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DROUGHTS: LEARNING CONTINUITY AND RECOVERY

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Abstract

In this paper, we study the nuanced relationship between drought, academic performance, and the efficacy of preventive measures, focusing on two drought-prone regions from the states of Maharashtra and Karnataka in India. Utilizing an event study framework relying on difference-in-differences regressions, we address the recurrent and non-permanent nature of droughts, elucidating their impact on learning outcomes over time. In Maharashtra, which lacks preventive schemes, successive droughts lead to a significant drop in standardized test scores for math and reading skills, followed by intermittent recovery and further interruptions. The school dropout rate also exhibits a similar pattern. Contrarily, Karnataka's existing government-led preventive programs demonstrate resilience in academic achievement during drought periods.

Keywords: climate variability, human capital investment, educational attainment

JEL Classification: I21, O12, Q54, Q58

1 Introduction

A major consequence of climate change is prolonged extreme weather events (Scoones, 1992; Angassa and Oba, 2008), including the recurrence of natural disasters such as droughts (Parry et al., 2010; IPCC, 2014; World Bank, 2019). While this has direct implications for global development in general (Stocker et al., 2013), among the various types of natural disasters, drought is perceived as the most severe hazard affecting agricultural productivity (Wilhite and Buchanan-Smith, 2005; Arshad et al., 2017; Arshad et al., 2018). Given that a considerable proportion of the population in low- and middle-income countries depends on agriculture either directly or indirectly (Mahendra Dev, 2012; Mehar et al., 2016), these adverse impacts can precipitate forced migration (Munshi, 2003; Henry et al., 2003; Feng et al., 2010; Dillon et al., 2011; Gray and Mueller, 2012; Mbaye, 2017) and affect household incomes (Paxson, 1992; Miguel et al., 2004; Skoufias et al., 2012; Keshavarz and Karami, 2013), thereby subsequently influencing household consumption expenditures and investments in human capital, such as investments in education (Benson and Clay, 2004; Fitzsimons, 2007; Duryea et al., 2007; Barrios et al., 2008; Bjorkman-Nyqvist, 2013; Agamile et al., 2021).

While this literature seems to suggest that there is a negative impact of poor rainfall on education outcomes, more generally, the evidence on the impacts of such extreme weather events on human capital outcomes is mixed (Randell and Gray, 2016; Shah and Steinberg, 2017). For instance, there is some evidence that water scarcity induced by droughts could lead to higher opportunity costs of enrollment and results in a transition away from school participation towards labor market participation (Glory and Nsikak-Abasi, 2013). Other studies have attempted to link extreme weather events to outcomes such as school dropout rates (Khalili, 2020), education expenditures (Amjath-Babu et al., 2016), and the labor supply (Graff Zivin and Neidell, 2014). Moreover, the literature highlights the multifaceted impact of early-life rainfall on socioeconomic, health, and educational outcomes (Maccini and Yang, 2009). However, the estimates of educational attainment among students as a consequence of exposure to these shocks remain limited, with the exception of Shah and Steinberg (2017), who utilize test scores as a proxy for human capital attainment and demonstrate that positive rainfall shocks result in reduced school enrollment and attendance, along with diminished overall test scores for school-aged children.^[1]

Our paper is closely related to this, and we study an analogous outcome variable, i.e., standardized test scores. However, unlike Shah and Steinberg (2017), who concentrate on gauging the average annual

¹Interestingly, an alternative viewpoint is presented here by Shah and Steinberg (2017), emphasizing the importance of human capital investments and the alternative value of time. A substitute for education is engagement in agricultural activities or household responsibilities. Consequently, during years with favorable monsoons, households experience an increased opportunity cost for keeping their children enrolled in school, as the children could contribute to the household's earnings if they were not in school. Shah and Steinberg's findings from India indicate that children are more likely to drop out of school and perform poorly during good rainfall years, suggesting that higher rainfall negatively affects their academic performance (or conversely, students attend school and perform better during poor rainfall years).

precipitation and its current or next-year effects, our objective is two-fold. First, we intend to analyze the repercussions of drought events in regions prone to drought over an extended period. We show that droughts lead to learning losses as well, although in the context of our study, this is imprecisely estimated. Second, we take advantage of this approach to investigate recovery times and assess the efficacy of preventive measures. Essentially, we compare and contrast two distinct regions directly affected by droughts in the context of India. However, one of the regions had in place certain measures targeted towards coping with the aftermath of the drought event, whereas the other did not. We use these settings as a natural experiment to analyze the recovery from drought in these regions in the context of the estimated learning losses, which in turn allows us to estimate the efficacy of public policy designed to cope with the droughts.

