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BENEATH THE CLOUDS: A MICRODATA APPROACH TO UNDERSTANDING STORM IMPACTS IN INDIA

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Beneath the Clouds: A Microdata Approach to Understanding Storm Impacts in India

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Abstract/Résumé

Extreme weather events, like tropical storms, pose significant threats to economies by damaging infrastructure and disrupting human capital development. This study examines the economic impacts of storms in India using microdata. We leverage estimates of storm impact on physical assets and educational attainment from the economic literature to compute a back-of-the-envelope approximation of the financial impact of storms. Using wind, firm, and demographic information, we estimate that, in 2021, damage to fixed assets reached USD2.8 billion and losses in sales in manufacturing totaled USD14.5 billion. On the other hand, the reduction in lifetime earnings due to lower educational attainment amounted to approximately USD25.0 billion. These findings highlight the importance of targeted resilience policies to mitigate the economic risks of extreme weather events.

Les événements météorologiques extrêmes, comme les tempêtes tropicales, menacent gravement les économies en endommageant les infrastructures et en perturbant le développement du capital humain. À partir de microdonnées, nous analysons les impacts économiques des cyclones en Inde. En nous basant sur des estimations provenant de la littérature économique sur les effets des cyclones sur les actifs physiques et la scolarisation, nous approximons leur coût financier. En combinant des données sur la vitesse des vents, les entreprises et la démographie, nous estimons qu'en 2021 les dommages aux immobilisations ont atteint 2,8 milliards USD, tandis que les pertes de revenus dans le secteur manufacturier ont totalisé 14,5 milliards USD. De plus, l'impact sur les niveaux de scolarisation a réduit les revenus cumulés à vie d'environ 25 milliards USD. Ces résultats rappellent l'importance de politiques de résilience ciblées afin de limiter les risques économiques liés aux événements météorologiques extrêmes.

Keywords/Mots-clés: Storms, India, Economic impacts, Human capital, Firms, Capital / Tempêtes, Inde, Impacts économiques, Capital humain, Entreprises, Capital

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ABBREVIATIONS

ADB	–	Asian Development Bank
ASI	–	Annual Survey of Industries
CAGR	–	compound annual growth rate
EC	–	Economic Census
NOAA	–	National Oceanic and Atmospheric Administration
NPV	–	net present value
PLFS	–	Periodic Labour Force Survey
PRC	–	People’s Republic of China

I. INTRODUCTION

Extreme weather events, such as storms, pose significant threats to economies worldwide, as they can cause extensive damage to infrastructure, disrupt human capital development, and hinder economic growth. Excluding indirect costs such as nonmarket damages, pain, suffering, and loss of life, the annual direct costs of natural disasters are estimated to be between USD100–USD200 billion on average (Kousky 2019). Understanding the comprehensive impacts of such events on economies is crucial for effective policymaking and resilience planning. In this study, we examine two key indirect cost channels through impacts on physical capital and human capital formation. Losses in these channels have been rising over time, largely because of how and where we build (Pielke and Downton 2000; Pielke et al. 2003). By leveraging detailed microdata, this research aims to provide a back-of-the-envelope approximation of the economic impacts of tropical storms in India.[1]

Many macroeconomic growth models, including those commonly used in disaster economics, have been criticized for neglecting the role of geography and overlooking the heterogeneous effects of major climate events (Krugman 2011).[2] Given the heavy reliance of emerging disaster economics literature on these mainstream macroeconomic frameworks, such criticism is increasingly relevant. Microdata offers detailed insights into the specific effects on physical and human capital, enabling a more precise evaluation of economic consequences. As climate change potentially increases the frequency, intensity, and duration of extreme weather events (Lavell et al. 2012), the relevance of microdata-driven studies becomes even more critical.

India, with its diverse economy and frequent exposure to storms, provides a compelling case for this study. The availability of detailed storm occurrences, demographic data, and firm-specific information makes this country an ideal context for analyzing storm impacts using microdata. Although we do not propose a catastrophe model per se, our approximation provides valuable insights that could enhance the precision of economic assessments of storms. India's extensive 7,516-kilometer coastline and high cyclone frequency – accounting for approximately 10% of the

[1] A tropical cyclone is a rotating, organized system of clouds and thunderstorms that originates over tropical or subtropical waters and has a closed low-level circulation. A tropical depression is a tropical cyclone with maximum sustained winds of 38 miles per hour (33 knots) or less, while a **tropical storm** has maximum sustained winds between 39 and 73 miles per hour (34–63 knots). In this paper, we use the term "storm" and "tropical storm" when referring to any system with sustained winds above 33 knots.

[2] See Botzen, Deschenes, and Sanders (2019) for a review of those models.

world's total – position it as a critical region for studying the economic impacts of storms, with over 370 million people annually affected, highlighting its immense human and structural vulnerabilities (NCRMP 2023). Low- and middle-income countries face a disproportionately high risk from natural disasters because of more frequent exposure to climate-related hazards and less resilience, as discussed by Dell, Jones, and Olken (2014). In India, these challenges are compounded by the need for improved building codes and construction practices, underscoring the importance of enhancing infrastructural resilience and regulatory frameworks to mitigate economic losses. Furthermore, the vulnerability of children in these regions is of particular concern, with projections like those from Emanuel (2021) suggesting an increase in the frequency and severity of extreme weather events due to climate change. This heightens the need for targeted interventions to improve resilience and protective measures, making India a vital case study for understanding both the immediate and long-term economic consequences of cyclonic disturbances and providing valuable insights into disaster management and economic preparedness.

In this study, we focus on the economic impacts of storms on physical capital, sales, and education. Our assessment is partial, as we estimate only the damages to (i) physical capital and sales losses in manufacturing establishments, and (ii) human capital through the delay in educational attainment. We do not study the impact on other sectors such as agriculture, construction, retail, and essential services like health care and transportation—meaning, the total damages are likely underestimated.

However, our analysis remains pertinent, offering valuable insights into the significant disruptions caused by storms. Using established coefficients from the literature, we assess how storms impact critical physical assets and long-term economic growth, based on storm occurrences, demographic data, and district-level information on manufacturing establishments across India for 2021.

Our methodology integrates multiple data sources and builds on the causal estimates from Pelli et al. (2023) and Pelli and Tschopp (2025) to conduct a back-of-the-envelope approximation of the economic effects of storms. This is possible since the two papers use the same measure to identify storms. We utilize (i) empirical data on wind exposure from the National Oceanic and Atmospheric Administration (NOAA), (ii) firm data from the Annual Survey of Industries (ASI) and the Economic Census (EC), and (iii) population data from the 15th India Census and the Periodic

Labour Force Survey (PLFS) to quantify these impacts. By combining these datasets, we analyze the interaction between extreme weather events, economic assets, and human capital development, providing valuable insights into the broader consequences of storms on India's economy and population.

To quantify storm-induced damages to manufacturing, we begin by calculating the annual physical capital within each district, utilizing state-level data from the ASI and district-level firm counts provided by the EC. This reported capital captures the impact of storms in affected districts during the given year. To estimate what the capital would be without the storms, we use the coefficients estimated by Pelli et al. (2023), who explore how the capital stock of Indian manufacturing firms responds to storm events, investigating the variations in responses both within and across industries. The study utilizes a rich panel dataset of Indian manufacturing firms from 1995 to 2006, derived from the Prowess database, and introduces a novel measure of storm intensity based on wind speeds at the locations of firms and their establishments. This measure captures the heterogenous impact of storms on physical capital and sales. The paper shows that storms at the 90th percentile of intensity lead to a reduction of 5.5% in fixed assets. For average storm exposures, fixed assets drop by 2.2%, equating to approximately USD74,000 for the average firm. In addition to the effects on physical capital, they also assess the impact on sales. Storms in the top decile of intensity decrease sales by at least 7.8%, while the average storm leads to a 3.1% reduction in sales, amounting to roughly USD178,000 for the average firm.[3]

Studies on the impact of climate-induced disasters on manufacturing in India generate similar results. Bahinipati et al. (2015) examined the effects of the 2006 flooding in Surat, India—caused by heavy rainfall in the upstream basin areas—on the textile manufacturing industry. The study estimated that the floods led to an average loss of INR1.5 million per textile unit, representing 23% of the industry's total annual profit. Losses encompassed damages to raw materials, finished goods, capital assets, and repair costs. Similarly, Goldar, Jain, and Dasgupta (2024) estimated that cyclones in Andhra Pradesh during 2018–2019 caused substantial damage to the manufacturing sector amounting to INR286.975 billion (USD3.7 billion).

Research conducted in the People's Republic of China (PRC) found similar results and magnitude of damages. Elliott et al. (2019) found that typhoons in the PRC reduced the turnover of

[3] An average storm exposure reduces fixed assets of an average firm by INR5.1 million and sales by INR12.5 million. Figures were converted to dollars using an exchange rate of INR70 for USD1.

manufacturing plants by approximately 1%, which translates to an annual loss of USD3.2 billion. These losses stemmed not only from direct damage to infrastructure and property but also from disruptions in the supply chain. Jin, Sumaila, and Yin (2020) further emphasized the ripple effects of disasters, particularly focusing on storm surges in Guangdong Province, PRC. The study estimated that storm surges in 2017 caused an indirect output loss of USD443.9 million to manufacturing, primarily due to their impact on agricultural production.

We assess the economic impact of storms on human capital by comparing aggregate potential earnings of individuals with various educational levels. Using the PLFS data at the state level, combined with storm and demographic data at the district level, we focus on regions where storms have impacted educational attainment. We contrast the hypothetical scenario of no-storm impact with adjusted educational levels in storm-affected regions, leveraging estimated coefficients from Pelli and Tschopp (2025), who investigate the short- and long-term effects of extreme weather events on educational outcomes and labor market prospects in rural and urban India. Their research employs a measure of childhood exposure to storms, constructed from exogenous variations in wind exposure across birth-year cohorts and districts during compulsory schooling years. This approach allows the authors to isolate the effects of storm exposure on education by leveraging natural variations in storm intensity and timing. Their findings reveal that exposure to super storms significantly affects educational trajectories. Specifically, experiencing a super storm increases the probability of having no formal education by 4.6 percentage points and decreases the probability of pursuing education beyond secondary school by 20 percentage points. These disruptions suggest a long-term deskilling of regions affected by storms, as individuals from storm-impacted areas tend to have lower educational attainment and limited labor market opportunities.

Storms significantly disrupt schooling by influencing both demand and supply aspects, which affect financial stability (demand) and educational infrastructure (supply). Demand-side impacts primarily result from financial hardships that diminish household capacity to support education. Storm-induced shifts in demand frequently emerge from detrimental effects on household income and children’s mental health. Damage to crops, farms, and production facilities can lead to temporary or permanent income shocks, resulting in considerable financial strain. This economic burden may compel children to work to assist their families, potentially leading to school dropouts and delays if parents can no longer afford educational expenses. For example, a US study suggests that natural disasters, which result in physical damages of at least USD500 per capita, can lead to a reduction in a region's human capital by roughly USD505 through increased out-migration, as well as student achievement and educational attainment (Opper, Park, and Husted 2023). Moreover, financial stress from such events can cause malnutrition, adversely affecting learning, especially in younger children. Although our study focuses on school-age shocks, which are less likely to influence long-term educational outcomes compared to prenatal or early-life events, storms can still have a profound impact on children's mental health.[4] On the supply side, disasters damage public infrastructure such as roads and schools, cause temporary schooling disruptions, and degrade the quality of educational environments because of reduced electricity, damaged facilities, and destroyed buildings—all of which hinder both student attendance and effective teaching. For example, post-Katrina operating expenditures for publicly funded schools in New Orleans rose by USD 1,358 per pupil compared to districts used for comparison, according to Buerger and Harris (2021).[5]

Our study finds considerable damage to physical capital in storm-prone districts, with fixed capital damage reaching USD 2.8 billion and sales losses amounting to USD 14.5 billion in 2021.[6] Concurrently, human capital costs, evaluated at different discount rates, reveal substantial economic impacts on educational outcomes and lifetime earnings, amounting to USD 25.0 billion under a 6% discount rate following the guidelines for social sector projects of the Asian Development Bank (ADB).[7]

This study contributes to the literature by offering a detailed examination of storm impacts through microdata. Unlike previous studies that often use aggregated data, this research provides a more granular understanding, enhancing the accuracy of economic impact assessments.

The paper is structured as follows: the next two sections describe the data and methodology, followed by the presentation of results in Section 4. Section 5 concludes with a discussion of our findings and their policy implications.

