel A) shows the predicted mean impact of floods on total assets over time, highlighting the gradual and persistent nature of the effects.

5.1.3 Heterogeneous Effects Across Sectors

Our analysis reveals substantial sectoral heterogeneity in flood impacts on capital (Table 3). The information and communication sector shows the largest decline (-43.50 billion INR per year; $p < 0.01$), raising questions about underestimated climate risks in this emerging

[4] In the remainder of this section, we only report figures in Indian Rupees, INR, that are easily converted using the benchmark used here.

sector. Manufacturing experiences significant losses (-8.18 billion INR; $p < 0.01$), reflecting supply chain vulnerabilities (Hossain, 2020), while utilities (electricity, gas, steam, and air conditioning supply) show substantial negative effects (-7.59 billion INR; $p < 0.01$), likely due to immobile infrastructure (Hallegatte et al., 2016).

The financial and insurance sector uniquely shows positive capital effects (9.67 billion INR, $p < 0.01$), primarily reflecting increased loan portfolios for post-flood reconstruction financing.[5] Construction shows a positive but insignificant impact (2.84 billion INR), possibly driven by rebuilding demand (Ashizawa et al., 2022), while other sectors exhibit smaller, insignificant impacts.

Figure 5 (Panel C) reveals heterogeneous geographical distribution of impacts on total assets, with predominant negative effects (orange shades) interspersed with positive effects (blue shades) in northern and central India. These patterns highlight the need for tailored policy responses and underscore how aggregate impacts may mask significant redistributional effects across industries and regions.

5.2 Impact on Labor

5.2.1 Overall Effects

Our analysis reveals significant impacts of floods on firm labor outcomes (Table 2). Flooded firms experience an average annual decline in employment of 8.20 thousand workers ($p < 0.01$) over the ten-year post-flood period—a 49.0% reduction relative to the sample mean. As visualized in Figure 5 Panel (B), this represents a dramatic divergence from control firms, with treated firms' employment falling sharply while control firms maintain stable employment levels, resulting in a persistent gap of approximately 10,000 workers.

The total wage bill shows a significant annual decrease of 5.52 billion INR ($p < 0.01$), representing a 74.5% decline relative to the sample mean. This decline, proportionally larger than the employment reduction, suggests floods affect both employment levels and wage rates. Executive wages also decline significantly (-11.65 million INR; $p < 0.01$), representing a 31.1% reduction relative to the sample mean and indicating that management bears substantial wage adjustment burden (Botzen et al., 2019).

[5]

5.2.2 Dynamic Effects

Employment impacts intensify gradually, becoming significant four years post-flood (-3.14 thousand workers, $p < 0.01$) and reaching -7.97 thousand workers ($p < 0.01$) by year six (Table A3). This lagged response suggests firms initially attempt to retain workers before implementing substantial layoffs, consistent with "wait-and-see" behavior (Bloom, 2009).

The wage bill shows immediate decline (-1.92 billion INR first year, $p < 0.01$), increasing to -2.98 billion INR ($p < 0.01$) by year five and -7.31 billion INR ($p < 0.01$) by year nine. The immediate wage impact coupled with gradual employment decline suggests initial combined wage-rate and employment adjustments, later dominated by layoffs (Bewley, 1998). Executive wages show delayed response, with significant impacts emerging from year three (-36.99 million INR, $p < 0.1$) through year seven (-15.27 million INR, $p < 0.05$), suggesting initial attempts to signal stability before accepting long-term adjustments. Figure 5 (Panel B) shows the predicted mean impact of floods on total employment over time.

5.2.3 Heterogeneous Effects Across Sectors

Sectoral analysis reveals substantial variation in labor impacts (Table 3). The information and communication sector experiences the largest wage decline (-18.06 billion INR; $p < 0.01$), highlighting unexpected vulnerability of knowledge-intensive industries to climate risks. Accommodation and food services show significant negative impacts (-0.56 billion INR; $p < 0.01$), reflecting sensitivity to local economic conditions, while utilities experience modest but significant wage declines (-0.11 billion INR; $p < 0.05$), possibly indicating shifts toward temporary workforce during reconstruction.

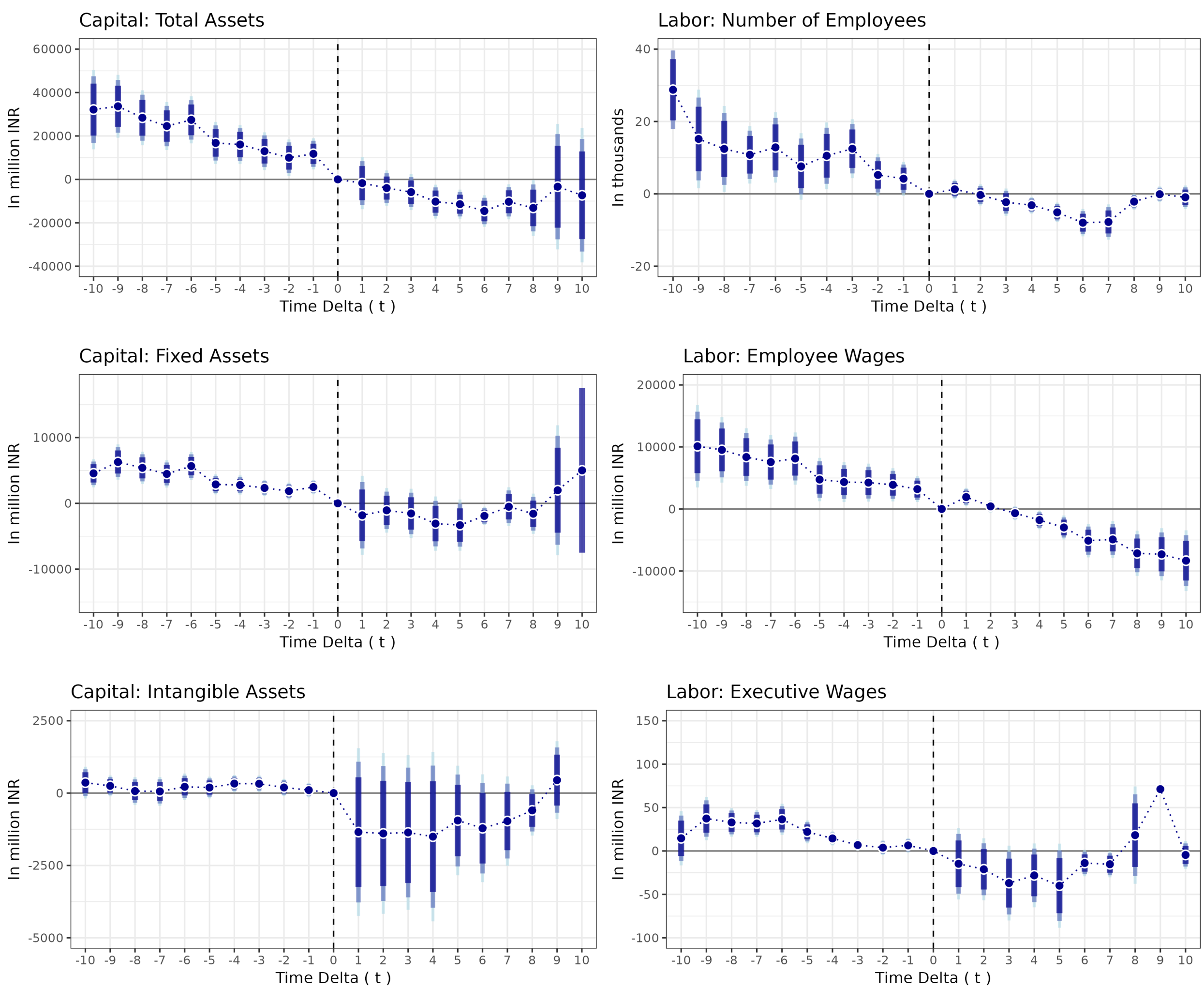
The construction sector shows positive but insignificant wage effects (0.04 billion INR), aligning with increased rebuilding demand (Ashizawa et al., 2022). Financial services exhibit minimal wage impact (-0.00 billion INR), suggesting employment resilience, while agriculture shows insignificant effects (0.03 billion INR), though our sample covers only formal enterprises.

Figure 5 (Panel D) shows that negative wage effects are more geographically widespread and uniform compared to asset impacts, suggesting direct and immediate flood effects on local labor markets.

5.3 Sensitivity Analysis

In the Appendix A.4, we examine the robustness of our results using varying flood exposure definitions (5 km, 10 km, 20 km, and 30 km thresholds). Results remain consistent across all distances. We also analyze differential impacts of severe floods using DFO severity classifications (see Appendix A.3.1).

Figure 4: Dynamics of Flood Impact on Capital and Labor



Note: The figure presents event study coefficients (β_τ) from the stacked difference-in-differences estimation (Eq. 4) for ten years before and after flood events (t=0, marked by vertical dashed line). Capital outcomes (left panels) show impacts on total assets, fixed assets, and intangible assets (in billion INR). Labor outcomes (right panels) show impacts on employment (thousands), employee wages (billion INR), and executive wages (million INR). Vertical bars represent 95% confidence intervals, with additional markers at 80% and 90% levels. All specifications include firm and year fixed effects, facility level clustering, and the full set of controls described in Table 2.