The Indian Meteorological Department (IMD) has established meteorological subdivisions, henceforth referred to as subdivisions (distinct from administrative districts, hereinafter called districts), based on similarities in climate and monsoon rainfall patterns. These subdivisions form the basis of our identification strategy. Unlike controlled experiments or policy implementations, drought transcends administrative boundaries, affecting broader geographical areas with diffused exposure. We acknowledge the non-permanent nature of drought and the fact that impact regions may change with each drought event. Therefore, to address this issue, we focus on subdivisions that are drought-prone and faced persistent drought in the decade starting from the year 2011. These drought events, along with their severity and the regions they affect. have been well documented in government reports, news articles, and other research papers. Additionally, we empirically validate the required relevance assumption for our identification strategy, confirming that these drought-prone subdivisions faced severe drought compared to the rest of their respective states during the study period. Consequently, the chosen setting for our study is the semi-arid regions of the Deccan Plateau. specifically Marathwada in Maharashtra and North Interior Karnataka (NIK), which face the highest frequency of severe droughts in India. Although administratively both subdivisions are in different states, they share meteorological borders and belong to the same arid zone of the Deccan Plateau, experiencing similar climatic conditions. Thus, they encountered comparable drought incidents in terms of intensity and timing during the study period, as corroborated by our dataset and secondary sources.

While these neighboring meteorological subdivisions share climatic similarities, they also provide a compelling backdrop for our comparative analysis of the recovery and coping strategies in the aftermath of droughts. This is because, unlike Maharashtra, the state of Karnataka had explicit government programs in place to assist with coping with these events. Essentially, this creates a natural experiment for studying our question. Our identification strategy relies on separately comparing drought-prone areas in the affected states to the non-drought areas before and after the drought events, over a period of time. We perform separate event studies for Maharashtra and Karnataka to find suggestive evidence of learning losses in both states as a result of the drought, but with different rates of recovery, with Karnataka outperforming Maharashtra. This lends support to the hypothesis that public policy directed towards recovery from these extreme weather events is effective in helping a region to recuperate from learning losses. We use data on test scores from the Annual Status of Education Report (ASER) in two states, Maharashtra and Karnataka, comprising 0.45 million observations between 2008 and 2018.

We find that, in Maharashtra, a significant decline in math and reading scores occurred in the aftermath of consecutive drought years in 2011–2012. Although there was a gradual recovery during the normal year of 2013, this progress was disrupted by another drought in 2014–2015. Conversely, in Karnataka, where preventive programs were in place, academic scores experienced a relatively modest decline following consecutive drought years. Notably, the recovery of learning losses after successive drought years was more prompt in the drought-prone region of Karnataka compared to Maharashtra. This observation underscores that the implementation of government-led drought preventive programs can enhance the resilience of academic scores, indicative of educational outcomes, against the adverse impacts of consecutive meteorological droughts to a certain extent. Additionally, the findings regarding dropout rates further support this assertion.

In Maharashtra, we compare Marathwada with the rest of the state to understand the impact of drought and the recovery period in the absence of preventive measures (we call this our baseline scenario). During the relevant study period, the state did not have any specific scheme or program to prevent the adverse effects of rainfall shortages, unlike the neighboring state of Karnataka, to the best of our knowledge. The Karnataka state government, however, implemented specific preventive initiatives such as the *Sujala scheme* and *Project Bhoochetana* to address water scarcity and the drought impact. Work under these projects was completed before the consecutive drought events starting in 2011. Additionally, before the consecutive drought years of 2014–2015, the government had also rolled out the next phase of these initiatives, along with newer initiatives supported by the World Bank. These drought preventive efforts were expected to have resulted in improved access to resources, enhanced agricultural productivity, and increased household income, demonstrating a commitment to sustainable water management. Therefore, the estimated impacts of droughts on learning for the state of Karnataka, where we compare NIK with the rest of the state, would likely be masked by the effectiveness of public sector preventive measures in drought-prone areas. Consequently, based on assumptions about the counterfactual, we fail to reject the hypothesis that the dampened learning losses in Karnataka and the phenomenal recovery may be attributed to these public policy measures.