[4] See Cianconi, Betrò, and Janiri (2020) for a review of the impact of extreme weather events on mental health.
[5] Hurricane Katrina (August 2005) became a large and extremely powerful hurricane that caused enormous destruction and significant loss of life. It is the costliest hurricane to ever hit the United States.
[6] Losses from storms that hit India in 2021
[7] ADB. 2017. *Guidelines for the Economic Analysis of Projects*.

II. DATA

In this section, we explain how we measure wind speeds and construct storm exposure index of firms and school-age population, following Pelli et al. (2023) and Pelli and Tschopp (2025). Additionally, we provide an overview of the data utilized to estimate the financial damage caused by storms.

A. Wind Speed in Districts

We use the same measure of storms that Pelli et al. (2023) and Pelli and Tschopp (2025) have constructed to produce their estimates, derived from the NOAA International Best Tracks. This database provides historical records of each storm, including latitude, longitude, date, and wind speed at 6-hour intervals for the eye of the storm. The calculation of wind speed follows standard practices in the climate literature, where storms are parametrically modeled as translating ranking vortices. The primary model used is based on the Deppermann (1947) formula, which is widely recognized for its reliability in simulating storm conditions.[8] The model calculates w_{dh}, which represents the maximum wind speed associated with storm h in district d:

$$w_{dh} = \max_{k \in H_t}\{w_{dk}\} \qquad \textbf{(Equation 1)}$$

where w_{dk} is the wind at the district's centroid, determined by the Rankine-combined formula. This formula describes wind fields as follows:

$$\mathrm{w}_{dk} = \begin{cases} e_k \cdot \frac{D_{dk}}{26.9978} & if\ D_{dk} \leq 26.9978 \\ e_k \cdot \left(\frac{26.9978}{D_{dk}}\right)^{0.5} & if\ D_{dk} > 26.9978 \end{cases} \qquad \textbf{(Equation 2)}$$

where w_{dk} is wind w in district d associated with a specific landmark k, and D_{dk} is the distance between the centroid of district d and landmark k. The number 26.9978 corresponds to the Simpson and Riehl (1981) radius of maximum wind speed in knots, which is the distance between the eye and the point where wind reaches its maximum speed. According to this formula, winds first increase exponentially up to a maximum and then decrease rapidly. Every wind speed can be specifically located since the NOAA best tracks of storms are linearly interpolated at every

[8] Additionally, the robustness of these estimates is validated using alternative wind field models, such as those developed by Holland (1980) and Boose, Serrano, and Foster (2004). This multimodel approach ensures the accuracy and consistency of the wind speed data across different storms and geographic locations.

kilometer, resulting in a set of landmarks *k*, each with a set of coordinates and a corresponding wind speed at the eye of the storm, denoted as e_k.

Yearly district exposure to storms index takes into account the force exerted by winds on physical structures determined by the following quadratic specification:

$$x_{dt} = \sum_{h \in H_t} \left(\frac{(w_{dh} - 50)^2}{(w_{\max} - 50)^2} \right) \text{ if } w_{dh} > 50 \qquad \textbf{(Equation 3)}$$

where the variable x_{dt} represents the yearly district exposure to storm, H_t is the set of storms in year *t*, w_{dh} is the maximum wind speed associated with storm *h* to which district *d* was exposed, and $w_{\max}$ refers to the highest wind speed observed throughout the entire sample. By definition, $x_{dt} \in (0, |H_t|)$, where a value of 0 indicates zero district exposure to storms (i.e., winds in district *d* are below the threshold limit), and $|H_t|$ represents the number of elements (storms) in set H_t. Considering the poor quality of construction materials in India, infrastructures and buildings are vulnerable even at low wind intensities. Thus, they focused on a threshold of 50 knots, as in Emanuel (2021) and as we did in our study, rather than 64 knots (the threshold for a Category 1 storm, according to the Saffir-Simpson scale).

B. Firms Storm Exposure, Physical Assets, and Sales

Pelli et al. (2023) employs a firm-level measure of exposure to storms from 1995 to 2006, as indicated in equation 4. This metric captures the cumulative wind exposure that firms (*f*) experience across all their establishments within a year (*t*). It entails the identification and geo-referencing of all establishments associated with a manufacturing firm to accurately compute the maximum wind speed encountered during each storm (*h*).

$$H_{ft} = \sum_{p \in F} \sum_{h \in T} x_{ph} \qquad \textbf{(Equation 4)}$$

The postal code exposure to storm (x_{ph}) follows a nonlinear specification, as indicated in equation 3. The study constructs an index for each postal code building on the firm-level data gathered from Prowess, which contains information on headquarters' postal codes and company names.[9] However, since publicly available data for computing physical and human capital in 2021 is

[9] Prowess is one of the largest databases containing detailed information on the financial performance of Indian firms, including firm-level product mix and sales in India.

available only at the district level, our study computes a storm exposure index for a district. Further, the study's baseline specification focuses on storms with wind speeds exceeding 33 knots (the threshold for tropical storms), recognizing that even moderate storms can cause significant damage to buildings, materials, and infrastructure in most developing countries. In the study's sample, manufacturing firms have an average exposure index of 0.02, with the highest value reaching 0.525.

This study attempts to estimate district-level physical capital impacts of storms by aggregating establishment-level data from the EC and the ASI. This study also estimates damages from stronger storms with wind speeds exceeding 50 knots, making it comparable to the estimated damages on human capital. We utilize estimated coefficients along with the annual district exposure to storms (equation 3) from the complete district wind exposure dataset from Pelli et al. (2023).

Table 1 presents the summary of the storm exposures and reported capital and sales per district in 2021, our year of interest. Of the 60 districts affected by tropical cyclones, only 14 were exposed to storms with intensities over 50 knots. An exposure index close to 1.0 is comparable to experiencing the strongest storms recorded over the period 1990-2021. In 2021, the average exposure to storms exceeding 50 knots was 0.03, while the maximum reached 0.18. This implies that storms that hit manufacturing firms during this period were generally not very strong compared to previous years. The standard deviation of the exposure index also surpasses the mean, indicating substantial variation in storm exposures across districts. Furthermore, the median exposure is significantly lower than the mean, implying that most districts experienced weaker storms.

Table 1: Storm Exposure and Reported Manufacturing Capital and Sales, 2021

Item	Mean	St. Dev.	Median	Min	Max	N
Manufacturing establishments	280	598	66	1	5,159	621
Fixed assets	169.49	428.54	36.49	0.0027	5,927.64	621
Sales	659.13	1,561.73	160.81	0.0180	20,242.41	621
Storm exposure (33 knots)	0.0232	0.0485	0.0070	0.00000	0.2638	60
Storm exposure (50 knots)	0.0328	0.0564	0.0052	0.00003	0.1778	14

Max = maximum, Min = minimum, N = number of observations, St. Dev. = standard deviation, Sum = total.

Notes: The storm exposure index is from the complete wind exposure dataset from Pelli et al. (2023). The count of establishments is from the Economic Census surveys, while fixed assets and sales are computed using data from the Annual Survey of Industries and the Economic Census surveys. The number of establishments, along with their corresponding fixed assets and sales, includes only manufacturing establishments with 10 or more workers. Fixed assets and sales are in nominal terms and are expressed in billions of Indian rupees (INR).

Source: Authors' calculations.

This study primarily uses data from the ASI and the EC of India to estimate the levels of capital and sales per district and year of interest.[10] From the ASI, we obtain the distribution of manufacturing establishments by fixed assets and sales for each state.[11] The ASI gathers establishment-level information on various aspects of registered industries in India, including employment, capital, input costs, and production, offering a detailed insight into the performance of manufacturing firms across the country.[12] However, since data from the ASI is aggregated at the state level, the EC supplements information to generate district-level estimates of sales and capital. The EC provides district-level data on the number of establishments, giving a broader view of distribution across regions.[13] By applying the state-level distribution of establishment sizes to the district-level counts from the EC, we are able to approximate the total value of fixed assets

[10] In the context of physical capital in this study, "year" refers to the fiscal year consistent with the data covered under the ASI survey. However, since majority of the data pertains to the early part of the year, we assume this reflects the value for the entire fiscal year when making comparisons to human capital. In addition, because the storms in this study's year of interest occur between May and December, the district exposure in a calendar year is equal to exposures in a fiscal year.

[11] Fixed assets refer to assets used in the production process or for administrative purposes that have a normal productive life of more than 1 year. These include land, buildings, machinery, furniture, computers, and transport equipment. In this study, the term "fixed assets" is used interchangeably with "physical capital" and "fixed capital." Sales refer to the total value of goods and services sold by the industrial units during the reference period.

[12] The ASI is the principal source of industry statistics in India. The survey is conducted annually and covers data over a fiscal year, which runs from 1 April to 31 March of the following year. It covers all factories registered as manufacturing establishments.

[13] The EC is a comprehensive survey of the Indian economy, encompassing all establishments engaged in economic activities across both agriculture and non-agriculture sectors. These units are involved in the production and/or distribution of goods and services, excluding those solely for personal consumption. The census provides detailed information on various operational and other characteristics, including the number of establishments, number of persons employed, sources of finance, and types of ownership. The latest economic census began in June 2019. However, the final results have yet to be finalized.

and sales in each district.[14] Since the study only focuses on manufacturing, non-manufacturing firms and establishments are excluded from the ASI and the EC datasets.[15] In the absence of storms, we assume that the levels of capital and sales are higher than those reported in the ASI and the EC since these already reflect the impact of storms that occurred in that year.

In 2021, there are a total of 173,697 manufacturing establishments spread across 621 districts (Table 1). The reported average fixed asset per district amounted to INR169.5 billion (USD2.29 billion), with mean sales reaching INR659.1 billion (USD8.92 billion).[16] The median capital and sales are significantly lower than the averages, suggesting that most districts had relatively lower levels of capital and sales, with higher levels being concentrated in a small number of districts.

We estimate that 12,193 manufacturing establishments across 14 districts were exposed to storms with speeds over 50 knots in 2021 (Table 2). The total reported fixed capital in these districts amounted to INR10.2 trillion (USD138.0 billion), with total sales of INR 40.2 trillion (USD 543.6 billion). We observe a lot of variation across districts. For instance, although Diu faced the highest storm exposure, it reported only three manufacturing establishments in 2021. In contrast, Greater Bombay, with 3,856 reported establishments and accounting for nearly 30% of the total fixed capital for the 14 storm-affected districts, had one of the lowest storm exposures in the same period.

[14] Since data from the 7th EC, which covers establishments in 2019, is not yet available, we utilize the state distribution from the ASI 2021–2022 and apply it to the district-level firm count from the 6th EC conducted in 2013. While this method yields more recent estimates, it assumes no increase in the number of firms between 2013 and 2021, which may lead to an underestimation of the overall impact.

[15] Establishments with less than 10 employees are also dropped from the EC dataset, for consistency with the coverage criteria of the ASI.

[16] Exchange rate: USD0.0135285 per INR1, from ADB's Key Indicators Database (accessed 6 October 2024).

Table 2: Storm Exposure and Reported Manufacturing Capital and Sales by District, 2021

	Storm Exposure		Reported	
	Index (50 knots)	Affected Establishments	Fixed Assets	Sales
District (State)	**(1)**	**(2)**	**(3)**	**(4)**
Amreli (GJ)	0.13270	359	497.16	1,704.87
Baleshwar (OD)	0.07623	103	390.75	913.56
Bhavnagar (GJ)	0.00779	1,718	2,386.34	8,146.78
Dadra and Nagar Haveli (DH)	0.0007	700	269.81	1,801.40
Daman (DD)	0.00219	556	214.32	1,433.78
Diu (DD)	0.17779	3	1.10	7.18
East Midnapore (WB)	0.00019	950	597.51	2,422.03
Greater Bombay (MH)	0.00970	3,856	2,716.62	11,420.02
Junagadh (GJ)	0.01723	196	271.51	928.24
Mayurbhanj (OR)	0.03046	73	282.19	657.55
Raigarh (CG)	0.00269	100	64.90	230.25
Ratnagiri (MH)	0.00003	142	100.69	417.34
Thane (MH)	0.00105	3,247	2,287.33	9,612.94
West Midnapore (WB)	0.00016	190	119.85	483.27
Total		**12,193.00**	**10,200.07**	**40,179.21**

CG = Chhattisgarh, DD = Daman and Diu, DH = Dadra and Nagar Haveli, GJ = Gujarat, MH = Maharashtra, OD = Odisha, WB = West Bengal.

Notes: Column (1) presents the storm exposure index of storm-affected districts in 2021 from the complete wind exposure dataset from Pelli et al. (2023), while column (2) indicates the estimated number of firms exposed to storms in 2021. Columns (3) and (4) are the estimated capital and sales in the corresponding districts using data from the Annual Survey of Industries and Economic Census surveys and are expressed in billions of Indian rupees (INR).

Source: Authors' calculations.