Table 2: Flooding impact on capital and labor

	Capital			Labor		
	Total Assets (INR billion)	Fixed Assets (INR billion)	Intangible Assets (INR billion)	Employ-ment (Number Thousand)	Employee Wages (INR billion)	Executive Wages (INR million)
Flooded x Post	-16.68***	-3.10***	-0.31***	-8.20**	-5.52***	-11.65***
	(5.12)	(0.71)	(0.11)	(3.42)	(1.86)	(3.86)
Flooded	12.25***	2.42***	0.27***	7.10**	4.06***	6.81**
	(3.88)	(0.54)	(0.10)	(3.08)	(1.41)	(2.65)
Post	-10.25***	-0.76	-0.26	-0.97	-2.60***	-13.85***
	(2.57)	(0.72)	(0.29)	(1.08)	(0.98)	(2.38)
Controls						
Firm Size	12.11***	2.03***	0.20***	5.14***	3.39***	15.74***
	(2.38)	(0.30)	(0.06)	(1.27)	(0.88)	(4.07)
Debt-to-Equity Ratio	0.16	0.29***	-0.00	0.17†	0.02	-0.80**
	(0.17)	(0.11)	(0.00)	(0.12)	(0.03)	(0.36)
R&D/Sales Ratio	-23.78	-1.08	-4.16**	-51.57	-23.72	476.89
	(57.46)	(7.19)	(1.93)	(44.32)	(27.28)	(421.16)
Advert./Sales Ratio	1.31***	0.13***	-2.83***	83.13**	0.42***	1.72***
	(0.29)	(0.04)	(1.09)	(32.51)	(0.11)	(0.44)
Water Area	-0.09	-0.03*	0.00	0.03†	-0.02	0.07
	(0.07)	(0.02)	(0.00)	(0.02)	(0.02)	(0.20)
Distance from River	-4.19	-0.20	-0.04	-2.96*	-0.94	3.50†
	(3.84)	(0.41)	(0.04)	(1.57)	(1.60)	(2.19)
Distance from Coast	-5.43	-3.20	0.11	6.80†	-1.53	-1.63
	(14.67)	(2.62)	(0.14)	(4.34)	(6.13)	(12.35)
Elevation	-0.01*	-0.00**	-0.00	-0.00	-0.00†	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Slope	10.43*	1.64**	0.06	6.39***	3.84†	4.19
	(6.13)	(0.75)	(0.05)	(2.42)	(2.52)	(4.00)
Ruggedness	-0.57†	-0.09**	-0.00	-0.37***	-0.21†	-0.20
	(0.36)	(0.04)	(0.00)	(0.14)	(0.15)	(0.24)
Flood Vulnerability Index	5.39†	0.61	-0.05	1.11	2.39*	-2.09
	(3.58)	(0.87)	(0.05)	(0.98)	(1.37)	(4.61)
Year Fixed Effects	✓	✓	✓	✓	✓	✓
Firm Fixed Effects	✓	✓	✓	✓	✓	✓
Num. Obs.	56841	56668	33415	21814	56448	34388
Adj. R2	0.700	0.769	0.222	0.840	0.692	0.284

Note: † : $p < 0.15$; *:$p < 0.1$; **:$p < 0.05$; ***:$p < 0.01$

This table presents estimates from the difference-in-differences specification in equation (5). The coefficient of interest is *Flooded* $\times$ *Post* (γ_3), representing the average treatment effect of flood exposure. All specifications include firm and year fixed effects. Standard errors are clustered at the project unit level

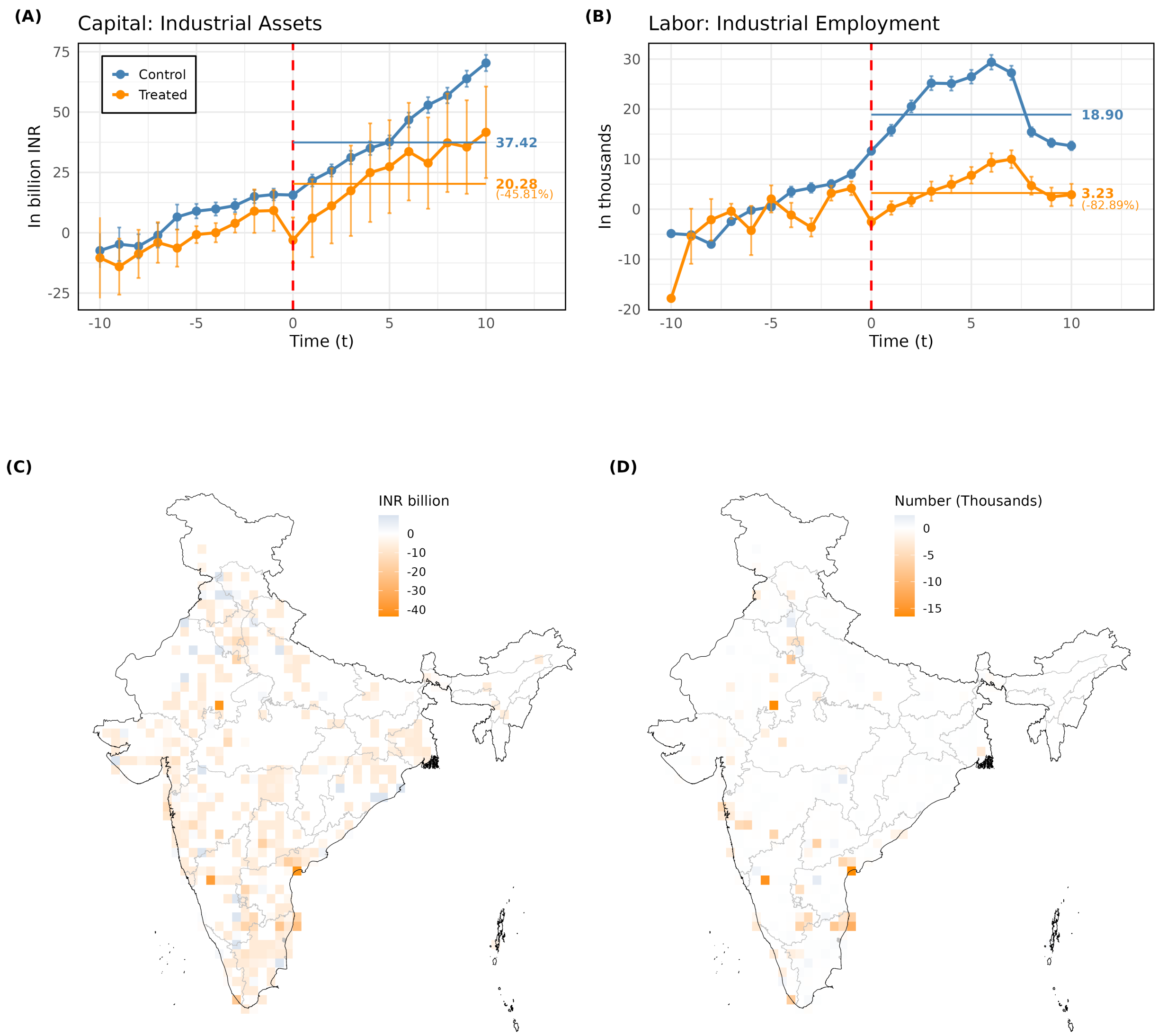
Table 3: Heterogenous impact on capital and labor by industry sector

	AGRI(A)	MANU(C)	ELEC(D)	CONS(F)	TRAD(G)	HOTL(I)	INFO(J)	FINS(K)
Capital: Total Assets (INR billion)								
Flooded x Post	-1.40	-8.18***	-7.59***	2.84	-1.48†	-5.47*	-43.50***	9.67***
	(1.53)	(2.68)	(2.57)	(24.93)	(0.99)	(2.84)	(15.47)	(2.77)
Flooded	1.24	5.78***	-14.68**	-1.22	1.03†	4.66*	30.78***	-7.57***
	(1.17)	(2.17)	(5.74)	(15.12)	(0.71)	(2.44)	(11.59)	(2.20)
Post	-2.62	-11.07***	2.31	5.59	0.31	0.43	-21.47†	-0.35
	(3.87)	(3.25)	(2.75)	(4.99)	(0.26)	(2.17)	(13.90)	(0.78)
All Controls	✓	✓	✓	✓	✓	✓	✓	✓
Firm Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Year Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Num. Obs.	1201	24235	927	2804	3233	3705	15275	5461
Adj. R2	0.721	0.726	0.962	0.758	0.793	0.872	0.727	0.921
Labor: Total Wages (INR billion)								
Flooded x Post	0.03	-0.11	-0.11**	0.04	-0.09	-0.56***	-18.06***	-0.00
	(0.11)	(0.09)	(0.05)	(0.15)	(0.09)	(0.18)	(6.39)	(0.03)
Flooded	-0.00	0.05	-0.59*	-0.09	0.06	0.47***	12.69***	0.01
	(0.10)	(0.08)	(0.31)	(0.15)	(0.06)	(0.16)	(4.78)	(0.02)
Post	-0.02	-0.34***	0.04	0.36	0.03	-0.02	-5.56	-0.02
	(0.12)	(0.10)	(0.05)	(0.36)	(0.02)	(0.13)	(6.36)	(0.02)
All Controls	✓	✓	✓	✓	✓	✓	✓	✓
Firm Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Year Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Num. Obs.	1179	24215	892	2775	3214	3672	15080	5421
Adj. R2	0.903	0.763	0.918	0.764	0.731	0.896	0.741	0.886

Note:† : $p < 0.15$; *:$p < 0.1$; **:$p < 0.05$; ***:$p < 0.01$; Standard errors are clustered at the project unit level

NIC Industry Division codes : AGRI(A) Agriculture, forestry and fishing, MANU(C) Manufacturing, ELEC(D) Electricity, gas, steam and air conditioning supply,CONS(F) Construction, TRAD(G) Wholesale and retail trade, HOTL(I) Accommodation and Food service activities, INFO(J) Information and communication, FINS(K) Financial and insurance activities. The included eight industry sectors are based on sufficient observations for reliable statistical inference in the final sample.

Figure 5: Predicted Spatio-Temporal Impact of Flood on Firm Capital and Labor



Note: The predictions are based on estimated model coefficients presented in Table 2. The spatial distribution of mean predicted impact is shown at a grid size of about 60 sqkm estimated from all available firms-facility locations in the data panel. Error bars represent the 95% confidence intervals.