The rest of the paper is structured as follows: Section 2 offers background information on the study's focus area. In Section 3, we detail the sources of our data. Section 4 examines the empirical framework, encompassing the identification strategy and methodology. In Section 5, we first validate identification assumptions and then present the main findings, along with supporting evidence and robustness test results.

The conclusion summarizes our findings and outlines future research avenues.

2 Background

India, characterized by its extensive geographical span and diverse climates, is particularly vulnerable to the impacts of climate change (MOEFCC, 2018). Among these, drought emerges as a persistent threat with widespread repercussions (Dai, 2013). It is widely acknowledged that drought has a detrimental impact on the economy, with the Global Assessment Report (GAR) revealing that severe droughts can lead to an estimated 2–5% reduction in India's gross domestic product (GDP). The phenomenon of drought is intricate and relies on interactions with various hydrological parameters such as evaporation, precipitation, infiltration, runoff, and surface water and groundwater storage (Sirdaş and Sen, 2003; Esfahanian et al., 2017; Kim et al., 2017). Based on these parameters, droughts are commonly classified into meteorological, agricultural, hydrological, and socio-economic categories (Heim, 2002). Meteorological drought is triggered by high temperatures and low precipitation, and it results in water scarcity. This, in turn, leads to agricultural drought, causing stress on crops and impacting people's livelihoods, the ecological environment, and socio-economic conditions (Uttaruk and Laosuwan, 2017; Du et al., 2018).

2.1 Drought-prone Zones in India

Drought is a non-permanent and recurring phenomenon caused by a prolonged deficiency in rainfall compared to long-term average conditions in a given area (Patel and Yadav, 2015; Sreekesh et al., 2019). This is especially prevalent in semi-arid ecosystems (Hind and Marwan, 2010; Mohammad et al., 2015; Hussein, 2018; Mohammad et al., 2018; Sandeep et al., 2021).

Within India's climatic landscape, the southern semi-arid zone, spanning the states of Maharashtra, Karnataka, Telangana, and Andhra Pradesh, faces climatic vulnerability due to its location on the leeward side of the Western Ghats. The Western Ghats, a formidable mountain range running parallel to the western coast, creates a rain shadow in the eastern region, known as the Deccan Plateau (Mohamed et al., 2019).

Because of where it is located, the Deccan Plateau often does not get enough water, making it dry on the leeward side of the Western Ghats, which block rain clouds coming from the Arabian Sea. Consequently, water scarcity persists as a significant challenge for the states in the Deccan Plateau².

 $^{^{2}}$ Refer to Figure 2 of the case study titled "Drought Characteristics over the Deccan Plateau Region of India," by Srinivasan et al., in the GAR Special Report on Drought 2021 by the United Nations Office for Disaster Risk Reduction. The published documents of the case study can be accessed here. In this case study, Figure 2 presents the areas showing composite rainfall deviations from the climatological normal (1981–2010) from June–September of very dry years (2002, 2004, and 2015). It highlights that the most affected areas in the two states, Maharashtra and Karnataka, fall within their respective most-drought-prone meteorological subdivisions, i.e., Marathwada in Maharashtra and North Interior Karnataka (NIK) in Karnataka.

Low and irregular rainfall, along with extreme temperatures and intense solar radiation, makes these semiarid regions in southern peninsular India highly vulnerable (INECC, 2010). Water scarcity is prevalent, with low groundwater tables, minimal rainfall, and high water runoff. The primary water source throughout the year in these regions is small and medium amounts of stored water. Consequently, the Global Assessment Report (GAR) on Drought 2021, released by the UN Office for Disaster Risk Reduction, identifies the Deccan region as experiencing the highest frequency (more than 6%) of severe droughts in all of India.