C. School-Age Storm Exposure and Human Capital

To consider a school-age storm exposure, we adapt the storm exposure index developed by Pelli and Tschopp (2025), which captures the long-term effects of school-age exposure to storms on educational outcomes and labor market prospects. Their measure of exposure accounts for storms occurring during the first 9 years of compulsory schooling (starting at age six) and the preschool year. Since the school-age exposure index has a cumulative nature, it could in theory exceed 1.0. The index is designed to vary by cohort and location, reflecting the differential exposure to storms during critical educational periods and capturing the cumulative impact of storm exposure on each cohort. It is computed as follows:

$$C_{bd} = \sum_{t=b+5}^{b+15} x_{dt}\,,\ t \in [1990{,}2021] \qquad \textbf{(Equation 5)}$$

where *b* represents a birth-year cohort, *d* indicates a district, *t* denotes a year, and x_{dt} is the yearly district exposure detailed in equation 3.

In our back-of-the-envelope approximation, we want to measure school-age exposure for a typical year, so we compute the mean exposure. We use the complete wind exposure dataset from Pelli et al. (2023), focusing on years with wind events exceeding 50 knots, like they did. We calculate a rolling 10-year sum of storm exposures by summing the wind intensities for these event years. From this, we derive the average school-age storm exposure for each district over a 23-year period from 1999 to 2021.

The 23-year mean school-age storm exposure across districts ranges from zero to 0.447, with a median value of 0.0058. The distribution is highly skewed, with a mean of 0.036 and a standard deviation of 0.086, with most-exposed districts experiencing relatively low exposure, while a few are significantly more affected. Column (1) of Table 3 shows the mean school-age storm exposure by district.

To estimate the number of school-age population in districts affected by storms in 2021, we relied on the 2011 Population Census, which provides detailed demographic data by age group at the district level, with projections extending until 2021.[17] School-age population in at-risk states, defined as individuals aged between 5 and 24, are shown in column (2) of Table 3.

To compute the financial impact of storm on human capital, we use state-level earnings and educational attainment data from the PLFS.[18] Demographic data from the 2011 Population Census is also incorporated to provide district-level school-age population-at-risk. We categorize educational attainment into five levels: (i) below primary school, (ii) primary school, (iii) middle school, (iv) secondary school, and (v) post-secondary education.[19] Individuals with no formal schooling are excluded from our analysis, as we assume their educational attainment is not impacted by school-age storm exposure.

Puducherry is the state identified as having the highest proportion of individuals with post-

[17] The 2021 Population Census has been delayed several times and is now projected to begin in September 2024.

[18] The PLFS provides detailed information on the number of years individuals have spent in formal education, excluding years spent in pre-primary education. The survey does not differentiate between students in schools with automatic promotion and those where grade repetition is possible. It also collects data on earnings of the regular salaried or wage employees and casual laborers, as well as gross earnings of self-employed persons.

[19] Details outlined in Table A.4 of the Appendix.

secondary education, at 31.7%. Conversely, in the Islands of Daman and Diu, only 13.1% of the educated population pursued education beyond secondary school. In West Bengal, 12.9% of the educated individuals in the sample had only below primary education. Mizoram recorded the lowest proportion at 3.1%. State-level proportions of the population with various educational attainments are presented in columns (3) to (7) of Table 3.

Table 3: Proportion of Educational Attainment in At-Risk Districts, Assuming No Storms

	Exposure		Educational Attainment Proportion				
	Storm	Population	Below Primary	Primary	Middle School	Secondary	Post-Secondary
District (State)	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
East Godavari (AP)	0.0003461	1,638,512	0.07131	0.19781	0.32432	0.15383	0.25273
Guntur (AP)	0.0004267	1,547,642	0.07131	0.19781	0.32432	0.15383	0.25273
Krishna (AP)	0.0016441	1,424,357	0.07131	0.19781	0.32432	0.15383	0.25273
Nellore (AP)	0.0015992	951,172	0.07131	0.19781	0.32432	0.15383	0.25273
Srikakulam (AP)	0.0610607	864,223	0.07131	0.19781	0.32432	0.15383	0.25273
Visakhapatnam (AP)	0.0495476	1,371,422	0.07131	0.19781	0.32432	0.15383	0.25273
Vizianagaram (AP)	0.0281793	732,554	0.07131	0.19781	0.32432	0.15383	0.25273
West Godavari (AP)	7.14e-08	1,238,792	0.07131	0.19781	0.32432	0.15383	0.25273
Junagadh (DD)	0.0049337	26,078	0.06430	0.10643	0.44346	0.25499	0.13082
Amreli (GJ)	0.0031228	571,743	0.08895	0.17101	0.42214	0.16003	0.15787
Bhavnagar (GJ)	0.0001407	878,796	0.08895	0.17101	0.42214	0.16003	0.15787
Junagadh (GJ)	0.0005919	698,160	0.08895	0.17101	0.42214	0.16003	0.15787
Kachchh (GJ)	0.0001641	831,365	0.08895	0.17101	0.42214	0.16003	0.15787
Pashchim Singhbhum (JH)	0.0003347	656,558	0.06647	0.14602	0.46095	0.15183	0.17472
Greater Bombay (MH)	0.0001613	3,053,892	0.08965	0.13634	0.37995	0.18580	0.20826
Lawngtlai (MZ)	0.0076817	55,074	0.03099	0.13127	0.48268	0.12261	0.23245
Lunglei (MZ)	0.0039692	67,534	0.03099	0.13127	0.48268	0.12261	0.23245
Baleshwar (OD)	0.0926110	814,688	0.10049	0.16603	0.44047	0.13818	0.15483
Boudh (OD)	0.0407423	159,038	0.10049	0.16603	0.44047	0.13818	0.15483
Cuttack (OD)	0.4470581	850,309	0.10049	0.16603	0.44047	0.13818	0.15483
Dhenkanal (OD)	0.0878728	398,917	0.10049	0.16603	0.44047	0.13818	0.15483
Ganjam (OD)	0.2132895	1,275,897	0.10049	0.16603	0.44047	0.13818	0.15483
Keonjhar (OD)	0.0503895	645,140	0.10049	0.16603	0.44047	0.13818	0.15483
Mayurbhanj (OD)	0.0204917	921,100	0.10049	0.16603	0.44047	0.13818	0.15483
Puri (OD)	0.3588883	554,649	0.10049	0.16603	0.44047	0.13818	0.15483
Sambalpur (OD)	0.0002886	355,681	0.10049	0.16603	0.44047	0.13818	0.15483
Sundargarh (OD)	0.0000162	753,511	0.10049	0.16603	0.44047	0.13818	0.15483
Karaikal (PY)	0.0269009	68,355	0.05781	0.10938	0.35313	0.16250	0.31719
Puducherry (PY)	0.0365622	311,500	0.05781	0.10938	0.35313	0.16250	0.31719
Yanam (PY)	0.0105229	22,520	0.05781	0.10938	0.35313	0.16250	0.31719
Chennai (TN)	0.0049250	1,330,475	0.06666	0.16822	0.39431	0.15778	0.21303
Cuddalore (TN)	0.0265917	844,192	0.06666	0.16822	0.39431	0.15778	0.21303
Kancheepuram (TN)	0.0009859	1,234,212	0.06666	0.16822	0.39431	0.15778	0.21303
Pudukottai (TN)	0.0004572	512,977	0.06666	0.16822	0.39431	0.15778	0.21303
Salem (TN)	0.0001123	1,072,076	0.06666	0.16822	0.39431	0.15778	0.21303
Thanjavur (TN)	0.0174199	739,804	0.06666	0.16822	0.39431	0.15778	0.21303
Tiruchchirappalli (TN)	0.0074335	823,230	0.06666	0.16822	0.39431	0.15778	0.21303
Villupuram (TN)	0.0184537	1,159,291	0.06666	0.16822	0.39431	0.15778	0.21303
North Tripura (TR)	3.29e-06	156,863	0.11802	0.13557	0.48046	0.10885	0.15710
South Tripura (TR)	0.0048199	162,369	0.11802	0.13557	0.48046	0.10885	0.15710
West Tripura (TR)	0.0002846	312,330	0.11802	0.13557	0.48046	0.10885	0.15710
East Midnapore (WB)	0.0093753	1,810,524	0.12884	0.17164	0.38581	0.13897	0.17474
Haora (WB)	0.0067034	1,613,795	0.12884	0.17164	0.38581	0.13897	0.17474
Hugli (WB)	0.0015881	1,705,448	0.12884	0.17164	0.38581	0.13897	0.17474
Kolkata (WB)	0.0122806	1,230,719	0.12884	0.17164	0.38581	0.13897	0.17474

District (State)	Exposure: Storm (1)	Population (2)	Educational Attainment Proportion: Below Primary (3)	Primary (4)	Middle School (5)	Secondary (6)	Post-Secondary (7)
North 24 Parganas (WB)	0.0345758	3,170,555	0.12884	0.17164	0.38581	0.13897	0.17474
South 24 Parganas (WB)	0.0333296	3,017,210	0.12884	0.17164	0.38581	0.13897	0.17474
West Midnapore (WB)	0.0000553	2,044,172	0.12884	0.17164	0.38581	0.13897	0.17474

AP = Andhra Pradesh, DD = Daman and Diu, GJ = Gujarat, JH = Jharkhand, MH = Maharashtra, MZ = Mizoram, OD = Odisha, PY = Pondicherry, TN = Tamil Nadu, TR = Tripura, WB = West Bengal.

Notes: Column (1) presents district-level school-age storm exposure, calculated as the mean intensity of storms over a 10-year period, considering only years where significant storm events (with wind speeds exceeding 50 knots) occurred, between 1999 and 2021. Non-event years, where no such storms were recorded, are excluded. Wind speed is calculated using the Deppermann (1947) formula. West Godavari district's wind exposure is almost zero and is excluded from the financial calculations. Column (2) is the estimated school-age population between 5 and 24 years old from the 2011 Population Census. Columns (3) to (7) show the state-level proportion of the population in at-risk districts from the Periodic Labour Force Survey 2021–2022, with below primary (3), primary (4), middle school (5), secondary (6), and post-secondary (7) education. Educational attainment proportions here represent π_{ij} from equation 10.

Source: Authors' calculations.

Mean state-level annual earnings by educational level for 2017 and 2021 are presented in Table 4. In 2017, the earnings spectrum shows a clear trend between higher educational attainments and increased earnings. For example, in Andhra Pradesh, individuals who did not complete their primary education earned on average INR99,984 annually, while those with post-secondary education earned substantially more with average annual earnings of INR274,304. Notably, states like Daman and Diu and West Bengal, despite being among the lower earners even with post-secondary education, followed this upward trend, indicating the overarching benefit of having an education. Moving forward to 2021, there is an increase in earnings across the same educational levels, likely reflective of broader economic growth and inflationary impacts. Andhra Pradesh saw increases at every educational stage, with post-secondary earners receiving on average INR330,295 annually, marking significant growth from 2017. Comparatively, states like Tamil Nadu and Mizoram also saw substantial increases, especially at higher educational levels, showing a potential growing value of education in enhancing economic outcomes.

Table 4: Annual Earnings by Education Level in At-Risk States, 2017 and 2021 (INR)

	Below Primary		Primary		Middle School		Secondary		Post-Secondary	
State	**2017**	**2021**	**2017**	**2021**	**2017**	**2021**	**2017**	**2021**	**2017**	**2021**
Andhra Pradesh	99,984	109,759	101,797	130,013	119,739	149,380	165,988	180,465	274,304	330,295
Daman and Diu	82,255	91,390	119,164	130,668	164,379	153,361	154,635	196,286	207,221	249,071
Gujarat	105,371	121,434	118,327	132,542	132,036	146,839	169,752	177,779	242,249	299,004
Jharkhand	77,182	98,129	91,427	105,830	98,205	126,610	153,140	176,127	275,384	327,760
Maharashtra	95,364	110,916	100,946	123,055	124,212	146,716	146,728	179,797	308,411	352,045
Mizoram	118,900	156,635	137,714	179,083	171,251	205,212	218,534	281,625	320,651	381,555
Odisha	71,011	98,822	75,916	101,940	95,024	121,798	143,804	177,809	237,694	277,236
Pondicherry	90,231	82,080	113,090	137,458	135,251	171,067	165,165	227,942	276,717	374,570
Tamil Nadu	86,761	114,083	96,947	122,846	121,987	143,741	148,201	178,900	234,289	305,858
Tripura	91,003	112,595	93,993	121,379	135,001	156,844	169,800	212,834	250,071	281,822
West Bengal	69,218	92,967	78,856	103,203	95,066	123,174	106,096	143,343	224,028	276,627

Source: The data are sourced from the Periodic Labour Force Surveys 2017–2018 and 2021–2022.