6 Object Lessons for Adaptation & Mitigation

Our study reveals significant negative impacts of floods on industrial capital and labor in India, with heterogeneous effects across sectors, highlighting the need for targeted climate change adaptation and resilience policies. The heterogeneous effects underscore the complex relationship between climate shocks and socio-economic outcomes, with some sectors experiencing persistent declines while others display resilience or positive effects. These differential impacts contribute to the broader literature on economic responses to natural disasters and the "creative destruction" hypothesis (Skidmore and Toya, 2002; Leiter et al., 2009).

Moreover, our findings challenge the assumption of short-term capital destruction and rapid labor market equilibration after climate shocks. Using an expanded ten-year analysis window, we document persistent disequilibria in local capital cycles and labor markets (Pelli et al., 2023), aligning with literature on hysteresis effects of large economic shocks (Martin, 2012).

The heterogeneous impacts across sectors indicate that a one-size-fits-all approach to climate change adaptation and mitigation will prove ineffective (Ashizawa et al., 2022). Our results highlight the need for targeted policies that account for specific vulnerabilities and adaptive capacities of different industries, particularly in regions prone to recurring floods where cumulative effects can compound over time.

Our findings underscore the importance of developing comprehensive risk assessment frameworks that incorporate long-term flood impacts on industrial assets and labor markets. Policymakers should prioritize the collection and dissemination of high-resolution geospatial data to facilitate accurate risk mapping and informed decision-making (Chang and Zheng, 2022). This information can guide land-use planning, infrastructure development, and resource allocation for flood prevention and mitigation.

The persistent nature of flood impacts necessitates long-term support mechanisms for affected firms and workers. These may include subsidized disaster loans, tax incentives for capital reinvestment, and targeted skill development programs. Dedicated funds for post-disaster reconstruction and recovery efforts should focus on supporting vulnerable small and medium-sized enterprises.

While our estimates capture significant direct effects of floods on firm capital and labor, they likely represent lower bounds of total economic impacts, as they do not account for potential amplification through supply chain networks (Lyu et al., 2023). Our granular firm-level analysis provides a crucial foundation, but future research combining our approach with input-output frameworks could provide insights into flood impacts propagating through industrial chains. The integration of supply chain perspectives could enhance our understanding of how flood impacts cascade through the economy and inform comprehensive disaster risk management strategies.

The integration of geospatial data and econometric techniques offers potential for improved monitoring and evaluation of climate change adaptation policies. This approach enables evidence-based decision-making to optimize resource allocation. Future research should incorporate additional dimensions of industrial heterogeneity, investigate spillover effects, and explore how institutional factors and regional policy variations shape resilience to floods.

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References

T. Ashizawa, N. Sudo, and H. Yamamoto. How Do Floods Affect the Economy? An Empirical Analysis using Japanese Flood Data. Working Paper 22-E-6, Bank of Japan, 2022. Number: 22-E-6 Publisher: Bank of Japan.

T. F. Bewley. Why not cut pay? *European Economic Review*, 42(3):459–490, May 1998.

N. Bloom. The Impact of Uncertainty Shocks. *Econometrica*, 77(3):623–685, 2009.

W. J. W. Botzen, O. Deschenes, and M. Sanders. The Economic Impacts of Natural Disasters: A Review of Models and Empirical Studies. *Review of Environmental Economics and Policy*, 13(2):167–188, 2019.

M. I. Brunner, D. L. Swain, R. R. Wood, F. Willkofer, J. M. Done, E. Gilleland, and R. Ludwig. An extremeness threshold determines the regional response of floods to changes in rainfall extremes. *Communications Earth & Environment*, 2(1):1–11, 2021.

P.-L. Chang and F. Zheng. Using satellite-observed geospatial inundation data to identify the impacts of flood on firm-level performances: The case of China during 2000–2009. Singapore Management University Working Paper 11-2022, 2022.

S. Clò, F. David, and S. Segoni. The impact of hydrogeological events on firms: Evidence from Italy. *Journal of Environmental Economics and Management*, 124:102942, 2024.

C. de Chaisemartin and X. D'Haultfœuille. Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects. *American Economic Review*, 110(9):2964–2996, Sept. 2020.

M. Dell, B. F. Jones, and B. A. Olken. What Do We Learn from the Weather? The New Climate-Economy Literature. *Journal of Economic Literature*, 52(3):740–798, 2014.

J. Di Noia, A. Caiani, L. Cesarini, and B. Monteleone. A high resolution input-output model to assess the economic impact of floods, feb 2024.

A. Dube, D. Girardi, O. Jorda, and A. M. Taylor. A Local Projections Approach to Difference-in-Differences, Apr. 2023.

L. Galbusera and G. Giannopoulos. On input-output economic models in disaster impact assessment. *International Journal of Disaster Risk Reduction*, 30:186–198, sep 2018. ISSN 2212-4209.

S. Gandhi, M. E. Kahn, R. Kochhar, S. Lall, and V. Tandel. Adapting to Flood Risk: Evidence from a Panel of Global Cities, June 2022.

A. Goodman-Bacon. Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, 225(2):254–277, 2021.

J. Grames, A. Prskawetz, D. Grass, A. Viglione, and G. Blöschl. Modeling the interaction between flooding events and economic growth. *Ecological Economics*, 129:193–209, 2016.

D. Guha-Sapir, D. Hargitt, and P. Hoyois. *Thirty Years of Natural Disasters 1974-2003: The Numbers*. Presses Univ. De Louvain, 2004. ISBN 978-2-930344-71-3.

S. Hallegatte, A. Vogt-Schilb, M. Bangalore, and J. Rozenberg. *Unbreakable: Building the Resilience of the Poor in the Face of Natural Disasters*. World Bank Publications, 2016.

K. Hayakawa, T. Matsuura, and F. Okubo. Firm-level impacts of natural disasters on production networks: Evidence from a flood in thailand. *Journal of the Japanese and International Economies*, 38:244–259, dec 2015. ISSN 0889-1583.

F. Hossain. Creative Destruction or Just Destruction? Effects of Floods on Manufacturing Establishments in India, 2020.

S. Hsiang. Climate Econometrics. *Annual Review of Resource Economics*, 8(Volume 8, 2016): 43–75, 2016. Publisher: Annual Reviews.

X. Hu, R. Pant, J. W. Hall, S. Surminski, and J. Huang. Multi-Scale Assessment of the Economic Impacts of Flooding: Evidence from Firm to Macro-Level Analysis in the Chinese Manufacturing Sector. *Sustainability*, 11(7):1933, 2019.

H. Inoue and Y. Todo. Firm-level propagation of shocks through supply-chain networks. *Nature Sustainability*, 2(9):841–847, sep 2019. ISSN 2398-9629.

Y. Kashiwagi, Y. Todo, and P. Matous. Propagation of economic shocks through global supply chains—evidence from hurricane sandy. *Review of International Economics*, 29(5): 1186–1220, 2021. ISSN 1467-9396.

C. Kousky. Informing climate adaptation: A review of the economic costs of natural disasters. *Energy Economics*, 46:576–592, Nov. 2014.

H. Kreibich and A. H. Thieken. Coping with floods in the city of Dresden, Germany. *Natural Hazards*, 51(3):423–436, 2009.

A. M. Leiter, H. Oberhofer, and P. A. Raschky. Creative Disasters? Flooding Effects on Capital, Labour and Productivity Within European Firms. *Environmental and Resource Economics*, 43(3):333–350, 2009.

Y. Lyu, Y. Xiang, and D. Wang. Evaluating indirect economic losses from flooding using input–output analysis: An application to china's jiangxi province. *International Journal of Environmental Research and Public Health*, 20(5):4509, mar 2023.

R. Martin. Regional economic resilience, hysteresis and recessionary shocks. *Journal of Economic Geography*, 12(1):1–32, 2012.

NDEM. Flash Flood Vulnerability Index India - National Database For Emergency Management, 2024.

X. Pan and B. Qiu. The impact of flooding on firm performance and economic growth. *PLoS ONE*, 17(7):e0271309, July 2022.

D. Patel. Floods. Working Paper, Harvard University, 2024.

M. Pelli, J. Tschopp, N. Bezmaternykh, and K. M. Eklou. In the eye of the storm: Firms and capital destruction in India. *Journal of Urban Economics*, 134:103529, 2023.

H.-O. Pörtner, D. C. Roberts, M. M. B. Tignor, E. S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, and B. Rama, editors. *Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change.* IPCC, 2022.

A. Rabano and J. N. Rosas. The Transmission of Climate Shocks: The Case of Floods in India. Working Paper, 2023.

M. Skidmore and H. Toya. Do Natural Disasters Promote Long-Run Growth? *Economic Inquiry*, 40(4):664–687, 2002.

Washed Away: Industrial Capital, Labor, and Floods

Online Supplement

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A Appendix

A.1 Data Construction

A.1.1 Firm-level Data: CMIE PROWESS and CAPEX Datasets

Dataset Descriptions

Our firm-level data are sourced from two main databases provided by the Centre for Monitoring Indian Economy Pvt. Ltd. (CMIE): Prowess$_{dx}$ and CapEx.

Prowess$_{dx}$[6] is a comprehensive database of the financial performance of companies, constructed from annual and quarterly statements of companies. It is the largest dataset on the financial performance of Indian firms and includes detailed information on firm-level product mix and sales. The data are standardized and free from deliberate survival bias. Prowess$_{dx}$ covers over 40,000 Indian companies, including listed companies, unlisted public companies, and private companies of all sizes and ownership groups. This database provides detailed financial data on firms that we use for analysis including total assets, fixed assets, intangible assets, total employment, employee wages, and executive wages.

CapEx[7] is a crucial component of our study, providing detailed data on capital investment projects with precise location information. This database contains details on over 60,000 continuously monitored projects, in various stages of completion. For our analysis, we specifically utilize the location data of completed projects to identify the physical locations of firm facilities or plants.