The severe repercussions of drought-related crop failures are vividly highlighted by a concerning statistic in the most recent report from the National Crime Records Bureau (NCRB) in the year 2021—49.6% of farmer suicides in India are concentrated in the state of Maharashtra, followed by Karnataka (Accidental Deaths & Suicides in India (ADSI), 2022). Notably, both states are situated in the geographical region beneath the Western Ghats on the Deccan Plateau. This region, identified as experiencing the highest frequency (more than 6%) of severe droughts in all of India, according to the Global Assessment Report (GAR), further emphasizes the correlation between geographical location, drought situations, and their distressing consequences.

Maharashtra is the third largest state in India based on geographical area and the highest contributor to India's GDP at 14% (Deshpande, 2023). Agriculture plays an important role in the economy of Maharashtra. The total population of the state is 112 million according to the 2011 census, of which 57.8% are dependent on agriculture. About 84% of the total area under agriculture in the state is directly dependent on monsoon rainfall (Economic Survey of Maharashtra 2012-13, 2013). At the same time, a substantial portion of the state lies in the semi-arid regions in the rain shadow of the Western Ghats (Todmal, 2019).

Thus, drought is one of the major natural disasters that pose a great threat to the state economy and agricultural development. To study and forecast weather, the state has been divided into four meteorological subdivisions³ Konkan (west coast), Madhya Maharashtra, Marathwada, and Vidarbha. Meteorological subdivisions are created by the Indian Meteorological Department based on similar climate and monsoon rainfall patterns (Kelkar and Sreejith, 2020). Historically, Maharashtra has been plagued by numerous drought events, such as in the years 1972, 2000, and 2004, and most recently, Maharastra faced a distressing series of consecutive droughts from 2011–2012 (Maharashtra Ahead, 2013), 2014–2015 (Kulkarni et al., 2016), and 2018–2019 (Singh et al., 2022). When a drought event occurs for two or more consecutive years, then it is considered to be a persistent drought event (Amrit et al., 2018).

Marathwada, a region in arid portions of Maharashtra, has particularly been the epicenter of such persistent droughts. Nearly 73.83% of the population of the Marathwada region depends on agriculture as their primary source of income (Kelkar, 2013). Nonetheless, the irrigation provision in this area is quite deficient,

³Refer to the Indian Meteorological Department's website for more detail: https://mausam.imd.gov.in/

currently standing at merely 14.08%. This is much lower than the state average of 18%, which is already less than half of the national average of 38%. The development deficit for Marathwada is also high; it stands at 20.16% (Kelkar, 2013).

Mishra et al. (2020) highlighted that the arid landscape of Marathwada, which is the only meteorological zone in Maharashtra with an arid region (Bhandari et al., 2014), is prone to heat extremes during dry conditions. In 2015, Marathwada experienced a severe 40% deficit in rainfall (Purohit and Kaur, 2017). The Marathwada region experienced continuous low rainfall for a long time without this being noticed. From 2011 to 2020, there were six years in which the area received a 50% deficit monsoon (Kulkarni et al., 2020).

2.2 Drought Events and Policy

In 2011–2012, Marathwada faced a significant challenge due to insufficient rainfall, which had a detrimental impact on both the Kharif and Rabi crops⁴. As a result of these adverse conditions, the final paisewari for 3,493 villages in the region fell below 50 paise (0.6 cents⁵) (Maharashtra Ahead, 2013)⁶. Furthermore, in response to the drought, the government mobilized water tankers to deliver crucial water supplies to villages in Marathwada (Maharashtra Ahead, 2013). Tragically, Marathwada has also been plagued by a high number of farmer suicides in recent decades (Kulkarni et al., 2016).

These recurring droughts highlight the need to address the multifaceted challenges confronted by both the agricultural sector and the communities in this region. In an effort to tackle these challenges, the Maharashtra government initiated the Jalyukt Shivar Scheme in 2015 to combat drought. However, despite investing Rs 96,337 million over the past five years, a recent report from the Comptroller and Auditor General of India revealed that the scheme had limited success in achieving water neutrality and boosting groundwater levels. Key reasons cited for this outcome included "inadequate monitoring" and a "lack of transparency" in project execution.