III. METHODOLOGY

Our approximation of the economic costs of storms in India is grounded in the findings of Pelli et al. (2023) and Pelli and Tschopp (2025), who estimated the impact of storms on physical and human capital, as summarized in Table 5. We build on their estimates to analyze both physical and human capital at risk across districts, integrating multiple data sources. This approach allows us to explore the interaction between extreme weather events, economic assets, and human capital development, offering valuable insights into the broader consequences of storms on the economy.

Table 5: Ordinary Least Squares and Ordered Logit Coefficients of Storms on Physical Assets, Sales, and Educational Attainment

	Firms		Education				
Item	Fixed Assets (1)	Sales (2)	Below Primary (3)	Primary (4)	Middle School (5)	Secondary (6)	Post-Secondary (7)
Storm exposure (50 knots)	-1.37**	-2.42**	0.046***	0.11***	0.096***	-0.055***	-0.20***
	(0.011)	(0.69)	(1.01)	(0.029)	(0.027)	(0.015)	(0.052)
Observations	14,936	14,521	70,003	70,003	70,003	70,003	70,003

FE = fixed effect, TFP = total factor productivity.

Notes: The table presents ordinary least squares coefficients for firms—columns (1) and (2)—and ordered logit coefficients for education—columns (3) to (7). Effects are estimated for manufacturing firms' fixed assets (1) and sales (2), and on educational attainment across the following schooling levels: below primary school (3), primary school (4), middle school (5), secondary (6), and post-secondary (7) education. For columns (1) and (2), values are in logs. Controls, FE, and trends include the following: TFP ($t-1$), growth in night-lights ($t-1$), number of establishments, firm-type FE, industry-year FE, and district trends. See Table A.1 in the Appendix for more details.

$*$ $p < 0.10$

$**$ $p < 0.05$

$***$ $p < 0.01$

Sources: Pelli et al. (2023) for impact on firms and Pelli and Tschopp (2025) for impact on education.

A. Physical Capital Assessment

To quantify the storm-induced damage to fixed assets and sales, we use the estimated coefficients from Pelli et al. (2023) for storms with wind speeds above 50 knots (Table 5) and the annual district exposure data. Our analysis also follows the study's findings that the impacts of storms on capital and sales do not extend into subsequent periods, with firms generally recovering within a year after they are hit. We primarily focus on stronger storms with wind speeds exceeding 50 knots in the year 2021, allowing for comparisons with estimates related to human capital impacts.

Equation 6 and 7 are the formulas used in estimating the total damages to fixed assets (*DFA*) and sales (*DS*) in year (*t*). Total damage is the sum of damage to fixed assets and sales in each district *d*. To estimate the damage per district, the annual fixed assets (FA_{0t}) and sales (S_{0t}) in district (*d*), assuming no-storm impact, are multiplied by the damage coefficients for storms with wind speeds exceeding 50 knots from Pelli et al. (2023) and the annual district storm exposure for that year (x_{dt50}). This approach provides a quick approximation for evaluating the immediate economic consequences of storm exposure on manufacturing firms at the district level.

$$DFA_t = \sum_{d=1}^{n}\left(FA_{0dt} \cdot x_{dt50} \cdot (-1.37)\right) \qquad \textbf{(Equation 6)}$$

$$DS_t = \sum_{d=1}^{n} \left(S_{0dt} \cdot x_{dt50} \cdot (-2.42)\right) \qquad \textbf{(Equation 7)}$$

However, since the reported fixed assets (FA_{rdt}) and sales (S_{rdt}) from the ASI already reflect the impact of typhoons in affected districts, we also estimate the hypothetical levels of fixed assets (FA_{0dt}) and sales (S_{0dt}) as if no storms had occurred. To do this, we use the coefficients from the baseline specification of Pelli et al. (2023) that captures the impact of all tropical storms. Since the reported levels of capital and sales per district are equal to the no-storm values plus the storm damage, the formula for approximating the levels of fixed assets (FS_{0dt}) and sales (S_{0dt}), if the district was not hit by a storm, would be equations 8 and 9. In these equations, the annual district exposure (x_{dt33}) accounts for all storms with wind speeds above 33 knots.

If a district is not exposed to a storm (x_{dt33} = 0), the reported levels of fixed assets (FA_{rdt}) and sales (S_{rdt}) would be equal to their no-storm values (FA_{0dt} and S_{0dt}). However, if the district is hit by a typhoon (x_{dt33} > 0), the no-storm values are calculated by adjusting the reported levels to remove the estimated impact of storm damage using the estimated coefficients from Pelli et al. (2023) and the exposure index for all tropical storms (x_{dt33}).[20]

$$FA_{0dt} = \begin{cases} FA_{rdt}, & if\ x_{dt33} = 0 \\ \frac{FA_{rdt}}{1+\left(\chi_{dt33}\cdot(-1.09)\right)}, & if\ x_{dt33} > 0 \end{cases} \qquad \textbf{(Equation 8)}$$

$$S_{0dt} = \begin{cases} S_{rdt}, & if\ x_{dt33} = 0 \\ \frac{S_{rdt}}{1+\left(\chi_{dt33}\cdot(-1.56)\right)}, & if\ x_{dt33} > 0 \end{cases} \qquad \textbf{(Equation 9)}$$

B. Human Capital Assessment

We assess the economic impact of storms on human capital in India in 2021 by comparing potential earnings across various educational levels, assuming no-storm impact, against adjusted educational levels in storm-affected regions. Our methodology relies mainly on the assumption that school-age storm exposure lowers the proportion of the individuals with higher educational attainment, therefore lowering the aggregated expected lifetime earnings in the population-at-risk.

[20] The study by Pelli et al. (2023) finds that a unit of exposure to storms will reduce fixed assets by 1.09% and sales by 1.56%.

Assuming no impact from storms, the net present value (NPV) of t years of future earnings in storm-prone district d, considering educational levels j, is calculated using the formula:

$$NPV_{djt}^{nostorm} = \sum_{d=1}^{48} \sum_{j=1}^{5} \sum_{t=1}^{45} \left[\frac{Y_{djt}}{(1+r)^t} P_d \, \pi_{dj} \right] \qquad \textbf{(Equation 10)}$$

where Y_{djt} denotes the annual earnings in district d of an individual with education level j after t years of work; r is the real discount rate; P_d represents the school-age (5–24 years old) population-at-risk in district d; and π_{dj} is the proportion of the population in district d with educational level j. We use a real discount rate of 6% following ADB's guidelines for social sector projects, particularly those with significant long-term impacts (footnote 7). Certainly, the NPV of education in India is expected to rise alongside projected earnings. Consistent with this, annual earnings are believed to grow correspondingly with higher educational attainment—a correlation substantiated by the PLFS descriptive data on earnings presented in Table 4. Therefore, the aggregated NPV of future earnings in a district is positively correlated with larger proportions of highly educated individuals.

We assume that future annual earnings across different educational levels will increase over time. To project earnings Y_{djt}, we calculate a nationwide compounded annual growth rate (CAGR) for earnings from 2017 to 2022, using the PLFS data. Individuals with below primary education experienced a CAGR of 4.0%, while individuals with primary education saw a growth rate of 3.9%. Middle school education is associated with a CAGR of 3.4%, and secondary education with 3.9%. The highest CAGR, at 4.1%, is observed for individuals with post-secondary education. The CAGR of annual earnings for each education level are reported in the first column of Table A.5 in the Appendix, along with the projected annual earnings over a 45-year period, which we hypothesize to be the typical length of an active work career.

In storm-vulnerable districts, assuming no-storm impact, we use the proportion of the population at each educational attainment level in each state π_{dj}, based on data from the PLFS (2021–2022). We multiply these proportions by the estimated population P_d aged between 5 and 24 years old for each district to obtain the number of individuals with a given educational level. The proportion of educated individuals and the estimated population of interest are presented in Table 3.

In storm-impacted districts *d*, educational attainment *j* is negatively affected for many individuals, altering the proportions of education completion π_{dj}. Therefore, the NPV of future earnings with storm impact discounted over *t* years is estimated as follows:

$$NPV_{djt}^{storm} = \sum_{d=1}^{48} \sum_{j=1}^{5} \sum_{t=1}^{45} \left[\frac{Y_{djt}}{(1+r)^t} P_d \pi_{dj}^{adj} \right] \qquad \textbf{(Equation 11)}$$

where π_{ij}^{adj} represents the adjusted proportion of the population achieving educational level *j* after considering storm impacts, according to the estimated coefficients by Pelli and Tschopp (2025). The critical variable central to our analysis is π^{adj}, which accounts for the hypothesized variation in the population of educated individuals subsequent to a storm. It is the only variable that differs from equation 10. The critical variable central to our analysis is π^{adj}, which accounts for the hypothesized variation in the population of educated individuals after a storm. It is the only variable that differs from equation 10.

To compute how storms affect the number of individuals at each level of educational attainment, we use the coefficients provided by Pelli and Tschopp (2025), which quantify the effect of storms on education in storm-affected regions. Their estimates are presented in a school-age storm exposure defined as a super storm, such as BOB 06 in 1999, where storm intensity C_{bd} from equation 5 is equal to 1.0. Using this reference point, we multiply the school-age storm exposure in each district by the estimates presented in Table 5, thus obtaining the marginal effects of school-age storm exposure by educational attainment for each district. This marginal effect, added to the proportion of population with a given educational level π_{ij}, is used to obtain the *adjusted* proportion of the population with a given educational level π^{adj}, which quantifies the effect of storms on education$_{ij}$. We multiply the school-age storm exposure in each district by the coefficients presented in Table 5, obtaining the marginal effects of school-age storm exposure by educational attainment for each district. This marginal effect, together with the proportion of population with a given educational level π_{ij}, is used to obtain the *adjusted* proportion of the population with a given educational level π^{adj}.

It is crucial to note that changes in the proportion of educated individuals across different educational levels constitute a zero-sum system. For example, if storms decrease the number of people achieving post-secondary education, the proportion of the population with educational attainment below the post-secondary level will mechanically increase. This is the basis for the estimation of Pelli and Tschopp (2025) that storms will reduce the proportion of individuals achieving secondary education or higher, while increasing the proportion of those attaining education below the secondary level—as shown in columns (3) to (7) of Table 5.

The lost income imputable to changes in educational attainments due to 2021 storms is calculated as the difference in the NPV of future earnings under the two scenarios:

$$C_{djt} = NPV_{djt}^{no\ storm} - NPV_{djt}^{storm} \qquad \textbf{(Equation 12)}$$

The economic cost of storms on human capital is calculated as the difference between potential earnings under two scenarios: (1) a baseline scenario assuming no storm impact on educational attainment, and (2) a storm-impact scenario where educational attainment distributions are adjusted based on estimated storm effects. This differential represents the lost lifetime earnings attributable to storm-induced disruptions in educational attainment. This provides a simple measure of the negative effects of storms on human capital development though the educational attainment channel. However, one limitation of this methodology is that the impacts of the storms may already be included in the baseline data, such as the PLFS earnings figures, which could lead to an underestimation of the true economic costs.

IV. RESULTS

Our results highlight the significant economic impact of storms on both physical and human capital. However, these estimates should be interpreted with caution as they combine two distinct methodological approaches: while physical capital losses reflect immediate damage to the firms' assets (USD2.8 billion) and sales (USD14.4 billion) in 2021, human capital costs are calculated as the present value of future earnings losses due to reduced educational attainment (USD25.0 billion using a 6% discount rate, following ADB guidelines for social sector projects). This difference in temporal scope—current versus future losses—means the two components are not directly comparable, though both contribute to our understanding of storms' total economic burden.

Table 6 summarizes the reported manufacturing fixed assets and sales per district in 2021, along with the approximated levels if no tropical storms had occurred that year. The reported fixed assets averaged USD2.29 billion, while the mean sales per district amounted to USD8.9 billion.[21] In 2021, 60 districts were exposed to storms. Without these storms, the mean values would have been higher, at USD2.32 billion for fixed assets and USD9.1 billion for sales. The estimated without-storm capital and sales for each district affected by storms are presented in Table A.3 of the Appendix.

Table 6: District Summary Statistics, 2021 (USD billion)

Item	Mean	St. Dev.	Median	Min	Max	Sum	N
Reported (with storm exposure)							
Fixed Assets	2.29	5.80	0.49	0.00	80.19	1,423.93	621
Sales	8.92	21.13	2.18	0.00	273.85	5,537.48	621
Estimated (no-storm exposure)							
Fixed Assets	2.32	5.89	0.49	0.00	81.05	1,443.28	621
Sales	9.09	21.66	2.18	0.00	278.06	5,645.96	621

Notes: Number of establishments is from the Economic Census surveys, while fixed assets and sales are computed using data from the Annual Survey of Industries and the Economic Census surveys. The number of establishments, along with their corresponding fixed assets and sales, includes only manufacturing establishments with 10 or more workers. Fixed assets and sales are in nominal terms and are expressed in USD billion using the 2021 annual average exchange rate of USD0.0135285 per INR1, from ADB's Key Indicators Database (accessed 6 October 2024).