The CapEx database is particularly valuable because it allows us to map multiple facilities or plants to each firm. This granular location data is essential for our study as it enables us to: (1) Precisely identify which firm facilities were exposed to flood events. (2) Account for the multi-plant nature of many firms in our sample, allowing for a more nuanced analysis of flood impacts. (3) Capture potential heterogeneity in flood exposure and impacts across different facilities of the same firm. (4) Construct more accurate measures of firm-level flood exposure by aggregating facility-level exposures.

Each project entry in the CapEx database includes latitude and longitude coordinates, allowing us to geocode the exact locations of firm facilities. This level of detail is crucial for our spatial analysis, enabling us to match flood event data with firm locations at a high level of precision.

We extracted data on 96,893 completed capital asset investment projects with latitude

[6] https://prowessdx.cmie.com/

[7] https://www.cmie.com/kommon/bin/sr.php?kall=wproducts&tabno=7010&prd=capex

and longitude data from 1969 to 2023 from CapEx. These projects were then mapped to their respective firms using unique company identifiers, allowing us to link the location data from CapEx with the financial data from Prowess$_{dx}$. This mapping process results in a rich dataset where each firm can have multiple associated locations, reflecting the reality of multi-plant operations for many companies in our sample.

The combination of Prowess$_{dx}$ and CapEx data provides us with a unique dataset that combines detailed financial information with precise location data for multiple facilities per firm. This allows for a more comprehensive analysis of flood impacts on firm outcomes, taking into account the spatial distribution of firm operations and the potential for differential exposure to flood events across a firm's various facilities.

Data Pre-processing

Our sample construction involved several sequential steps:

1. Initial Data Extraction:
   - Extracted 96,893 completed capital asset investment projects from CapEx (1969-2023)
   - Mapped these to firm-level financial data from Prowess$_{dx}$ (September 2023 vintage)
   - Restricted to 2000-2021 period: 45,145 facilities/plants
2. Ownership and Data Quality Filters:
   - Selected privately owned firms only (excluding state-owned enterprises)
   - Winsorized at 0.5% level for sales, assets, and debt-to-equity ratios
   - Resulting sample: 79,872 stacked firm-year observations
3. Industry Coverage Requirements:
   - Dropped NIC industry divisions with < 100 companies per fiscal year
   - Further excluded 4-digit NIC codes with < 30 companies per year
   - Remaining sample: 77,423 stacked firm-year observations
4. Final Analysis Sample Construction:
   - Created ± 10 year windows around each flood event

- Applied 10km flood exposure criterion
- Matched with "clean controls" (detailed in Appendix A.1.2)
- Final analysis sample: 57,426 stacked firm-year observations
- Represents 2,489 treated facilities (1,462 unique firms) and matched controls
- Covers 166 distinct flood events

5. Sector Coverage:

- Final sample spans 8 major industry divisions
- Detailed sector-wise composition presented in Table 3

Clean Control Creation

A crucial step in our empirical strategy is the creation of a "clean control" group for each treated facility. This process is designed to address potential biases arising from dynamic treatment effects and differences in underlying flood risk. Our approach, similar to Patel (2024), involves several key steps:

Identification of Treated Facilities: We first identified all facilities exposed to flood events within a 10km radius during our study period. These facilities form our treatment group.

Initial Control Pool: For each treated facility, we created an initial pool of potential control facilities from all untreated facilities in the same period and within 100 kilometers radius of the affected plant. Additionally, to mitigate geographic spillovers, we excluded any facility within 10 kilometers of any treated facility from this pool.

Flood History Matching: We implemented a novel flood history matching procedure, Patel (2024), to ensure that control facilities had identical flood exposure histories as treated facilities for the previous ten years. This step is crucial for isolating the effect of the current flood event from any lingering effects of past floods. We represented each facility's flood history as a binary string of length 10, where each position represents a year and '1' indicates flood exposure, '0' indicates no exposure. For example, "0001000100" would represent a facility exposed to floods 3 and 7 years ago in a 10-year history.

String Pattern Matching: We used a string pattern matching algorithm to identify control facilities with identical flood history strings as each treated facility. This ensures that our control group has experienced the same pattern of flood events in the recent past as our treatment group, up until the current treatment period.

Flood Risk Matching: To further refine our control group, we matched facilities based on their long-term flood vulnerability index. This step ensures that control facilities have similar underlying flood risk as treated facilities, helping to control for any unobserved factors related to flood-prone locations that might affect firm outcomes.

Stacked Panel Construction: For each flood event in our sample, we created a separate "mini-panel" consisting of the treated facilities and their matched controls. These mini-panels were then stacked to create our final dataset. This stacked structure allows us to analyze multiple flood events simultaneously while maintaining the integrity of our control group for each event.

This clean control creation process resulted in a final stacked panel of 57,659 firm-year observations, representing 2,489 treated plants/facilities (mapped to 1,462 unique firms) and their corresponding controls across 166 flood events. The clean control panel represents a diverse cross-section of Indian private firms, spanning 8 NIC industry divisions. By carefully constructing this control group, we aim to isolate the causal effect of flood exposure on firm outcomes, controlling for both observable and unobservable factors related to flood history and risk.

The use of this clean control methodology enhances the reliability of our difference-in-differences estimates by ensuring that our control group provides a credible counterfactual for the treated facilities. It addresses concerns about parallel trends assumptions and allows us to more confidently attribute observed differences in outcomes to the flood events themselves, rather than to pre-existing differences or confounding factors.

A.1.2 Enhancing Difference-in-Differences: The Stacked Clean Control Approach

Our empirical strategy builds upon and enhances the conventional Difference-in-Differences (DiD) methodology, drawing inspiration from recent advancements in econometric literature, particularly the work of Dube et al. (2023) on local projections and Patel (2024) on flood impact analysis.

The traditional two-way fixed effects (TWFE) DiD estimator can suffer from negative weighting issues in settings with dynamic and heterogeneous treatment effects (de Chaisemartin and D'Haultfœuille, 2020; Goodman-Bacon, 2021). To address these concerns, we employ a stacked DiD approach with clean controls, which offers several key advantages:

1. Addressing Dynamic Treatment Effects: By constructing event-specific clean control groups, we avoid the pitfalls associated with using previously treated units as controls. This is particularly crucial in our context, where the effects of floods may persist over time and influence future outcomes.

2. Heterogeneity in Treatment Timing: Our approach allows for the incorporation of multiple treatment periods, effectively dealing with the staggered adoption of treatment (in our case, flood occurrences at different times) that can bias conventional TWFE estimators.

3. Improved Counterfactual Construction: The clean control methodology ensures that our control group provides a credible counterfactual for the treated facilities. By matching on flood history and vulnerability, we control for both observable and unobservable factors related to flood risk and historical exposure.

4. Flexibility in Event Study Design: Following Dube et al. (2023), our approach allows for a flexible event study design that can accommodate varying pre- and post-treatment windows. This is particularly valuable for examining the dynamic effects of floods over time. The stacked structure of our dataset enables us to analyze multiple flood events simultaneously, providing a more comprehensive understanding of flood impacts on firm outcomes.

5. Robustness to Treatment Effect Heterogeneity: The stacked structure of our dataset, combined with the clean control approach, makes our estimates more robust to heterogeneity in treatment effects across different flood events and locations.

6. Mitigation of Spillover Effects: By excluding nearby facilities from the control group, we reduce the risk of contamination from spatial spillovers, which could bias our estimates of the flood impacts.

7. Enhanced Parallel Trends Validity: The stringent matching on flood history and vulnerability substantially strengthens the parallel trends assumption underlying DiD designs, as treated and control units are more likely to have followed similar trajectories in the absence of treatment.

The effectiveness of our stacked clean control approach in satisfying the parallel trends assumption, crucial for the validity of DiD estimates, is visually demonstrated in Figure 3. This figure illustrates the pre-treatment trends for both treated (flooded) and control (non-flooded) firms across various capital and labor outcomes. The close alignment of trends prior to the flood event ($t = 0$) provides strong visual evidence supporting the parallel trends assumption. Furthermore, Table A1 presents the results of a formal pre-treatment placebo test. The insignificant coefficients for the 'Flooded (Placebo)' variable across all outcome measures in the pre-treatment period offer statistical support for the parallel trends assumption. Together, these visual and statistical examinations reinforce the robustness of our empirical strategy and the credibility of our subsequent causal estimates of flood impacts on firm outcomes.

This enhanced DiD approach allows us to estimate the Average Treatment Effect on the Treated (ATT) with greater confidence, providing a more nuanced and accurate picture of how floods impact firm outcomes over time. By addressing the limitations of conventional DiD methods, we aim to produce more reliable and policy-relevant estimates of flood impacts on Indian firms. Our approach not only contributes to the growing literature on causal inference in settings with staggered treatment adoption but also provides a framework that can be adapted to study other natural disasters or economic shocks with similar spatiotemporal characteristics.

A.1.3 Dataset Limitations and Caveats

While the CMIE Prowess$_{dx}$ and CapEx datasets provide rich and detailed information, it's important to acknowledge their limitations and the caveats associated with their use in our study:

Prowess$_{dx}$ Limitations:

1. Non-representativeness: The dataset primarily covers formal sector firms and may not be fully representative of the entire Indian economy, particularly the informal sector.

2. Survivorship bias: While Prowess$_{dx}$ is designed to be free from deliberate survival bias, there may still be some inherent bias towards surviving firms, potentially under-representing firms that have ceased operations.

3. Reporting lags: There can be delays in updating information for some firms, particularly for the most recent years.

4. Missing data: Some variables may have missing values for certain firms or years, which could lead to uneven sample sizes across different analyses.

5. Size bias: Larger firms are likely to be overrepresented in the dataset compared to smaller firms, potentially skewing our results towards the experiences of larger, more established companies.

CapEx Project-Level Data Limitations:

1. Incomplete coverage: While the CapEx database covers a large number of projects, it may not capture all capital investments made by firms, particularly smaller-scale projects or those in certain sectors.

2. Project-to-facility mapping: The database records capital investment projects, which may not always correspond one-to-one with operational facilities. Some projects may involve expansions or upgrades to existing facilities rather than new establishments.