In a similar vein to Maharashtra, the neighboring state of Karnataka also faces drought-related challenges. Based on the common rainfall distribution pattern, Karnataka is classified into three meteorological subdivisions, namely North Interior Karnataka, South Interior Karnataka, and the Coastal Region⁷. According to Srinivasareddy et al. (2021), North Interior Karnataka consistently showed the highest susceptibility to drought among the four subdivisions. The North Interior Karnataka meteorological division mirrors the

 $^{^{4}}$ Rabi and Kharif are terms used in Indian agriculture to categorize crops based on the timing of their cultivation and harvesting. Rabi crops are sown in winter, typically between October and December, and harvested in spring. Kharif crops, on the other hand, are sown in the monsoon season, from June to July, and harvested in autumn.

⁵The utilized exchange rate is the average dollar-rupee rate for the year 2023, set at 1 USD = 82.57 INR.

⁶In India, the declaration of drought is typically recommended by district collectors after they obtain crop production estimates through the paisewari system, which essentially measures the value of crops. This system assesses the actual yield after the harvest in relation to the value of the crop grown and provides an estimate of agricultural losses, making it an indicator of drought (Department of Agriculture and Farmers Welfare, Government of India, 2016).

⁷Refer to the Indian Meteorological Department's website for more details: https://mausam.imd.gov.in/

vulnerability observed in Marathwada. North Interior Karnataka and Marathwada receive 73.1 cm and 88.2 cm of average annual rainfall, respectively. Additionally, Soni et al. (2023) reported that both Marathwada and North Interior Karnataka have experienced a decrease in their rainfall trends over the last 72 years.

Despite being geographically adjacent and facing similar climatic challenges due to their locations on the semi-arid and arid Deccan Plateau, Maharashtra and Karnataka have adopted distinct responses to these challenges. This divergence is primarily due to their distinct state boundaries, leading to different jurisdictions, policies, and programs. The Karnataka state government, cognizant of the need to improve resilience against water scarcity, took proactive steps. Initiatives such as the Sujala scheme Phase 1 (2001– 2009), Project Bhoochetana (2009–2011), Phase 2 of Sujala (2014–2018), and the ongoing Krishi Bhagya scheme (commencing 2014–2015) highlight the commitment to mitigating the impact of drought through sustainable and preemptive interventions.

The Sujala Watershed Development Project in Karnataka, supported by the World Bank, significantly increased the average annual household income from USD 222 to USD 373^[9] Additionally, a study by Mahalakshmi et al. (2019) found that the project reduced the distance to accessible drinking water, fuel wood, and fodder for beneficiary farmers. The Krishi Bhagya program focuses on enhancing agricultural productivity in rainfed areas by promoting efficient water management practices, leading to a 25–30% improvement in crop productivity. Meanwhile, Project Bhoochetna had the primary goal of increasing the rainfed crop productivity in Karnataka by introducing better crop varieties and management practices, resulting in significant benefits totaling USD 453.34 million from 2009 to 2016^[10].

3 Data

This section provides a description of the data sources utilized in the analysis, outlines data processing procedures, and presents descriptive statistics for the constructed dataset. The primary data source for assessing the academic impact of drought pertains to the Annual Status of Education Report (ASER) data from two states in southwest India, situated within the Deccan Plateau and falling under the rain shadow of the Western Ghats. This primary dataset is complemented by the climatic data from the India Meteorological Department and the Consumer Pyramids Household Survey (CPHS) data from the Center for Monitoring Indian Economy (CMIE).

 $^{^{8}}$ http://www.rainwaterharvesting.org/Urban/Rainfall.htm

⁹https://documents1.worldbank.org/curated/en/948321468040740553/pdf/427250optmzd0NWP0South0Asia031Sujala .pdf

¹⁰National Conference on "Drought Management Strategies" Compendium of Best Practices in Drought Management

3.1 Cognitive Ability

The primary objective of this paper is to gauge the influence of drought on the education of children in drought-prone regions. To assess educational levels, we utilize test scores as outcome variables, given the evidence indicating their efficacy as predictors of long-term economic outcomes (Chatterjee et al., 2023). We measure standardized test scores from the Annual Survey of Education Report (ASER). This nationwide survey concentrates on the educational achievements of primary school children in India, covering over 570 districts, 15,000 villages, 300,000 households, and approximately 700,000 children annually. The survey is implemented by the nongovernmental organization Pratham every year to assess the status of education in rural India. ASER gave us their survey data for the years 2007 to 2014, 2016, and 2018. The sample, representative at the district level, encompasses 20 villages from each of India's 580 rural districts. In each village, they randomly selected 20 to 30 households to participate. The survey do to school or not. Out of these, testing focuses on children aged 5 to 16, assessing their math and reading skills.