Source: Authors' calculations.

[21] Data in the ASI and the PLFS are in Indian rupees (INR). For 2021, we use an exchange rate of USD0.0135285 per INR1, from ADB's Key Indicators Database (accessed 6 October 2024).

Using the approximated levels of fixed assets and sales without storms, we compute the damage of stronger storms to fixed assets and sales per district (Table 7). District Amreli, which had the second highest storm exposure at 0.13, had the highest damage to capital (USD1.2 billion) and sales (USD7.2 billion). On the other hand, despite having the highest exposure level at 0.17, Diu incurred relatively lower damages to capital amounting to USD4.1 million. The district of Greater Bombay, which had the largest number of affected establishments, also suffered significant losses, with fixed assets reduced by USD415.0 million and sales by USD2.6 billion because of more severe storms. In total, the estimated damages of storms over 50 knots reached USD2.8 billion for capital, representing 0.16% of the total in 2021. Meanwhile, losses in sales amounted to USD 14.5 billion, or 0.30% of the total sales. These are presented in columns (1) and (2) of Table 8.

Table 7: Damages to Fixed Assets and Sales per District, 2021 (USD billion)

	Estimated (no-storm damage)		Damage	
	Fixed Assets	Sales	Fixed Assets	Sales
District (State)	**(1)**	**(2)**	**(3)**	**(4)**
Amreli (GJ)	7.78	29.01	1.2734	7.2103
Baleshwar (OD)	5.67	13.73	0.5272	1.9306
Bhavnagar (GJ)	33.31	115.35	0.2914	1.4638
Dadra and Nagar Haveli (DH)	3.72	25.03	0.0029	0.0281
Daman (DD)	2.97	20.04	0.0072	0.0707
Diu (DD)	0.02	0.12	0.0041	0.0458
East Midnapore (WB)	8.65	36.34	0.0017	0.0100
Greater Bombay (MH)	37.75	160.64	0.4150	2.5725
Junagadh (GJ)	3.81	13.24	0.0749	0.3806
Mayurbhanj (OD)	4.00	9.51	0.1411	0.4948
Raigarh (CG)	0.89	3.20	0.0027	0.0139
Ratnagiri (MH)	1.38	5.75	0.0000	0.0003
Thane (MH)	31.36	132.59	0.0368	0.2251
West Midnapore (WB)	1.67	6.83	0.0003	0.0017
Total	**142.95**	**571.37**	**2.7788**	**14.4482**

CG = Chhattisgarh, DD = Daman and Diu, DH = Dadra and Nagar Haveli, GJ = Gujarat, MH = Maharashtra, OD = Odisha, WB = West Bengal.

Notes: Fixed assets and sales with no-storm impacts are estimated using data from the Annual Survey of Industries and the Economic Census surveys, and coefficients of storm damages from Pelli et al. (2023). Values are in nominal terms and are expressed in USD billion using the 2021 annual average exchange rate of USD 0.0135285 per INR 1, from ADB's Key Indicators Database (accessed 6 October 2024).

Source: Authors' calculations.

Table 8: Cost of Storms on Firms and Educational Attainment in India, 2021
(USD billion)

Item	Firms		Education		
	Fixed Assets (1)	Sales (2)	r=9% (3)	r=6% (4)	r=4% (5)
Total value **before** storm	1,443.3	5,646.0	1,892.2	3,080.3	4,611.6
Total value **after** storm	1,440.5	5,631.5	1,877.2	3,055.3	4,573.5
Estimated costs	2.8	14.5	15.1	25	38.1
Percent of total (%)	0.2	0.3	0.8	0.8	0.8

Notes: Columns (1) and (2) represent total cost of storms to fixed assets (1) and sales (2). The total value before-storm is the estimated level of capital and sales in the absence of storms. Columns (3) to (5) represent total costs of storms on human capital as measured by educational attainment loss, with discount rates of 9%, 6%, and 4% used to calculate net present value of education. Storm exposure is measured at 50 knots wind speed threshold.

Source: Authors' calculations.

The NPV of lifetime projected earnings for each educational level using discount rates of 9%, 6%, and 4% are presented in Table A.6 of the Appendix. These different discount rates are used for robustness checks to assess the financial impact of storm exposure on human capital in India.

Storms impact the proportions of educational completion, which are associated with different expected lifetime earnings. These proportions (π^{adj}) in the population-at-risk, presented in equation 12, are adjusted using coefficients from Pelli and Tschopp (2025). Variations of mean educational attainment proportions before and after storm for storm-exposed districts are presented in columns (1) to (5) of Table 9, while the approximated financial impact with a 6% discount rate are shown in columns (6) to (8) of the same table. Several districts exhibit substantial financial impacts on human capital due to storms, with noticeable costs in the states of Odisha (formerly Orissa) and West Bengal. Cuttack district in Odisha stands out with a human capital cost of USD 6.2 billion, the highest in the dataset. This significant impact can be attributed to the district's high storm exposure of 0.447, which has led to a marked reduction in higher educational attainment levels, thereby lowering projected lifetime earnings for its population. Similarly, Ganjam (USD4.5 billion) and Puri (USD3.3 billion), also in the state of Odisha, face considerable human capital costs, reflecting a consistent trend of educational disruptions in this region.

Table 9: Educational Attainment Changes and Financial Impact of Storms (r = 6%)

	Change in Educational Attainment					Financial Impact		
District (State)	**Below Primary (1)**	**Primary (2)**	**Middle School (3)**	**Secondary (4)**	**Post-Secondary (5)**	**Before Storm (6)**	**After Storm (7)**	**Cost (8)**
East Godavari (AP)	-0.00002	-0.00004	-0.00003	0.00002	0.00007	125.8397	125.8292	0.0105
Guntur (AP)	-0.00002	-0.00005	-0.00004	0.00003	0.00008	118.8608	118.8486	0.0122
Krishna (AP)	-0.00008	-0.00019	-0.00015	0.00010	0.00033	109.3924	109.3490	0.0433
Nellore (AP)	-0.00008	-0.00018	-0.00015	0.00009	0.00032	73.0512	73.0230	0.0282
Srikakulam (AP)	-0.00281	-0.00672	-0.00586	0.00336	0.01221	66.3734	65.3970	0.9764
Visakhapatnam (AP)	-0.00228	-0.00545	-0.00475	0.00273	0.00991	105.3268	104.0695	1.2573
Vizianagaram (AP)	-0.00130	-0.00310	-0.00270	0.00155	0.00563	56.2610	55.8791	0.3820
Junagadh (DD)	-0.00023	-0.00054	-0.00047	0.00027	0.00099	1.7248	1.7233	0.0016
Amreli (GJ)	-0.00014	-0.00034	-0.00030	0.00018	0.00062	38.2394	38.2116	0.0279
Bhavnagar (GJ)	-0.00001	-0.00002	-0.00001	0.00001	0.00003	58.7758	58.7738	0.0019
Junagadh (GJ)	-0.00003	-0.00007	-0.00006	0.00004	0.00012	46.6945	46.6880	0.0064
Kachchh (GJ)	-0.00001	-0.00002	-0.00002	0.00001	0.00003	55.6035	55.6014	0.0021
Pashchim Singhbhum (JH)	-0.00002	-0.00004	-0.00003	0.00001	0.00007	42.3206	42.3161	0.0045
Greater Bombay (MH)	-0.00001	-0.00001	-0.00001	0.00001	0.00003	228.3410	228.3308	0.0102
Lawngtlai (MZ)	-0.00036	-0.00084	-0.00074	0.00043	0.00153	5.3923	5.3839	0.0085
Lunglei (MZ)	-0.00019	-0.00043	-0.00038	0.00022	0.00079	6.6124	6.6070	0.0054
Baleshwar (OD)	-0.00426	-0.01019	-0.00889	0.00510	0.01852	47.1600	45.9206	1.2393
Boudh (OD)	-0.00188	-0.00448	-0.00391	0.00224	0.00815	9.2062	9.0998	0.1064
Cuttack (OD)	-0.02057	-0.04918	-0.04292	0.02459	0.08941	49.2219	42.9777	6.2443
Dhenkanal (OD)	-0.00404	-0.00967	-0.00844	0.00484	0.01757	23.0922	22.5164	0.5758
Ganjam (OD)	-0.00981	-0.02346	-0.02048	0.01174	0.04265	73.8580	69.3878	4.4702
Keonjhar (OD)	-0.00232	-0.00554	-0.00484	0.00278	0.01007	37.3453	36.8113	0.5340
Mayurbhanj (OD)	-0.00094	-0.00225	-0.00197	0.00113	0.00409	53.3198	53.0098	0.3100
Puri (OD)	-0.01651	-0.03948	-0.03445	0.01974	0.07177	32.1070	28.8372	3.2698
Sambalpur (OD)	-0.00001	-0.00003	-0.00003	0.00002	0.00005	20.5894	20.5877	0.0017
Sundargarh (OD)	0.00000	0.00000	0.00000	0.00000	0.00000	43.6186	43.6183	0.0002
Karaikal (PY)	-0.00124	-0.00295	-0.00258	0.00148	0.00538	6.4273	6.3857	0.0417
Puducherry (PY)	-0.00168	-0.00402	-0.00350	0.00201	0.00731	29.2901	29.0319	0.2582
Yanam (PY)	-0.00049	-0.00115	-0.00101	0.00058	0.00211	2.1176	2.1122	0.0054
Chennai (TN)	-0.00022	-0.00055	-0.00047	0.00027	0.00099	93.4567	93.3462	0.1105
Cuddalore (TN)	-0.00122	-0.00293	-0.00255	0.00146	0.00532	59.2987	58.9200	0.3786
Kancheepuram (TN)	-0.00004	-0.00011	-0.00009	0.00006	0.00020	86.6949	86.6744	0.0205
Pudukottai (TN)	-0.00002	-0.00005	-0.00004	0.00003	0.00009	36.0331	36.0292	0.0040
Salem (TN)	0.00000	-0.00002	-0.00001	0.00001	0.00002	75.3060	75.3039	0.0020
Thanjavur (TN)	-0.00080	-0.00192	-0.00167	0.00096	0.00348	51.9662	51.7488	0.2174
Tiruchchirappalli (TN)	-0.00034	-0.00082	-0.00071	0.00041	0.00149	57.8262	57.7230	0.1032
Villupuram (TN)	-0.00085	-0.00203	-0.00177	0.00102	0.00369	81.4322	81.0714	0.3608
North Tripura (TR)	0.00000	0.00000	0.00000	0.00000	0.00000	10.4970	10.4970	0.0000
South Tripura (TR)	-0.00022	-0.00053	-0.00047	0.00026	0.00097	10.8655	10.8535	0.0119
West Tripura (TR)	-0.00002	-0.00003	-0.00003	0.00001	0.00006	20.9006	20.8993	0.0014
East Midnapore (WB)	-0.00043	-0.00103	-0.00090	0.00051	0.00188	103.5687	103.3035	0.2652
Haora (WB)	-0.00031	-0.00074	-0.00064	0.00036	0.00134	92.3151	92.1461	0.1690
Hugli (WB)	-0.00007	-0.00018	-0.00015	0.00008	0.00032	97.5579	97.5156	0.0423
Kolkata (WB)	-0.00056	-0.00135	-0.00118	0.00067	0.00246	70.4017	70.1656	0.2361
North 24 Parganas (WB)	-0.00159	-0.00381	-0.00332	0.00190	0.00692	181.3676	179.6550	1.7126
South 24 Parganas (WB)	-0.00153	-0.00367	-0.00320	0.00183	0.00667	172.5957	171.0246	1.5710
West Midnapore (WB)	0.00000	-0.00001	-0.00000	0.00000	0.00001	116.9342	116.9325	0.0018
Total	**–**	**–**	**–**	**–**	**–**	**3,080.32**	**3,055.28**	**25.04**

AP = Andhra Pradesh, DD = Daman and Diu, GJ = Gujarat, JH = Jharkhand, MH = Maharashtra, MZ = Mizoram, OD = Odisha, PY = Pondicherry, r = discount rate, TN = Tamil Nadu, TR = Tripura, WB = West Bengal.

Notes: Columns (1) to (5) show differences in educational attainment proportions for each level (no-storm minus storm impact). Columns (6) to (8) show financial value of human capital (USD billion, 2021) before storm, after storm, and the resulting cost at 6% discount rate. Districts showing 0.00000 generally experienced very small but non-zero changes that are not visible at this level of decimal precision.