3. Temporal mismatch: The timing of project completion in the CapEx database may not perfectly align with the operational start date of a facility, potentially leading to some imprecision in the timing of flood exposure relative to facility operations.

4. Selection bias: Firms that undertake large, reportable capital projects (and thus appear in the CapEx database) may systematically differ from those that don't, potentially biasing our sample towards more capital-intensive or rapidly growing firms.

5. Location precision: While the database provides latitude and longitude coordinates, the precision of these coordinates may vary, especially for older projects or those in less developed areas.

Caveats for This Study: Given these limitations, several caveats should be considered when interpreting our results:

1. Generalizability: Our findings may be most applicable to formal sector, relatively large firms in India. Caution should be exercised when extrapolating results to smaller firms or the informal sector.

2. Facility-level versus firm-level effects: While we use facility locations to determine flood exposure, our outcome variables are at the firm level. This aggregation may mask heterogeneous effects across different facilities of the same firm.

3. Potential underestimation of impacts: If flood-affected firms are more likely to exit the market (and thus drop out of our sample), our estimates may understate the true impact of floods.

4. Timing of effects: Due to potential lags in reporting and the nature of the CapEx data, the timing of observed effects may not precisely match the actual timing of flood impacts on operations.

5. Spatial precision: While we use a 10km radius to determine flood exposure, the actual area affected by a flood may vary. This could lead to some imprecision in our treatment assignment.

6. Capital intensity bias: Our sample may be biased towards more capital-intensive firms, potentially overstating the importance of physical capital in flood impacts relative to other factors.

Despite these limitations and caveats, the combined Prowess$_{dx}$ and CapEx dataset remains one of the most comprehensive and detailed sources of firm-level data available for India. By acknowledging these issues and interpreting our results with appropriate caution, we can still derive valuable insights into the impacts of floods on Indian firms. Future research using complementary data sources or alternative methodologies could help address some of these limitations and further validate our findings.

A.2 Flood Data: Sources, Construction, and Limitations

A.2.1 Historical Context and Data Sources

The India Flood Inventory (IFI) addresses significant historical gaps in systematic flood data collection for India. Prior to the IFI, researchers relied primarily on three imperfect sources:

1. *Disastrous Weather Events (DWE)*: Published by the Indian Meteorological Department since 1967, this source provided comprehensive coverage but was available only in print format, limiting computational analysis.

Table A1: Pre-Treatment Placebo Test of Parallel Trends

	Capital			Labor		
	Total Assets (INR billion)	Fixed Assets (INR billion)	Intangible Assets (INR billion)	Employment (Number Thousand)	Employee Wages (INR billion)	Executive Wages (INR million)
Flooded (Placebo)	-0.25	-0.10	0.00	-0.04	-0.00	-0.30
	(0.20)	(0.11)	(0.00)	(0.04)	(0.01)	(0.25)
Controls						
Firm Size	3.04***	2.41***	0.00	0.69***	0.12***	1.99***
	(1.04)	(0.75)	(0.01)	(0.18)	(0.03)	(0.55)
Debt-to-Equity Ratio	0.36	0.68†	0.00	-0.06*	-0.00	0.11
	(0.50)	(0.42)	(0.00)	(0.04)	(0.01)	(0.28)
R&D/Sales Ratio	6.20***	3.73***	1.65**	105.39**	0.14	2.12**
	(2.37)	(1.16)	(0.70)	(53.54)	(0.11)	(1.06)
Advert./Sales Ratio	0.35	0.19	0.17	2.58	0.02***	0.26**
	(0.31)	(0.18)	(0.35)	(5.99)	(0.00)	(0.11)
Water Area	-0.16	-0.08	-0.00†	-0.00	-0.00†	0.00
	(0.11)	(0.06)	(0.00)	(0.01)	(0.00)	(0.05)
Distance from River	-2.03†	-1.44†	-0.01	-0.01	0.08	-0.93
	(1.40)	(0.89)	(0.01)	(0.18)	(0.06)	(1.01)
Distance from Coast	-41.81†	-22.94†	-0.04	0.86	-0.30	-9.01
	(26.63)	(13.99)	(0.06)	(2.22)	(0.43)	(12.02)
Elevation	-0.01†	-0.00†	-0.00	0.00	-0.00	-0.00
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Slope	6.41	4.77*	0.03	-0.36	0.04	7.44*
	(4.46)	(2.77)	(0.02)	(0.29)	(0.09)	(4.46)
Ruggedness	-0.26	-0.23	-0.00	0.02	-0.00	-0.39*
	(0.27)	(0.17)	(0.00)	(0.02)	(0.01)	(0.22)
Flood Vulnerability Index	2.37	1.43	0.02*	1.05***	-0.03	1.15
	(3.65)	(1.93)	(0.01)	(0.31)	(0.11)	(2.37)
Year Fixed Effects	✓	✓	✓	✓	✓	✓
Firm Fixed Effects	✓	✓	✓	✓	✓	✓
Num. Obs.	11422	11404	3905	2635	11366	5894
Adj. R2	0.864	0.802	0.835	0.948	0.890	0.739

Note: † : $p < 0.15$; *:$p < 0.1$; **:$p < 0.05$; ***:$p < 0.01$; Standard errors are clustered at the project unit level

2. *International Disaster Database (EM-DAT)*: While globally recognized, EM-DAT only recorded events meeting specific criteria (10+ fatalities or 100+ people affected), potentially under-representing smaller but economically significant floods.

3. *Dartmouth Flood Observatory (DFO)*: Starting from 1985, DFO offered broader coverage but lacked detailed geo-referencing for pre-2006 events.

A.2.2 IFI Database Construction

The IFI database construction involved several key steps:

1. *Data Integration*: Merging of three primary sources:
   - IMD DWE records (1967-2016)
   - DFO database (1985-2019)
   - EM-DAT records (1926-2019)

2. *Geocoding Process*:
   - Direct coordinate extraction from DFO records where available
   - Generation of centroids for IMD DWE events based on affected districts
   - Cross-validation of locations using multiple sources

3. *Attribute Standardization*:
   - Assignment of Unique Event Identifiers (UEI)
   - Standardization of dates to ISO 8601 format
   - Unified coding of event causes and impacts

A.2.3 Flood Data Quality and Limitations

The IFI database has several important limitations that warrant consideration:

1. *Temporal Coverage Variation*:
   - Pre-1967 data relies heavily on EM-DAT, with potential coverage gaps
   - Most comprehensive coverage exists post-1985 when all three sources overlap
   - Quality of geo-referencing improves significantly post-2006

2. *Spatial Precision*:
   - Variation in location precision between directly geo-referenced events and district-centroid based events
   - Potential urban bias in reporting and geocoding accuracy
   - Uncertainty in flood extent delimitation, particularly for historical events
3. *Reporting Biases*:
   - Possible under-reporting in remote or less populated areas
   - Variation in reporting standards across different states
   - Potential bias towards events with significant human impact
4. *Impact Assessment*:
   - Inconsistent recording of economic impacts across sources
   - Limited standardization of damage assessment methodologies
   - Varying detail in affected area measurements

Despite these limitations, the IFI database offers several advantages for economic analysis. Its comprehensive coverage, standardized attributes, and detailed geocoding provide a valuable resource for studying the economic impacts of floods in India. By acknowledging these limitations and conducting robustness checks, we aim to provide reliable estimates of the effects of floods on firm outcomes.

Our empirical strategy accounts for these data limitations through, using conservative flood exposure definitions (10km radius), conducting robustness checks with varying distance thresholds, employing firm and year fixed effects to control for reporting heterogeneity, and focusing on the post-2000 period where data quality is highest. Future research could further refine the flood data and explore additional sources to enhance the accuracy and completeness of flood impact assessments.

A.3 Flood Severity Impact

A.3.1 Flood Severity Data and Analysis

To provide a more nuanced analysis of the impact of flood severity on firm outcomes, we incorporated flood severity data from the India Flood Inventory (IFI) dataset. This severity data is sourced from multiple sources, primarily the Dartmouth Flood Observatory (DFO) Flood Magnitude Scale, which measures the hydrological severity of flood events on a scale from 0 (no flooding) to 10 (flood of record).

However, the flood severity data presents significant limitations for our analysis. Only about 10% of our sample observations have severity data available. To address this limitation, we created a binary severity indicator, classifying floods with available severity data as "severe" if their DFO Flood Magnitude Scale value was greater than or equal to 2. All other observations, including those with no severity data, were classified as "not severe."

We augmented our main specification by interacting the flood exposure variables with this binary severity indicator. The results of this analysis are presented in Table A2, which shows both the main flood effects and the severity interaction effects.

The results in Table A2 reveal some unexpected patterns when accounting for flood severity. Contrary to our initial expectations, the coefficient on the interaction term between the post-flood indicator and the severity dummy (Flooded x Post x Severity) is not statistically significant for total assets, fixed assets, and intangible assets. More surprisingly, it is positive and significant for employment (14.07 thousand, $p < 0.05$) and employee wages (7.07 billion INR, $p < 0.05$).

We caution against drawing strong conclusions from these counterintuitive findings due to several important limitations:

1. Limited data availability: With only 10% of our sample having severity data, the analysis may not be representative of the full dataset.

2. Potential classification bias: Our binary classification method, necessitated by data limitations, may not accurately capture the true severity of flood events.

3. Inconsistency in severity data: The severity classifications come from multiple sources and may lack consistency across different time periods and geographical areas.

4. Potential selection effects: There might be systematic differences in the characteristics of areas or firms for which severity data is available, potentially biasing our results.