A distinctive feature of the ASER survey is the administration of tests at the subject's home, in contrast to the conventional school setting. This approach facilitates the evaluation of achievement scores independent of school-level inputs. The tests are conducted in the child's local language and each test contains four questions to assess the learning levels of the child. The reading test checks if students can recognize letters and words and read texts from different grades. The math test assesses whether students can understand single- and double-digit numbers, do subtraction with borrowing, and do division with three-digit numbers. Scores range from 0 to 4, with 0 signifying an inability to answer the most basic question and 4 indicating proficiency in solving the highest-level question. In our study, standardized test scores are employed, focusing on two variables as the outcomes of interest: the reading score and math score. Since this survey is conducted every year, we control for factors such as the family size, the mother's education, the mother's age, the child's gender, and their age.

3.2 Complementary Datasets

We augmented the ASER dataset with district-wise monthly rainfall data sourced from the India Meteorological Department¹². This dataset spans the entirety of India for the years 2008 to 2018, providing monthly rainfall figures (in millimeters) at the district level, calculated as arithmetic averages of the stationspecific rainfall within each district. Additionally, it includes the monthly deviations of rainfall from the

¹¹For more information on ASER, see http://www.asercentre.org/

¹²https://hydro.imd.gov.in/hydrometweb/(S(2rbbqpbeon05nt55qzlsvo45))/DistrictRaifall.aspx, accessible through the KAPSARC Data Portal: https://datasource.kapsarc.org/pages/home/

long-term district averages. Using this district-wise rainfall data, we computed both the average annual precipitation and average monsoon precipitation for each district annually from 2008 to 2018. To ascertain the average monsoon precipitation, we focused on the Indian summer monsoon, typically occurring from June to September. This emphasis was due to the fact that substantial portions of western and central India—encompassing our focal study area—receive over 90% of their total annual precipitation during this monsoonal period. Utilizing this rainfall information, we identified districts experiencing severe meteorological drought between 2008 and 2018. The criterion for defining severe meteorological drought was drawn from the Manual of Drought Management (2009) issued by the Ministry of Agriculture, Union of India^[13]. Specifically, the manual characterizes severe meteorological drought as a deficiency in seasonal rainfall surpassing 50% of its long-term average value. It is noteworthy that the survey period of the ASER spans from September to November, thus implying that the survey would have been conducted after the occurrence of the drought.

We combined the district-wise rainfall data with the ASER dataset, focusing specifically on the states of Maharashtra and Karnataka. These states constitute our primary areas of study. The resulting merged dataset serves as the primary dataset for assessing the impact of drought-like conditions on the learning loss and recovery period for children. It encompasses the educational status of around 4.5 lakh (0.45 million) children across all districts of Maharashtra and Karnataka from 2008 to 2018, excluding 2015 and 2017, and includes district-wise annual rainfall information. Table [] summarizes the mean test scores and control variables in our sample.

Additionally, acknowledging the diverse consequences of extreme climatic events from the existing literature (Agamile et al., 2021; Bjorkman-Nyqvist, 2013; Barrios et al., 2008), we broaden our study to explore the impact on household expenditure, particularly focusing on education-related expenses. For this purpose, household-level data are drawn from the Consumer Pyramids Household Survey (CPHS) conducted by the Center for Monitoring Indian Economy (CMIE), which is a comprehensive and expansive survey of Indian families, providing insights into household well-being. It covers over 232,000 sample households and 1.19 million individuals, making it the largest household panel survey globally. The CPHS incorporates information on consumption expenditures, household assets, perceptions, decisions regarding asset purchases or investments, and the demographic details of each household member. Consistency in our analysis is maintained by utilizing a set of controls similar to those employed in the primary dataset.