Source: Authors' calculations.

In West Bengal, the districts of North and South 24 Parganas show high storm-related educational costs, with human capital losses of USD1.7 billion and USD1.6 billion, respectively. This impact emphasizes the vulnerability of coastal districts in West Bengal, where recurrent storm exposure directly affects educational outcomes and, consequently, the economic potential of these populations. The aggregated human capital costs in these areas underline the long-term economic consequences of storm exposure, reinforcing the need for targeted educational and economic resilience policies in the most affected districts.

The total cost for India is estimated to be USD25 billion, using our main discount rate of 6%. With a more conservative 4% real discount rate, the estimated total cost rises to USD38.1 billion, while with a 9% rate, it would be USD15.1 billion.[22] This variation demonstrates the sensitivity of projected costs to the choice of discount rate and highlights the significant long-term economic impact of storms on human capital in storm-exposed districts across India.

V. CONCLUSION

This paper provides a novel microdata-driven assessment of the economic impact of storms on India's economy by examining both physical and human capital across districts. Our analysis reveals substantial economic costs through two key channels: (i) damage to manufacturing firms' physical assets and sales, and (ii) disruptions to educational attainment. Using detailed district-level data from the Economic Census, the Annual Survey of Industries, and the Population Census, combined with wind exposure data from the NOAA, we estimate that storms in India have resulted in substantial economic costs in 2021.

Our findings demonstrate that storms caused significant damage to physical capital in manufacturing, with fixed capital losses of USD2.8 billion (0.2% of total manufacturing fixed assets) and sales losses of USD14.5 billion (0.3% of total manufacturing sales) in 2021. The impact is particularly severe in certain districts, with Amreli experiencing the highest damage to both capital (USD1.2 billion) and sales (USD7.2 billion). These losses highlight the vulnerability of India's manufacturing sector to extreme weather events, especially in coastal regions. Similarly, the analysis of human capital costs reveals an even more concerning picture. Using a 6% discount rate, we find that several districts experience substantial financial impacts on human

[22] Human capital cost by districts and for India as a whole, with real discount rates of 6%, 4% and 9%, are presented in Table A.8 of the Appendix.

capital because of storms, especially in the Cuttack, Ganjam, and Puri districts in Odisha.

These findings carry important policy implications. First, they underscore the need for targeted infrastructure resilience programs in storm-prone districts, particularly those with high concentrations of manufacturing activity. Second, the substantial human capital costs highlight the importance of developing educational continuity plans and implementing protective measures for schools in vulnerable regions. Third, the geographic concentration of damages suggests that disaster risk reduction strategies should be tailored to local vulnerabilities and economic structures.

It is important to remember that our analysis likely understates the total economic impact of storms, as it focuses solely on manufacturing firms and educational outcomes. We do not account for damages to other sectors such as agriculture, construction, retail, and essential services, nor do we consider indirect effects such as supply chain disruptions, population displacement, or changes in investment behavior due to perceived risk. The exclusion of these factors suggests that the true economic cost of storms in India could be substantially higher than our estimates indicate.

Our findings contribute to the growing literature on disaster economics by demonstrating the value of microdata in assessing climate-related risks. This granular approach not only provides more precise damage estimates but also reveals important spatial and sector variations in vulnerability that may be obscured in aggregate analyses. As climate change potentially increases the frequency and intensity of storms, such detailed assessments become increasingly crucial for effective policy design and risk management.

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APPENDIX

Table A.1: Summary of Estimates for Impact of 50-Knot Storms on Education and Firms

	Marginal Effects by Educational Level				
Educational Attainment	**Below Primary (1)**	**Primary (2)**	**Middle School (3)**	**Secondary (4)**	**Post-Secondary (5)**
School-age exposure	0.046***	0.11***	0.096***	-0.055***	-0.20***
	(0.011)	(0.029)	(0.027)	(0.015)	(0.052)
Individual controls	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes
District trends	Yes	Yes	Yes	Yes	Yes
Observations	70,003	70,003	70,003	70,003	70,003
Mean dep. var.	0.027	0.098	0.239	0.365	0.272

	Marginal Effects on Firms	
	Fixed Capital (6)	**Sales (7)**
Firm exposure	-1.37**	-2.42**
	(0.69)	(1.01)
District trends	Yes	Yes
Postal code FE	No	Yes
Firm and industry FE	Yes	Yes
Observations	14,936	14,521
Mean dep. var.	45.202	63.4

FE = fixed effect, GDP = gross domestic product, TFP = total factor productivity.

Notes: The table presents the marginal effects of childhood exposure to storms on educational attainment across various schooling levels, and the marginal impact of a 50-knot storm intensity on firms' fixed capital and sales. Educational attainment is a categorical variable indicating the reported level of education. Columns (1) to (5) report the marginal effects of childhood exposure to storms for each of these educational levels: below primary school (1), primary school (2), middle school (3), secondary education (4), and post-secondary education (5). The firm data include controls for firm-specific TFP, the yearly growth of district night-light intensity (a proxy for local GDP growth), number of establishments per firm, and district and firm-type FE. The sales regressions also include postal code FE. Values inside the parentheses are standard errors. Standard errors are clustered at the firm, district-year, and state levels.

* $p < 0.10$

** $p < 0.05$

*** $p < 0.01$.

Sources: Pelli and Tschopp (2025) for impact on education; and Pelli et al. (2023) for impact on firms.

Table A.2: Total Storm Damage and Losses to Manufacturing per Year

Item	2005	2013	2021
Fixed Capital			
Reported (with storm exposure)	518.98	1,144.47	1,423.93
Estimated (no-storm exposure)	525.45	1,158.50	1,443.28
Storm damage (50 knots)	0.00	-6.72	-2.78
As percentage of total	**0.00%**	**-0.59%**	**-0.20%**
Sales			
Reported (with storm exposure)	1,977.91	4,353.61	5,537.48
Estimated (no-storm exposure)	2,010.69	4,425.35	5,645.96
Storm damage (50 knots)	0.00	-14.97	-14.45
As percentage of total	**0.00%**	**-0.34%**	**-0.26%**

Notes: Fixed assets and sales with no-storm impacts are estimated using data from the Annual Survey of Industries and the Economic Census surveys, and coefficients of storm damage from Pelli et al. (2023). Figures are in nominal terms and are expressed in USD million using the 2021 annual average exchange rate of USD0.0135285 per INR 1, from ADB's Key Indicators Database (accessed 6 October 2024). Numbers inside the parentheses represent the percentage of damage and losses with respect to total fixed assets and sales.

Source: Authors' calculations.

Table A.3: Fixed Assets and Sales of Storm-Affected Districts

	Exposure (33 knots)		Reported		Estimated (no-storm impact)	
	Storm	Firms	Fixed Assets	Sales	Fixed Assets	Sales
District (State)	(1)	(2)	(3)	(4)	(5)	(6)
Ahmadabad (GJ)	0.0042	1,506	2,091.83	7,143.04	2,101.44	7,190.06
Ahmednagar (MH)	0.0034	402	284.05	1,192.35	285.12	1,198.77
Amreli (GJ)	0.2166	359	497.16	1,704.87	574.87	2,144.22
Aurangabad (BR)	0.0004	7	1.15	8.82	1.15	8.83
Baleshwar (OD)	0.1530	103	390.75	913.56	418.94	1,014.64
Bankura (WB)	0.0034	158	98.70	403.60	99.33	407.36
Barddhaman (WB)	0.0003	2,287	1,439.93	5,828.81	1,454.37	5,913.20
Belgaum (KA)	0.0002	370	279.19	953.23	279.24	953.50
Bharuch (GJ)	0.0078	905	1,258.18	4,294.64	1,269.01	4,347.75
Bhavnagar (GJ)	0.0544	1,718	2,386.34	8,146.78	2,462.02	8,526.80
Bid (MH)	0.0000	27	18.17	80.89	18.17	80.90
Cuttack (OD)	0.0161	215	824.87	1,918.21	870.95	2,094.36
Dadra and Nagar Haveli (DH)	0.0329	700	269.81	1,801.40	274.86	1,850.42
Daman (DD)	0.0394	556	214.32	1,433.78	219.17	1,481.06
Dhenkanal (OD)	0.0024	43	162.79	383.70	165.86	394.31
Dhule (MH)	0.0015	76	54.32	227.08	54.41	227.61
Diu (DD)	0.2638	3	1.10	7.18	1.26	8.93
East Midnapore (WB)	0.0291	950	597.51	2,422.03	639.07	2,686.35
Gandhinagar (GJ)	0.0003	581	806.91	2,751.98	807.15	2,753.16
Goa (GA)	0.0076	611	224.66	1,223.44	225.60	1,230.80
Greater Bombay (MH)	0.0585	3,856	2,716.62	11,420.02	2,790.14	11,873.91
Haora (WB)	0.0060	1,032	650.32	2,629.95	694.57	2,909.98
Hugli (WB)	0.0021	513	322.52	1,309.03	334.29	1,379.89
Jalgaon (MH)	0.0000	259	183.36	768.17	183.36	768.19
Jamnagar (GJ)	0.0080	339	470.42	1,607.71	473.37	1,622.20
Junagadh (GJ)	0.0726	196	271.51	928.24	281.51	978.74
Kachchh (GJ)	0.0000	271	374.84	1,284.05	374.85	1,284.09
Keonjhar (OD)	0.0185	78	303.89	694.18	310.21	715.12
Kheda (GJ)	0.0013	195	271.51	927.63	271.89	929.47
Kolhapur (MH)	0.0037	1,292	910.89	3,826.11	912.77	3,837.41
Kolkata (WB)	0.0026	894	562.22	2,275.29	612.26	2,597.35
Mahesana (GJ)	0.0001	454	630.98	2,157.85	631.04	2,158.14
Mayurbhanj (OD)	0.0935	73	282.19	657.55	295.31	702.87
Nashik (MH)	0.0070	1,471	1,035.95	4,352.79	1,043.93	4,400.94
North 24 Parganas (WB)	0.0007	4,210	2,650.69	10,728.15	2,843.05	11,962.86
Panch Mahals (GJ)	0.0000	219	305.87	1,035.87	305.89	1,035.95
Pashchim Singhbhum (JH)	0.0072	15	15.53	54.02	15.62	54.46
Pune (MH)	0.0108	2,457	1,731.15	7,278.92	1,742.14	7,345.32
Puri (OD)	0.0005	228	879.13	2,027.75	989.44	2,490.50
Puruliya (WB)	0.0016	113	70.52	287.58	70.73	288.79
Raigarh (CG)	0.0410	100	64.90	230.25	66.06	236.29
Rajkot (GJ)	0.0201	1,919	2,665.58	9,106.54	2,698.13	9,267.11
Ranchi (JH)	0.0000	162	181.00	546.23	181.20	547.09
Ratnagiri (MH)	0.0268	142	100.69	417.34	101.93	424.78
Sangli (MH)	0.0016	411	290.11	1,214.54	290.60	1,217.51
Satara (MH)	0.0075	461	324.51	1,367.75	325.45	1,373.44
Sindhudurg (MH)	0.0193	112	78.55	329.43	79.41	334.63
Solapur (MH)	0.0003	599	421.22	1,770.29	421.36	1,771.12
South 24 Parganas (WB)	0.0059	742	467.03	1,890.18	519.04	2,233.44
Srikakulam (AD)	0.0124	436	510.18	1,774.29	559.07	2,040.88
Sundargarh (OD)	0.0000	176	672.94	1,571.14	676.32	1,582.47
Surat (GJ)	0.0097	4,266	5,927.64	20,242.41	5,991.07	20,553.85
Surendranagar (GJ)	0.0070	122	168.31	582.29	168.96	585.52
Thane (MH)	0.0347	3,247	2,287.33	9,612.94	2,317.99	9,800.48
The Dangs (GJ)	0.0089	3	3.88	11.24	3.92	11.40

	Exposure (33 knots)		Reported		Estimated (no-storm impact)	
	Storm	Firms	Fixed Assets	Sales	Fixed Assets	Sales
District (State)	(1)	(2)	(3)	(4)	(5)	(6)
Uttar Kannand (KA)	0.0002	182	137.49	467.74	137.51	467.85
Vadodara (GJ)	0.0019	1,045	1,453.24	4,963.48	1,456.28	4,978.39
Valsad (GJ)	0.0239	949	1,319.31	4,499.46	1,337.02	4,586.88
Vizianagaram (AD)	0.0107	206	241.51	838.84	253.22	900.11
West Midnapore (WB)	0.0288	190	119.85	483.27	123.54	504.98
Total		45,212	43,977.11	161,009.88	45,106.42	167,267.40

AP = Andhra Pradesh, BR = Bihar, CG = Chhattisgarh, DD = Daman and Diu, DH = Dadra and Nagar Haveli, GA = Goa, GJ = Gujarat, JH = Jharkhand, KA = Karnataka, MH = Maharashtra, OD = Odisha, WB = West Bengal.