Given these significant limitations and the counterintuitive nature of the results, we have chosen not to present this severity analysis in the main body of the paper. While the exploration of flood severity effects is theoretically important, the current data constraints

Table A2: Flooding severity impact on capital and labor

	Capital			Labor		
	Total Assets (INR billion)	Fixed Assets (INR billion)	Intangible Assets (INR billion)	Employ-ment (Number Thousand)	Employee Wages (INR billion)	Executive Wages (INR million)
Flooded x Post	-16.68***	-3.10***	-0.31***	-8.20**	-5.52***	-11.65***
	(5.12)	(0.71)	(0.11)	(3.42)	(1.86)	(3.86)
Flooded	12.25***	2.42***	0.27***	7.10**	4.06***	6.81**
	(3.88)	(0.54)	(0.10)	(3.08)	(1.41)	(2.65)
Post	-10.25***	-0.76	-0.26	-0.97	-2.60***	-13.85***
	(2.57)	(0.72)	(0.29)	(1.08)	(0.98)	(2.38)
All Controls	✓	✓	✓	✓	✓	✓
Year Fixed Effects	✓	✓	✓	✓	✓	✓
Firm Fixed Effects	✓	✓	✓	✓	✓	✓
Num. Obs.	56841	56668	33415	21814	56448	34388
Adj. R2	0.700	0.769	0.222	0.840	0.692	0.284
Flood Severity Impact						
Flooded x Post	-19.81***	-3.38***	-0.34***	-9.36**	-6.35***	-13.41***
	(5.57)	(0.77)	(0.11)	(3.70)	(2.08)	(4.37)
Flooded x Post x Severity	34.96†	2.32	0.60	14.32**	7.06**	14.21
	(22.74)	(2.18)	(0.42)	(5.73)	(2.88)	(10.83)
Flooded x Severity	-27.82**	-2.64*	-0.55	-6.10†	-6.84***	-16.67**
	(13.19)	(1.45)	(0.46)	(4.12)	(2.34)	(6.96)
Post x Severity	-24.34***	-2.84***	-0.43***	-14.31***	-8.85***	-9.68**
	(6.09)	(0.93)	(0.12)	(3.27)	(2.33)	(3.90)
Flooded	14.67***	2.64***	0.29***	8.07**	4.70***	8.37***
	(4.23)	(0.59)	(0.10)	(3.32)	(1.58)	(2.98)
Post	-6.97***	-0.37	-0.23	0.78	-1.41†	-12.50***
	(2.54)	(0.76)	(0.29)	(1.17)	(0.94)	(2.36)
Severity	14.82***	1.41†	0.41***	11.66***	5.97***	7.80**
	(4.67)	(0.88)	(0.12)	(2.81)	(1.69)	(3.74)
All Controls	✓	✓	✓	✓	✓	✓
Year Fixed Effects	✓	✓	✓	✓	✓	✓
Firm Fixed Effects	✓	✓	✓	✓	✓	✓
Num. Obs.	56841	56668	33415	21814	56448	34388
Adj. R2	0.701	0.769	0.222	0.841	0.693	0.284

Note: † : $p < 0.15$; *:$p < 0.1$; **:$p < 0.05$; ***:$p < 0.01$; Standard errors are clustered at the project unit level

prevent us from drawing reliable conclusions about the differential impacts of severe floods on firm outcomes.

Future research with more comprehensive and consistent severity data would be valuable to better understand how flood intensity modulates the economic impacts on firms. For now, our main analysis, which focuses on the overall effects of flood exposure without distinguishing severity, provides the most reliable insights into the impacts of floods on firm capital and labor outcomes.

A.4 Sensitivity to distance thresholds

This section examines the sensitivity of our main results to different definitions of flood exposure based on varying distances from firm facilities. Our baseline analysis uses a 100 km radius for matching treated and control facilities, balancing the need for comparable units while ensuring sufficient sample size. To examine the sensitivity of our results to this choice and its implications for capturing regional policy variations, we re-estimate our main specifications using alternative distance thresholds of 5, 20, and 30 km distance threshold are presented in Table A3 and Figure 4.

A.4.1 Capital Outcomes

For capital outcomes (Table A4):

Total Assets: The negative impact of floods on total assets is most pronounced and statistically significant across all distance thresholds, with stronger effects at shorter distances. The magnitude of the effect decreases monotonically from -19.72 billion INR ($p < 0.05$) at 5 km to -9.38 billion INR ($p < 0.01$) at 30 km. This pattern suggests that while flood impacts on total assets remain significant even at larger distances, the effects are most severe for firms in close proximity to flood events.

Fixed Assets: The impact on fixed assets shows remarkable consistency across all distance thresholds, with significant negative effects ranging from -2.36 billion INR ($p < 0.01$) at 5 km to -3.49 billion INR ($p < 0.01$) at 30 km. Unlike total assets, the magnitude of the effect on fixed assets remains relatively stable and even slightly increases at larger distances, suggesting that physical capital destruction exhibits less spatial decay than other forms of asset impairment.

Intangible Assets: The negative impact on intangible assets shows a non-linear pattern across distances. The effect is significant at shorter distances (5 km: -0.67 billion INR, $p < 0.01$; 10 km: -0.32 billion INR, $p < 0.01$) and becomes larger in magnitude but less precisely estimated at 20 km (-1.87 billion INR, $p < 0.05$) before losing statistical significance at 30 km (-0.99 billion INR, not significant). This pattern suggests that the impact on intangible assets may operate through more complex spatial channels than physical capital destruction.

Table A3: Dynamic impact impulse response of capital and labor

	Capital			Labor		
	Total Assets (INR billion)	Fixed Assets (INR billion)	Intangible Assets (INR billion)	Employ-ment (Number Thousand)	Employee Wages (INR billion)	Executive Wages (INR million)
$\beta_{\tau=-10}$	32.15***	4.56***	0.36	28.77***	10.12***	14.62
	(9.33)	(1.09)	(0.28)	(6.60)	(3.39)	(15.89)
$\beta_{\tau=-9}$	33.67***	6.28***	0.25	15.17**	9.53***	37.37***
	(7.38)	(1.37)	(0.18)	(6.95)	(2.69)	(12.72)
$\beta_{\tau=-8}$	28.39***	5.40***	0.07	12.43**	8.38***	32.88***
	(6.44)	(1.25)	(0.24)	(6.04)	(2.36)	(8.35)
$\beta_{\tau=-7}$	24.56***	4.47***	0.06	10.79***	7.57***	31.65***
	(5.64)	(1.06)	(0.25)	(4.05)	(2.21)	(7.89)
$\beta_{\tau=-6}$	27.42***	5.66***	0.22	12.85***	8.13***	36.44***
	(5.53)	(1.09)	(0.23)	(4.95)	(2.15)	(9.13)
$\beta_{\tau=-5}$	16.78***	2.88***	0.19	7.58†	4.74***	21.99***
	(4.93)	(0.77)	(0.19)	(4.69)	(1.78)	(6.69)
$\beta_{\tau=-4}$	16.06***	2.79***	0.33**	10.52**	4.34***	14.46***
	(4.55)	(0.74)	(0.15)	(4.70)	(1.64)	(4.05)
$\beta_{\tau=-3}$	12.98***	2.34***	0.32**	12.48***	4.25***	6.84**
	(4.43)	(0.62)	(0.14)	(4.15)	(1.56)	(3.33)
$\beta_{\tau=-2}$	9.98**	1.86***	0.19	5.23*	3.90***	3.84
	(4.28)	(0.65)	(0.15)	(2.95)	(1.36)	(4.29)
$\beta_{\tau=-1}$	11.77***	2.48***	0.10	4.18*	3.20***	6.44†
	(3.64)	(0.56)	(0.13)	(2.38)	(1.06)	(4.20)
$\beta_{\tau=1}$	-1.73	-1.82	-1.35	1.25	1.92***	-14.75
	(6.14)	(3.06)	(1.48)	(1.38)	(0.74)	(20.93)
$\beta_{\tau=2}$	-4.00	-1.06	-1.39	-0.30	0.42	-21.09
	(4.15)	(1.73)	(1.42)	(1.49)	(0.50)	(18.19)
$\beta_{\tau=3}$	-5.87	-1.54	-1.36	-2.30	-0.68	-36.99*
	(4.20)	(1.92)	(1.36)	(1.92)	(0.56)	(21.95)
$\beta_{\tau=4}$	-10.25**	-3.08†	-1.50	-3.14***	-1.79**	-28.14†
	(3.98)	(2.10)	(1.49)	(1.17)	(0.76)	(18.75)
$\beta_{\tau=5}$	-11.43***	-3.31*	-0.95	-5.11***	-2.98***	-39.99†
	(3.42)	(1.98)	(0.96)	(1.37)	(0.98)	(24.69)
$\beta_{\tau=6}$	-14.58***	-1.91***	-1.22	-7.97***	-5.11***	-13.88*
	(3.70)	(0.72)	(0.95)	(1.93)	(1.38)	(7.78)
$\beta_{\tau=7}$	-10.33**	-0.51	-0.97	-7.78***	-4.91***	-15.27**
	(4.11)	(1.51)	(0.79)	(2.48)	(1.51)	(7.67)
$\beta_{\tau=8}$	-13.14**	-1.58	-0.60	-2.15*	-7.15***	18.23
	(6.57)	(1.56)	(0.44)	(1.12)	(1.86)	(28.57)
$\beta_{\tau=9}$	-3.37	1.99	0.45	-0.10	-7.31***	71.25
	(14.73)	(5.03)	(0.69)	(1.08)	(2.14)	(62.26)
$\beta_{\tau=10}$	-7.33	5.01	8.05	-0.94	-8.34***	-4.61
All Controls	✓	✓	✓	✓	✓	✓
Year Fixed Effects	✓	✓	✓	✓	✓	✓
Firm Fixed Effects	✓	✓	✓	✓	✓	✓
	(15.76)	(9.76)	(8.32)	(1.65)	(2.49)	(8.10)
Num. Obs.	56841	56668	33415	21814	56448	34388
Adj. R2	0.699	0.769	0.232	0.840	0.692	0.284

Note: † : $p < 0.15$; *:$p < 0.1$; **:$p < 0.05$; ***:$p < 0.01$; Standard errors are clustered at the project unit level