¹³https://nidm.gov.in/pdf/manuals/drought_manual.pdf

4 Empirical Framework

In this study, we explore the impact of drought-induced disruptions on students' educational achievements. Droughts can significantly influence educational outcomes by altering agricultural production, which in turn can affect educational preferences (Agamile et al., 2021; Bjorkman-Nyqvist, 2013; Barrios et al., 2008). Moreover, households facing water scarcity during climate-related disasters like droughts may struggle to keep their children in school, often leading them to prioritize other responsibilities, such as work outside of school or at home, over their education (Glory and Nsikak-Abasi, 2013).

To study the relationship between drought-induced disruptions and academic performance, we utilize an event study framework. Our primary empirical methodology involves employing difference-in-differences regressions across multiple years relative to a baseline year. This approach helps address potential concerns regarding endogeneity arising from selection biases and unobservable heterogeneity. By doing this, we aim to estimate both the immediate impact of drought events on learning outcomes and the subsequent period required for implementing learning loss recovery strategies in drought-affected contexts.

4.1 Identification Strategy

Unlike controlled experiments, policy implementations, or alterations in regulations within specific administrative regions, drought is a natural phenomenon that extends beyond predefined boundaries designated for administrative purposes. Even within a given administrative region, the occurrence of drought is influenced by various hydrological factors and therefore varies significantly in terms of intensity and frequency (Kim et al., 2017; Esfahanian et al., 2017; Sirdaş and Sen, 2003). Consequently, isolating cross-sectional identifying variation for drought events is extremely challenging.

A related methodological concern is that the primary dataset used in this paper relies on districts as the lowest geographical identifier, whereas state governments typically operate at a lower administrative level, such as a taluka or block, to identify and determine the prevalence of droughts (Ministry of Agriculture and Farmers Welfare, 2023). Drought, as established by Patel and Yadav (2015), is a non-permanent and recurring phenomenon with a varied intensity across different years at different locations. Consequently, the list of declared drought-impacted talukas/blocks evolves over time, with the inclusion of new blocks and the removal of past ones not affected in a given year.

To sidestep this issue, we instead focus on drought-prone regions based on historical drought instances and the intensity of exposure to drought-like situations during the time period considered for our analysis. To identify drought-prone areas, we utilize meteorological subdivisions as the defining boundaries. These subdivisions, established by the Indian Meteorological Department (IMD), are characterized by similar climate and monsoon rainfall patterns for the purpose of weather forecasting, climate change study, and other meteorological services (Kelkar and Sreejith, 2020).^[14]

Our analysis is therefore largely concentrated on two neighboring states. The case of Maharashtra serves as the baseline scenario in our study, where we assess the impact of drought situations over time and estimate the recovery period for learning loss in the absence of any preventive measures. In contrast to the neighboring state of Karnataka, which had implemented and completed several proactive projects to address rainfall shortages, Maharashtra did not have any such program in place during the span of our study, to the best of our knowledge. Our examination of Karnataka aims to understand the impact of drought with public sector preventive measures in place. This approach of focusing on bordering states with similar climates and analogous climatic challenges provides us with an opportunity to estimate the impact of drought on learning outcomes (baseline scenario) and to evaluate the effectiveness of drought preventive strategies implemented by the government.

Within Maharashtra, Marathwada has historically been and continues to be the most severely droughtprone division. Similarly, in Karnataka, the North Interior Karnataka (NIK) division is the state's most drought-prone division. Although administratively, both subdivisions are in different states, they share meteorological borders and belong to the same arid zone of the Deccan Plateau, with similar climatic conditions.¹⁵

Furthermore, we examine rainfall patterns in the drought-prone regions in comparison to other regions within their respective states to confirm that these areas are indeed drought-affected. Specifically, we compare Marathwada with the rest of Maharashtra and NIK with the rest of Karnataka. Using our primary dataset, we create graphical representations of the year-wise average monsoon rainfall for each group within each state. Figure A2 represents Maharashtra, while Figure A3 represents Karnataka in the online appendix. In both states, the blue line represents drought-prone subdivisions, while the red line represents the remaining regions of the state.