Notes: Column (1) presents the exposure index of districts affected by storms (33 knots threshold), while column (2) indicates the number of manufacturing establishments in the corresponding district. Columns (3) and (4) show fixed assets and sales level computed directly from the Annual Survey of Industries and the Economic Census, while columns (5) and (6) present the estimated capital and sales if the districts were not affected by storms using the coefficients from Pelli et al. (2023).

Source: Authors' calculations.

Table A.4: Years of Education Used for Educational Attainment

Level of Education	Duration (Years) (1)	Cumulated Years (2)
Lower Education		
Primary	5	5
Middle school	3	8
Secondary	2	10
Higher secondary	2	12
Higher Education		
Post-secondary	3	15

Notes: Column (1) shows the duration of each category of schooling in India's schooling system, which is the standard time required to complete each level of education. Column (2) gives the total number of years of education accumulated after completion of each category of schooling. For the post-secondary category, we aggregate all tertiary levels to only one category, which is equivalent to at least a graduate diploma.

Source: Authors' estimation based on standard duration of educational level completion

Table A.5: Projected Annual Earnings by Education Level in At-Risk States, 2021–2066

State	CAGR	2021	2022	2023	2065	2066
Post-Secondary Education						
Andhra Pradesh	0.0414	330,295	343,965	358,202	1,967,335	2,048,762
Daman and Diu	0.0414	249,071	259,380	270,116	1,483,544	1,544,946
Gujarat	0.0414	299,004	311,380	324,268	1,780,960	1,854,672
Jharkhand	0.0414	327,760	341,326	355,453	1,952,238	2,033,040
Maharashtra	0.0414	352,045	366,616	381,790	2,096,888	2,183,677
Mizoram	0.0414	381,555	397,348	413,794	2,272,659	2,366,723
Odisha	0.0414	277,236	288,711	300,660	1,651,304	1,719,650
Pondicherry	0.0414	374,570	390,073	406,218	2,231,054	2,323,396
Tamil Nadu	0.0414	305,858	318,517	331,700	1,821,783	1,897,185
Tripura	0.0414	281,822	293,486	305,634	1,678,617	1,748,094
West Bengal	0.0414	276,627	288,077	300,000	1,647,676	1,715,872
Secondary Education						
Andhra Pradesh	0.0394	180,465	187,578	194,971	988,662	1,027,626
Daman and Diu	0.0394	196,286	204,022	212,062	1,075,331	1,117,711
Gujarat	0.0394	177,779	184,785	192,068	973,944	1,012,328
Jharkhand	0.0394	176,127	183,069	190,284	964,895	1,002,924
Maharashtra	0.0394	179,797	186,883	194,248	984,999	1,023,819
Mizoram	0.0394	281,625	292,725	304,261	1,542,856	1,603,662
Odisha	0.0394	177,809	184,817	192,101	974,109	1,012,500
Pondicherry	0.0394	227,942	236,926	246,264	1,248,759	1,297,975
Tamil Nadu	0.0394	178,900	185,951	193,280	980,087	1,018,714
Tripura	0.0394	212,834	221,222	229,941	1,165,988	1,211,941
West Bengal	0.0394	143,343	148,993	154,865	785,292	816,242
Middle School						
Andhra Pradesh	0.03399	149,380	154,457	159,707	650,095	672,190
Daman and Diu	0.03399	153,361	158,574	163,963	667,420	690,104
Gujarat	0.03399	146,839	151,830	156,990	639,036	660,756
Jharkhand	0.03399	126,610	130,913	135,363	551,000	569,727
Maharashtra	0.03399	146,716	151,702	156,858	638,499	660,200
Mizoram	0.03399	205,212	212,187	219,399	893,073	923,427
Odisha	0.03399	121,798	125,938	130,218	530,057	548,073
Pondicherry	0.03399	171,067	176,882	182,894	744,476	769,779
Tamil Nadu	0.03399	143,741	148,626	153,678	625,553	646,814
Tripura	0.03399	156,844	162,175	167,687	682,575	705,775
West Bengal	0.03399	123,174	127,361	131,689	536,047	554,267
Primary School						
Andhra Pradesh	0.03921	130,013	135,112	140,410	706,309	734,006
Daman and Diu	0.03921	130,668	135,791	141,116	709,863	737,699
Gujarat	0.03921	132,542	137,740	143,141	720,048	748,284
Jharkhand	0.03921	105,830	109,980	114,293	574,931	597,476
Maharashtra	0.03921	123,055	127,880	132,895	668,506	694,720
Mizoram	0.03921	179,083	186,106	193,404	972,886	1,011,036
Odisha	0.03921	101,940	105,937	110,091	553,797	575,513
Pondicherry	0.03921	137,458	142,848	148,450	746,754	776,037

State	CAGR	2021	2022	2023	2065	2066
Tamil Nadu	0.03921	122,846	127,663	132,669	667,370	693,540
Tripura	0.03921	121,379	126,138	131,085	659,400	685,257
West Bengal	0.03921	103,203	107,250	111,456	560,661	582,646
Below Primary School						
Andhra Pradesh	0.04007	109,759	114,156	118,730	618,158	642,925
Daman and Diu	0.04007	91,390	95,052	98,860	514,708	535,330
Gujarat	0.04007	121,434	126,300	131,360	683,915	711,316
Jharkhand	0.04007	98,129	102,060	106,149	552,658	574,800
Maharashtra	0.04007	110,916	115,360	119,982	624,676	649,704
Mizoram	0.04007	156,635	162,911	169,438	882,167	917,511
Odisha	0.04007	98,822	102,781	106,899	556,561	578,860
Pondicherry	0.04007	82,080	85,369	88,789	462,273	480,794
Tamil Nadu	0.04007	114,083	118,653	123,407	642,511	668,253
Tripura	0.04007	112,595	117,106	121,798	634,133	659,539
West Bengal	0.04007	92,967	96,691	100,565	523,586	544,563

Notes: Projected annual earnings are expressed in 2021 Indian rupees (INR) for individuals by level of education over the 45-year period (2021–2066). We use 2021 earnings as the starting point and project future earnings based on the compound annual growth rate (CAGR) for each at-risk state. We only show the first and last 2 years of projected earnings. CAGR is calculated by comparing the Periodic Labour Force Survey earnings data from 2021–2022 and 2017–2018 presented in Table 4.

Source: Authors' calculations.

Table A.6: Net Present Values of Future Earnings by Educational Level and State

State	Below Primary	Primary	Middle School	Secondary	Post-Secondary
			Discount rate = 9%		
Andhra Pradesh	2,283,036	2,609,243	2,969,921	4,593,800	7,170,881
Daman and Diu	1,672,792	2,361,410	2,567,464	3,557,777	4,651,003
Gujarat	2,222,711	2,395,293	2,458,276	3,222,334	5,583,421
Jharkhand	1,796,127	1,912,549	2,119,613	3,192,397	6,120,387
Maharashtra	2,030,186	2,223,833	2,456,210	3,258,910	6,573,877
Mizoram	2,867,024	3,236,375	3,435,518	5,104,603	7,124,931
Odisha	1,808,813	1,842,244	2,039,052	3,222,881	5,176,941
Pondicherry	1,502,377	2,484,133	2,863,887	4,131,572	6,994,496
Tamil Nadu	2,088,148	2,220,055	2,406,407	3,242,661	5,711,404
Tripura	2,060,919	2,193,542	2,625,766	3,857,721	5,262,570
West Bengal	1,701,643	1,865,079	2,062,094	2,598,173	5,165,566
			Discount rate = 6%		
Andhra Pradesh	3,289,499	3,833,943	3,996,743	5,341,779	10,200,000
Daman and Diu	2,738,997	3,853,233	4,103,257	5,810,057	7,656,564
Gujarat	3,639,421	3,908,520	3,928,755	5,262,256	9,191,527
Jharkhand	2,940,941	3,120,804	3,387,513	5,213,367	10,100,000
Maharashtra	3,324,184	3,628,741	3,925,454	5,321,989	10,800,000
Mizoram	4,694,408	5,280,959	5,490,561	8,336,111	11,700,000
Odisha	2,961,714	3,006,083	3,258,761	5,263,152	8,522,374
Pondicherry	2,459,963	4,053,485	4,576,993	6,747,095	11,500,000
Tamil Nadu	3,419,093	3,622,576	3,845,859	5,295,452	9,402,216
Tripura	3,374,507	3,579,313	4,196,434	6,299,880	8,663,338
West Bengal	2,786,236	3,043,344	3,295,588	4,242,967	8,503,651
			Discount rate = 4%		
Andhra Pradesh	4,946,243	5,749,934	5,899,653	8,016,148	15,300,000
Daman and Diu	4,118,482	5,778,863	6,056,880	8,718,870	11,600,000
Gujarat	5,472,403	5,861,781	5,799,295	7,896,817	13,900,000
Jharkhand	4,422,136	4,680,408	5,000,359	7,823,453	15,200,000
Maharashtra	4,998,399	5,442,184	5,794,424	7,986,453	16,300,000
Mizoram	7,058,728	7,920,088	8,104,701	12,500,000	17,700,000
Odisha	4,453,371	4,508,357	4,810,307	7,898,158	12,900,000
Pondicherry	3,698,914	6,079,191	6,756,169	10,100,000	17,400,000
Tamil Nadu	5,141,106	5,432,939	5,676,934	7,946,632	14,200,000
Tripura	5,074,065	5,368,055	6,194,420	9,453,925	13,100,000
West Bengal	4,189,513	4,564,239	4,864,668	6,367,217	12,800,000
			Discount rate = 2%		
Andhra Pradesh	7,980,854	9,253,057	9,339,694	12,900,000	24,800,000
Daman and Diu	6,645,244	9,299,613	9,588,600	14,000,000	18,700,000
Gujarat	8,829,821	9,433,048	9,180,818	12,700,000	22,500,000
Jharkhand	7,135,196	7,531,926	7,916,030	12,600,000	24,600,000
Maharashtra	8,065,004	8,757,812	9,173,104	12,900,000	26,500,000
Mizoram	11,400,000	12,700,000	12,800,000	20,100,000	28,700,000
Odisha	7,185,593	7,255,054	7,615,159	12,700,000	20,800,000

State	Below Primary	Primary	Middle School	Secondary	Post-Secondary
Pondicherry	5,968,263	9,782,912	10,700,000	16,300,000	28,200,000
Tamil Nadu	8,295,268	8,742,934	8,987,108	12,800,000	23,000,000
Tripura	8,187,094	8,638,520	9,806,338	15,200,000	21,200,000
West Bengal	6,759,857	7,344,983	7,701,217	10,300,000	20,800,000

Notes: Net present values are expressed in 2021 Indian rupees (INR) of future earnings for different educational levels in at- risk states, using discount rates of 9%, 6%, 4%, and 2%. Earnings by educational level are estimated using the Periodic Labour Force Survey 2021–2022 data.

Source: Authors' calculations.