Table A4: Capital impact : Sensitivity to flood distance definition

	5 Km	10 Km	20 Km	30 Km
Capital: Total Assets (INR billion)				
Flooded x Post	-19.72**	-16.55***	-10.51***	-9.38***
	(8.48)	(5.13)	(2.95)	(3.22)
Flooded	14.39**	12.16***	8.06***	7.53***
	(6.41)	(3.88)	(2.35)	(2.11)
Post	-17.39**	-10.42***	-11.91***	-36.76***
	(7.70)	(2.57)	(1.85)	(7.90)
Num. Obs.	25183	57074	165993	378939
Adj. R2	0.696	0.700	0.687	0.569
Capital: Fixed Assets (INR billion)				
Flooded x Post	-2.36***	-3.11***	-3.54***	-3.49***
	(0.83)	(0.71)	(0.88)	(1.09)
Flooded	1.99***	2.42***	2.43***	2.37***
	(0.63)	(0.54)	(0.64)	(0.76)
Post	-5.72*	-0.80	-3.48***	-11.83***
	(3.31)	(0.72)	(0.77)	(2.64)
Num. Obs.	25087	56901	165619	378245
Adj. R2	0.726	0.771	0.703	0.651
Capital: Intangible Assets (INR billion)				
Flooded x Post	-0.67***	-0.32***	-1.87**	-0.99
	(0.21)	(0.11)	(0.76)	(1.06)
Flooded	0.58***	0.27***	1.18*	0.74
	(0.20)	(0.10)	(0.61)	(1.10)
Post	-1.55	-0.26	-3.25***	-8.88***
	(1.58)	(0.29)	(0.88)	(1.91)
Num. Obs.	15992	33595	87943	199253
Adj. R2	0.197	0.225	0.373	0.506

Note:† : $p < 0.15$; *:$p < 0.1$; **:$p < 0.05$; ***:$p < 0.01$; Standard errors are clustered at the project unit level; All specifications include the full set of controls, firm and year fixed effects.

A.4.2 Labor Outcomes

For labor outcomes (Table A5):

Total Employment: The negative impact on employment is strongest and most significant at shorter distances (5 km: -7.64 thousand, $p < 0.15$; 10 km: -8.18 thousand, $p < 0.05$). The effect shows a clear spatial decay pattern, declining in magnitude to -3.22 thousand ($p < 0.05$) at 20 km and becoming statistically insignificant (-0.75 thousand) at 30 km.

Employee Wages: The impact on employee wages demonstrates a strong distance gradient, with the largest negative effects observed at shorter distances (5 km: -8.34 billion INR, $p < 0.01$; 10 km: -5.51 billion INR, $p < 0.01$). The effect remains significant but diminishes at 20 km (-1.74 billion INR, $p < 0.05$) before becoming statistically insignificant (-0.38 billion INR) at 30 km.

Executive Wages: Executive compensation shows an intriguing non-linear spatial pattern. There are significant negative impacts at shorter distances (5 km: -10.68 million INR, $p < 0.05$; 10 km: -11.55 million INR, $p < 0.01$), but the effect becomes positive though statistically insignificant at larger distances (20 km: 10.87 million INR; 30 km: 2.79 million INR). This pattern suggests possible spatial reallocation of executive talent in response to localized flood events.

A.4.3 Creative Destruction or Regional Reallocation

The distance sensitivity analysis demonstrates that the impacts of floods on both capital and labor outcomes are most pronounced within a 10 km radius of firm facilities, supporting our choice of this distance as the preferred specification in the main analysis. The effects generally exhibit clear spatial decay patterns, with both magnitude and statistical significance diminishing at larger distances, highlighting the localized nature of flood impacts on firm outcomes.

Our findings do not support a straightforward creative destruction narrative. While we observe significant negative impacts on capital and labor measures at shorter distances, we find limited evidence of offsetting positive effects at larger distances. The exception is the suggestive evidence in executive wages, which shows a shift from negative to positive coef-

Table A5: Labor impact : Sensitivity to flood distance definition

	5 Km	10 Km	20 Km	30 Km
Labor: Total Employment (Thousand)				
Flooded x Post	-7.64†	-8.18**	-3.22**	-0.75
	(4.76)	(3.41)	(1.47)	(0.90)
Flooded	5.69	7.08**	3.01**	0.27
	(4.11)	(3.07)	(1.30)	(0.76)
Post	0.30	-0.97	-0.30	0.23
	(2.20)	(1.07)	(0.43)	(0.27)
Num. Obs.	10323	22009	62445	149955
Adj. R2	0.844	0.840	0.833	0.833
Labor: Employee Wages (INR billion)				
Flooded x Post	-8.34***	-5.51***	-1.74**	-0.38
	(3.22)	(1.86)	(0.68)	(0.61)
Flooded	6.15**	4.05***	1.57**	0.82**
	(2.44)	(1.41)	(0.62)	(0.35)
Post	-1.51	-2.57***	-1.78***	-0.48***
	(1.44)	(0.97)	(0.38)	(0.15)
Num. Obs.	24986	56678	165001	377201
Adj. R2	0.701	0.692	0.677	0.673
Labor: Excutive Wages (INR million)				
Flooded x Post	-10.68**	-11.55***	10.87	2.79
	(5.19)	(3.85)	(7.76)	(4.18)
Flooded	3.05	6.74**	-11.53*	-2.88
	(3.03)	(2.65)	(6.20)	(2.99)
Post	-7.88	-14.12***	-8.68***	-3.37***
	(6.64)	(2.37)	(1.94)	(1.23)
Num. Obs.	14545	34558	105427	250845
Adj. R2	0.271	0.285	0.294	0.281

Note:† : $p < 0.15$; *:$p < 0.1$; **:$p < 0.05$; ***:$p < 0.01$; Standard errors are clustered at the project unit level; All specifications include the full set of controls, firm and year fixed effects.

ficients as distance increases, though these positive effects are not statistically significant. This pattern suggests that rather than wholesale creative destruction, floods may induce more nuanced spatial reorganization of managerial talent and resources.

These results indicate that firms located farther from flood-affected areas do not consistently benefit from resource reallocation, contrary to what a strong creative destruction hypothesis would predict. Instead, our findings suggest that floods primarily generate localized negative impacts that dissipate with distance, with any potential benefits being subtle and primarily manifested in the spatial redistribution of executive talent. This interpretation suggests that the economic impacts of floods may be better characterized as generating spatial reorganization rather than creative destruction, though further research is needed to fully understand these complex spatial dynamics.

Figure A1: Flood Distance at 5km : Dynamics of Flood Impact on Capital and Labor

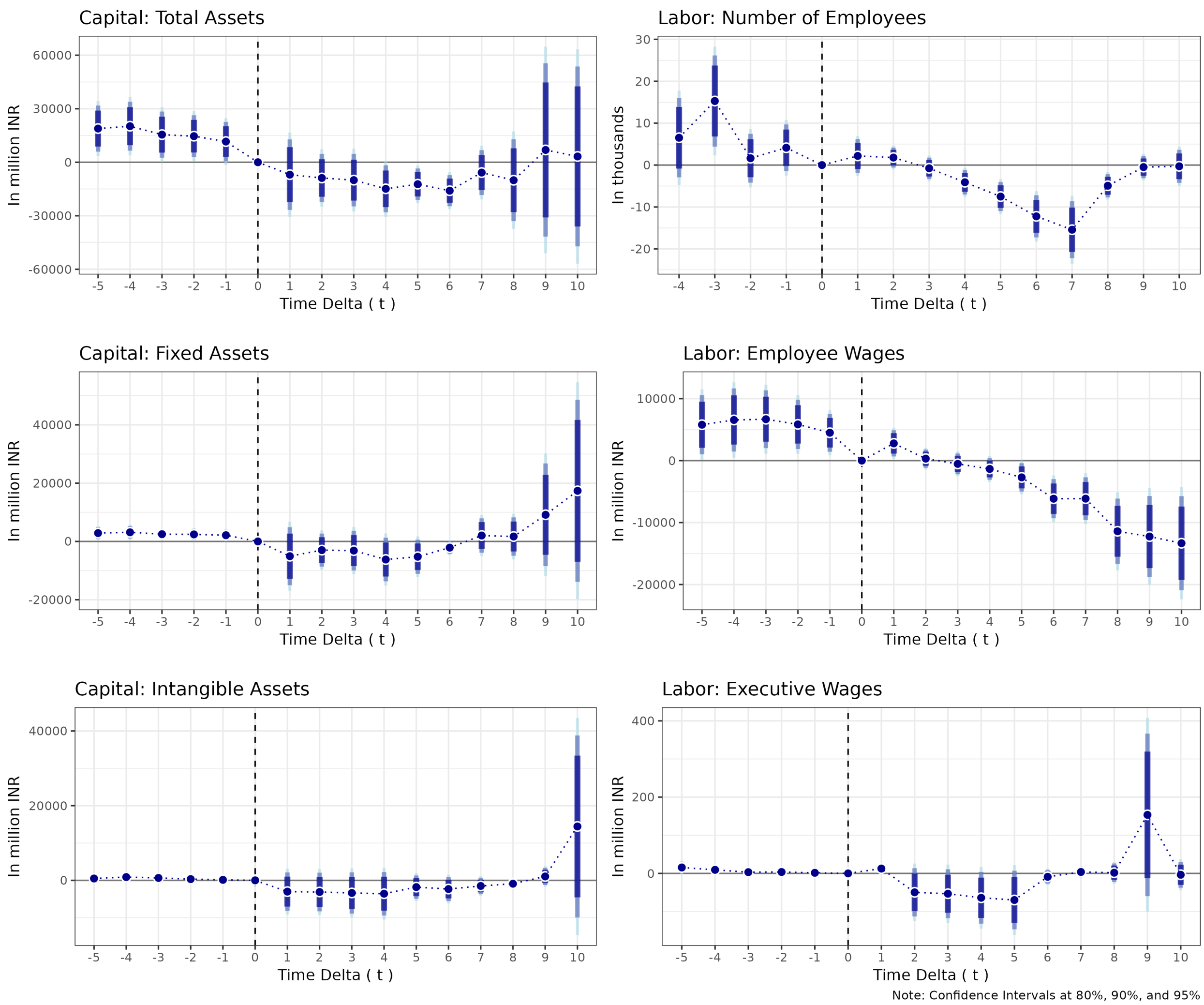


Figure A2: Flood Distance at 20km : Dynamics of Flood Impact on Capital and Labor

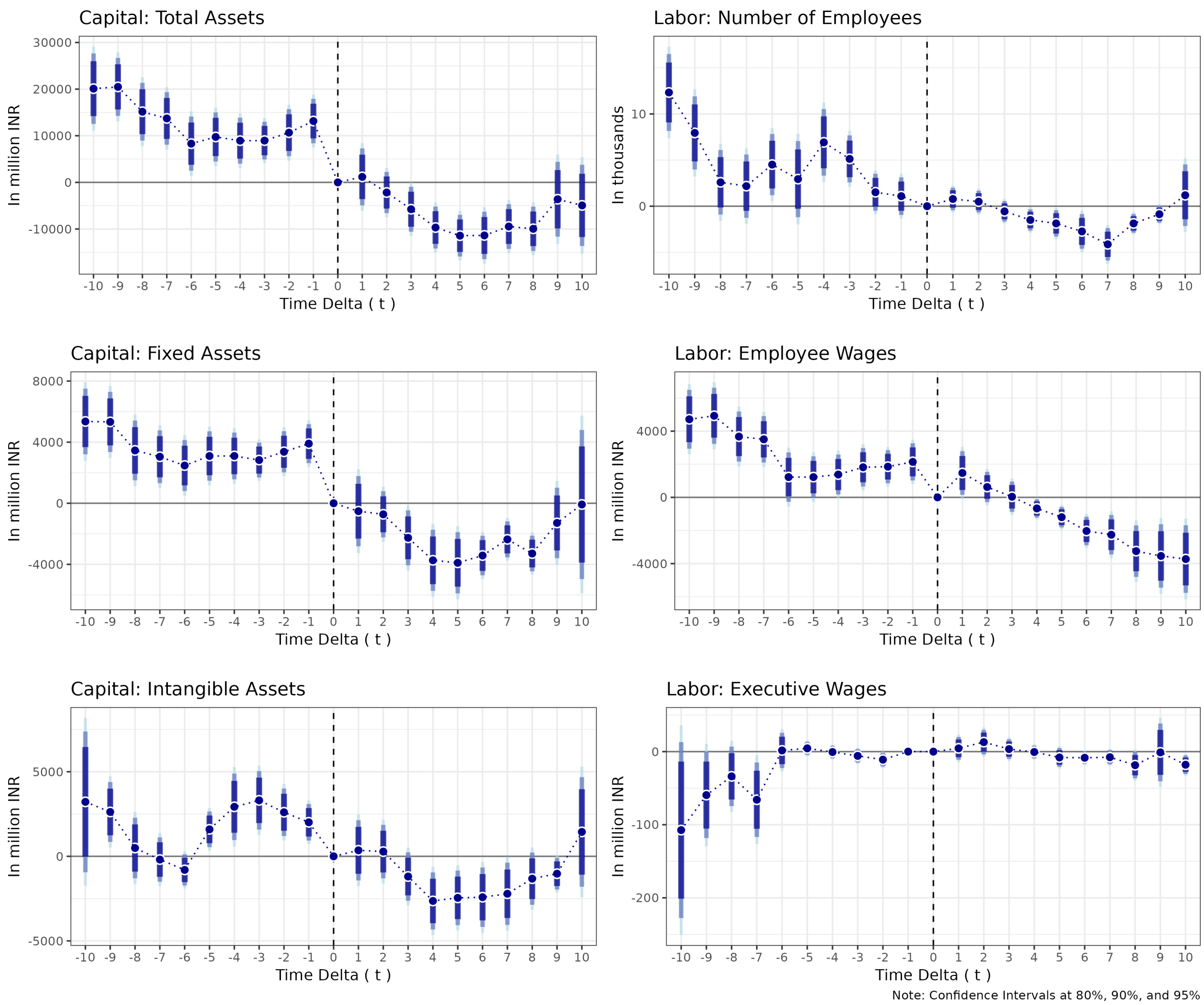
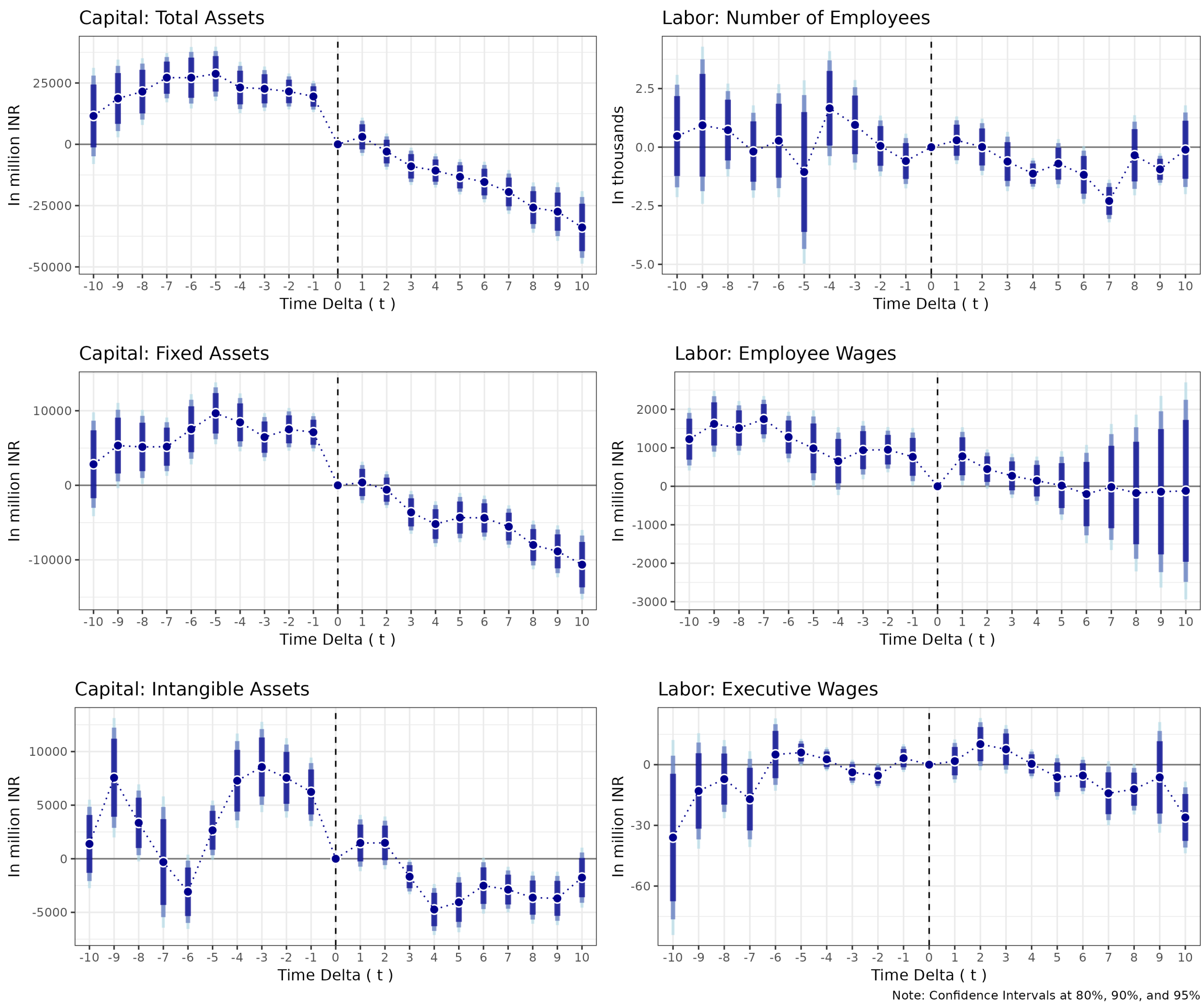


Figure A3: Flood Distance at 30km : Dynamics of Flood Impact on Capital and Labor



A.4.4 Regional policy variations

The systematic variation in estimates across distance thresholds provides compelling evidence of spatial heterogeneity in disaster response and recovery. While the clear distance decay pattern in our results primarily reflects the diminishing direct impact of floods, the spatial heterogeneity also reveals important features of India's disaster management framework and institutional environment.

First, the stronger negative effects within 10 km, followed by their gradual dissipation over larger distances, suggests that disaster relief programs may be most effectively targeted at immediately affected areas. However, the persistence of significant negative effects up to 20 km for most outcomes indicates that current administrative boundaries for disaster response may need reconsideration. Second, our finding of more consistent negative effects on employee wages compared to executive compensation points to potential distributional issues in how firms adjust to flood impacts, possibly reflecting differences in local labor market institutions and employment protection policies.

The spatial patterns we document have important implications for policy design. The clear distance-decay in flood impacts suggests that disaster relief should be spatially targeted, with intensity of support declining with distance from affected areas. However, the persistence of significant effects at larger distances (particularly for fixed assets, which show similar magnitudes of impact up to 30 km) indicates that relief programs should consider broader geographical coverage than current practice. Additionally, the differential patterns between labor and capital outcomes suggest a need for integrated policies that address both physical reconstruction and labor market adjustment.

Future research could build on these findings by explicitly modeling institutional features of disaster response. This could include examining how variations in local government capacity affect recovery trajectories, analyzing whether politically connected firms show differential recovery patterns, and studying if targeted assistance programs lead to more resilient industrial development. Particular attention should be paid to understanding why some effects (like those on fixed assets) show more spatial persistence than others, as this could inform the optimal spatial targeting of different types of disaster assistance.