Table A.7: Educational Attainment Proportions in At-Risk Districts Assuming Storm Impact

	Exposure		Educational Attainment Proportions				
	Storm	Population	Below Primary	Primary	Middle School	Secondary	Post-Secondary
District (State)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
East Godavari (AP)	0.0003461	1638512	0.07133	0.19785	0.32435	0.15381	0.25266
Guntur (AP)	0.0004267	1547642	0.07133	0.19786	0.32436	0.15380	0.25265
Krishna (AP)	0.0016441	1424357	0.07139	0.19800	0.32447	0.15373	0.25240
Nellore (AP)	0.0015992	951172	0.07139	0.19799	0.32447	0.15374	0.25241
Srikakulam (AP)	0.0610607	864223	0.07412	0.20453	0.33018	0.15047	0.24052
Visakhapatnam (AP)	0.0495476	1371422	0.07359	0.20326	0.32907	0.15110	0.24282
Vizianagaram (AP)	0.0281793	732554	0.07261	0.20091	0.32702	0.15228	0.24710
West Godavari (AP)	7.14e-08	1238792	0.07131	0.19781	0.32432	0.15383	0.25273
Junagadh (DD)	0.0049337	26078	0.06453	0.10697	0.44393	0.25472	0.12983
Amreli (GJ)	0.0031228	571743	0.08909	0.17135	0.42244	0.15985	0.15725
Bhavnagar (GJ)	0.0001407	878796	0.08896	0.17103	0.42215	0.16002	0.15784
Junagadh (GJ)	0.0005919	698160	0.08898	0.17108	0.42220	0.15999	0.15775
Kachchh (GJ)	0.0001641	831365	0.08896	0.17103	0.42216	0.16002	0.15784
Pashchim Singhbhum (JH)	0.0003347	656558	0.06649	0.14606	0.46098	0.15182	0.17465
Greater Bombay (MH)	0.0001613	3053892	0.08966	0.13635	0.37996	0.18579	0.20823
Lawngtlai (MZ)	0.0076817	55074	0.03135	0.13211	0.48342	0.12218	0.23092
Lunglei (MZ)	0.0039692	67534	0.03118	0.13170	0.48306	0.12239	0.23166
Baleshwar (OD)	0.0926110	814688	0.10475	0.17622	0.44936	0.13308	0.13631
Boudh (OD)	0.0407423	159038	0.10237	0.17051	0.44438	0.13594	0.14668
Cuttack (OD)	0.4470581	850309	0.12106	0.21521	0.48339	0.11359	0.06542
Dhenkanal (OD)	0.0878728	398917	0.10453	0.17570	0.44891	0.13334	0.13726
Ganjam (OD)	0.2132895	1275897	0.11030	0.18949	0.46095	0.12644	0.11218
Keonjhar (OD)	0.0503895	645140	0.10281	0.17157	0.44531	0.13540	0.14476
Mayurbhanj (OD)	0.0204917	921100	0.10143	0.16828	0.44244	0.13705	0.15074
Puri (OD)	0.3588883	554649	0.11700	0.20551	0.47492	0.11844	0.08306
Sambalpur (OD)	0.0002886	355681	0.10050	0.16606	0.44050	0.13816	0.15478
Sundargarh (OD)	0.0000162	753511	0.10049	0.16603	0.44047	0.13817	0.15483
Karaikal (PY)	0.0269009	68355	0.05905	0.11233	0.35571	0.16102	0.31181
Puducherry (PY)	0.0365622	311500	0.05949	0.11340	0.35663	0.16049	0.30988
Yanam (PY)	0.0105229	22520	0.05830	0.11053	0.35414	0.16192	0.31508
Chennai (TN)	0.0049250	1330475	0.06688	0.16877	0.39478	0.15751	0.21204
Cuddalore (TN)	0.0265917	844192	0.06788	0.17115	0.39686	0.15632	0.20771
Kancheepuram (TN)	0.0009859	1234212	0.06670	0.16833	0.39440	0.15772	0.21283
Pudukottai (TN)	0.0004572	512977	0.06668	0.16827	0.39435	0.15775	0.21294
Salem (TN)	0.0001123	1072076	0.06666	0.16824	0.39432	0.15777	0.21301
Thanjavur (TN)	0.0174199	739804	0.06746	0.17014	0.39598	0.15682	0.20955
Tiruchchirappalli (TN)	0.0074335	823230	0.06700	0.16904	0.39502	0.15737	0.21154
Villupuram (TN)	0.0184537	1159291	0.06751	0.17025	0.39608	0.15676	0.20934
North Tripura (TR)	3.29e-06	156863	0.11802	0.13557	0.48046	0.10885	0.15710
South Tripura (TR)	0.0048199	162369	0.11824	0.13610	0.48093	0.10859	0.15613
West Tripura (TR)	0.0002846	312330	0.11804	0.13560	0.48049	0.10884	0.15704
East Midnapore (WB)	0.0093753	1810524	0.12927	0.17267	0.38671	0.13846	0.17286
Haora (WB)	0.0067034	1613795	0.12915	0.17238	0.38645	0.13861	0.17340
Hugli (WB)	0.0015881	1705448	0.12891	0.17182	0.38596	0.13889	0.17442
Kolkata (WB)	0.0122806	1230719	0.12940	0.17299	0.38699	0.13830	0.17228
North 24 Parganas (WB)	0.0345758	3170555	0.13043	0.17545	0.38913	0.13707	0.16782
South 24 Parganas (WB)	0.0333296	3017210	0.13037	0.17531	0.38901	0.13714	0.16807

	Exposure		Educational Attainment Proportions				
	Storm	Population	Below Primary	Primary	Middle School	Secondary	Post-Secondary
District (State)	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
West Midnapore (WB)	0.0000553	2044172	0.12884	0.17165	0.38581	0.13897	0.17473

AP = Andhra Pradesh, DD = Daman and Diu, GJ = Gujarat, JH = Jharkhand, MH = Maharashtra, MZ = Mizoram, OD = Odisha. PY = Pondicherry, TN = Tamil Nadu, TR = Tripura, WB = West Bengal.

Notes: Column (1) presents district-level school-age storm exposure, calculated as the mean intensity of storms over a 10-year period, considering only years where significant storm events (with wind speeds exceeding 50 knots) occurred, between 1999 and 2021. Non-event years, where no such storms were recorded, are excluded. Wind speed is calculated using the Deppermann (1947) formula. West Godavari district's wind exposure is almost zero and is excluded from the financial calculations. Column (2) is the estimated school-age population between 5 and 24 years old from the 2011 Population Census. Columns (3) to (7) show the state-level proportion of the population in at-risk districts from the Periodic Labour Force Survey 2021–2022, with below primary (3), primary (4), middle school (5), secondary (6), and post-secondary (7) education. Educational attainment proportions here represent π_{ij} from equation 11, adjusted for storm impact.

Source: Authors' calculations.

Table A.8: Financial Impact of Storms on Human Capital Value Across Different Discount Rates

	r = 9%			r = 6%			r = 4%		
District (State)	**Pre**	**Post**	**Cost**	**Pre**	**Post**	**Cost**	**Pre**	**Post**	**Cost**
East Godavari (AP)	77.1631	77.1568	0.0063	125.8397	125.8292	0.0105	188.6538	188.6379	0.0160
Guntur (AP)	72.8838	72.8764	0.0073	118.8608	118.8486	0.0122	178.1914	178.1728	0.0186
Krishna (AP)	67.0779	67.0518	0.0261	109.3924	109.3490	0.0433	163.9966	163.9307	0.0659
Nellore (AP)	44.7939	44.7770	0.0169	73.0512	73.0230	0.0282	109.5154	109.4725	0.0428
Srikakulam (AP)	40.6992	40.1120	0.5872	66.3734	65.3970	0.9764	99.5043	98.0192	1.4851
Visakhapatnam (AP)	64.5849	63.8288	0.7561	105.3268	104.0695	1.2573	157.9018	155.9894	1.9124
Vizianagaram (AP)	34.4985	34.2688	0.2297	56.2610	55.8791	0.3820	84.3443	83.7633	0.5810
Junagadh (DD)	1.0630	1.0621	0.0009	1.7248	1.7233	0.0016	2.5759	2.5735	0.0024
Amreli (GJ)	23.5308	23.5141	0.0167	38.2394	38.2116	0.0279	57.1741	57.1317	0.0424
Bhavnagar (GJ)	36.1680	36.1668	0.0012	58.7758	58.7738	0.0019	87.8793	87.8763	0.0029
Junagadh (GJ)	28.7337	28.7298	0.0039	46.6945	46.6880	0.0064	69.8157	69.8059	0.0098
Kachchh (GJ)	34.2159	34.2147	0.0013	55.6035	55.6014	0.0021	83.1363	83.1330	0.0032
Pashchim Singhbhum (JH)	26.0229	26.0202	0.0027	42.3206	42.3161	0.0045	63.3117	63.3050	0.0068
Greater Bombay (MH)	140.1821	140.1759	0.0061	228.3410	228.3308	0.0102	342.0130	341.9975	0.0155
Lawngtlai (MZ)	3.3185	3.3134	0.0051	5.3923	5.3839	0.0085	8.0619	8.0490	0.0129
Lunglei (MZ)	4.0693	4.0661	0.0032	6.6124	6.6070	0.0054	9.8859	9.8778	0.0082
Baleshwar (OD)	29.0160	28.2698	0.7462	47.1600	45.9206	1.2393	70.5195	68.6361	1.8834
Boudh (OD)	5.6643	5.6002	0.0641	9.2062	9.0998	0.1064	13.7663	13.6046	0.1617
Cuttack (OD)	30.2846	26.5251	3.7595	49.2219	42.9777	6.2443	73.6028	64.1138	9.4890
Dhenkanal (OD)	14.2078	13.8612	0.3467	23.0922	22.5164	0.5758	34.5303	33.6553	0.8750
Ganjam (OD)	45.4424	42.7510	2.6914	73.8580	69.3878	4.4702	110.4418	103.6487	6.7931
Keonjhar (OD)	22.9773	22.6558	0.3215	37.3453	36.8113	0.5340	55.8433	55.0319	0.8115
Mayurbhanj (OD)	32.8059	32.6193	0.1867	53.3198	53.0098	0.3100	79.7305	79.2594	0.4712
Puri (OD)	19.7544	17.7857	1.9687	32.1070	28.8372	3.2698	48.0104	43.0416	4.9689
Sambalpur (OD)	12.6680	12.6669	0.0010	20.5894	20.5877	0.0017	30.7878	30.7852	0.0026
Sundargarh (OD)	26.8370	26.8369	0.0001	43.6186	43.6183	0.0002	65.2239	65.2236	0.0003
Karaikal (PY)	3.9392	3.9141	0.0251	6.4273	6.3857	0.0417	9.6392	9.5759	0.0633
Puducherry (PY)	17.9514	17.7960	0.1554	29.2901	29.0319	0.2582	43.9271	43.5348	0.3923
Yanam (PY)	1.2978	1.2946	0.0032	2.1176	2.1122	0.0054	3.1757	3.1676	0.0082
Chennai (TN)	57.4151	57.3487	0.0664	93.4567	93.3462	0.1105	139.9062	139.7381	0.1682
Cuddalore (TN)	36.4301	36.2026	0.2276	59.2987	58.9200	0.3786	88.7711	88.1950	0.5761
Kancheepuram (TN)	53.2610	53.2487	0.0123	86.6949	86.6744	0.0205	129.7837	129.7525	0.0312
Pudukkottai (TN)	22.1369	22.1346	0.0024	36.0331	36.0292	0.0040	53.9422	53.9361	0.0060
Salem (TN)	46.2642	46.2630	0.0012	75.3060	75.3039	0.0020	112.7343	112.7312	0.0031
Thanjavur (TN)	31.9254	31.7948	0.1306	51.9662	51.7488	0.2174	77.7942	77.4635	0.3307
Tiruchchirappalli (TN)	35.5256	35.4635	0.0620	57.8262	57.7230	0.1032	86.5668	86.4098	0.1570
Villupuram (TN)	50.0279	49.8110	0.2169	81.4322	81.0714	0.3608	121.9054	121.3563	0.5490
North Tripura (TR)	6.4700	6.4700	0.0000	10.4970	10.4970	0.0000	15.6752	15.6752	0.0000
South Tripura (TR)	6.6971	6.6900	0.0072	10.8655	10.8535	0.0119	16.2254	16.2073	0.0182
West Tripura (TR)	12.8825	12.8816	0.0008	20.9006	20.8993	0.0014	31.2110	31.2089	0.0021
East Midnapore (WB)	63.6502	63.4907	0.1595	103.5687	103.3035	0.2652	155.0019	154.5986	0.4033
Haora (WB)	56.7341	56.6324	0.1017	92.3151	92.1461	0.1690	138.1596	137.9026	0.2570
Hugli (WB)	59.9562	59.9307	0.0255	97.5579	97.5156	0.0423	146.0061	145.9418	0.0643
Kolkata (WB)	43.2668	43.1248	0.1420	70.4017	70.1656	0.2361	105.3638	105.0048	0.3591
North 24 Parganas (WB)	111.4631	110.4329	1.0302	181.3676	179.6550	1.7126	271.4364	268.8321	2.6044
South 24 Parganas (WB)	106.0721	105.1271	0.9450	172.5957	171.0246	1.5710	258.3083	255.9193	2.3891
West Midnapore (WB)	71.8643	71.8632	0.0011	116.9342	116.9325	0.0018	175.0049	175.0022	0.0027

District (State)	r = 9% Pre	Post	Cost	r = 6% Pre	Post	Cost	r = 4% Pre	Post	Cost
Total	**1892.23**	**1877.16**	**15.07**	**3080.32**	**3055.28**	**25.04**	**4611.59**	**4573.52**	**38.07**

AP = Andhra Pradesh, DD = Daman and Diu, GJ = Gujarat, JH = Jharkhand, MH = Maharashtra, MZ = Mizoram, OD = Odisha, PY = Pondicherry, r = discount rate, TN = Tamil Nadu, TR = Tripura, WB = West Bengal.

Notes: Columns show financial values of human capital in 2021 by district, before (Pre) and after (Post) storm impact for different discount rates. Values are expressed in USD billion (2021).

Source: Authors' calculations.