We observe that prior to 2011, the raw means of the average monsoon rainfall showed synchronous movement across successive time periods for both subdivisions in both states. However, in the monsoon

¹⁴As discussed above, the semi-arid regions of the Deccan Plateau, situated in the rain shadow of the Western Ghats, experience the highest frequency of severe drought in all of India. Specifically, Maharashtra, Karnataka, Telangana, and Andhra Pradesh comprise the majority of this geographical area, resulting in heightened climatic vulnerability. Notably, this region exhibits the highest frequency, exceeding 6%, of severe droughts across the entirety of India (GAR Special Report on Drought 2021, 2021). The agricultural sector bears the brunt of this climatic vulnerability, particularly evident in cases of farmers' suicides due to a vicious cycle of indebtedness. Maharashtra ranks highest in such instances, followed by Karnataka (Talule, 2020).

¹⁵The background section (Section 2) above cites government commentary, news articles, and reports indicating that Marathwada in Maharashtra and NIK in Karnataka have been persistent hotspots for droughts in the last decade (Amrit et al., 2018), experiencing drought for two or more consecutive years (2011–2012, 2014–2015) (Maharashtra Ahead, 2013). These sources support the "relevance assumption" for our identification strategy of considering Marathwada and NIK as drought-affected regions in the last decade for the examination of the impact of drought on education. These sources assert the presence of drought in these subdivisions, encompassing meteorological, hydrological, agricultural, and socio-economic dimensions.

of 2011, the subdivisions prone to drought (Marathwada in Maharashtra and NIK in Karnataka) received significantly lower rainfall compared to the rest of the regions of their respective states. For instance, in Maharashtra, in the year 2010, which was considered a normal year, this difference amounted to 97.734 mm. By 2011, this difference had increased to 168.6887 mm. In percentage terms, drought-prone regions in Maharashtra experienced a drastic 31.56% decrease in rainfall in the year 2011 compared to the previous year, whereas the rest of Maharashtra only saw a modest 2.52% decrease. Similarly, in Karnataka, droughtprone areas experienced a notable 29.41% drop in rainfall in 2011 from the previous year, while the rest of the state actually saw an increase of 7.28% during the same period. This substantial drop in rainfall persisted in the following year, marking two consecutive drought years for Marathwada and NIK. While other regions in both states also faced a shortfall in rainfall in 2012, it is crucial to note that even before this dip, the rainfall in these drought-prone subdivisions was consistently lower than that in the rest of their respective states.

The examination of the raw means of rainfall data, coupled with evidence from the background section, instills confidence that Marathwada and NIK were indeed severely impacted by drought in Maharashtra and Karnataka starting from 2011. However, we further rigorously test this in an event study setting and the results are presented in Figures A1 and A2, with a detailed discussion provided later in subsection 5.1

4.2 Methodology

Using the ordinary least squares (OLS) method to evaluate the impact of droughts is problematic. There can be unobservable factors that can lead to omitted variable bias. For instance, comparing children in the drought-prone division with those in other regions of the state might be confounded by pre-existing disparities between the two areas, possibly skewing outcomes. Similarly, comparing post-drought-period outcomes within the drought-prone division might yield biased results due to various factors, including shifts in the macroeconomic landscape over time.

To address these issues, we propose an event study framework using the difference-in-differences methodology. As a result, we leverage spatio-temporal variations arising from persistent drought occurrences to identify their causal impact on learning outcomes and the recovery period for learning losses. Our analysis focuses on a series of drought events starting in 2011 in drought-prone subdivisions of Maharashtra and Karnataka. Given that our primary dataset starts in 2008, a year not marked by severe drought conditions, we have designated 2008 as the reference period (base year) for our analysis within this framework.

To estimate the causal impact of drought on learning outcomes and the recovery period for learning losses, we employ the following regression equation for each child i from district d in state s during the time

period t:

$$TestScore_{idst} = \alpha_d + \beta_1 \cdot (Drought_{ds} * Time_t) + \beta_2 \cdot (Time_t) + \beta_i \cdot (X_i) + \mu_{idst}.$$
 (1)

In Equation 1, TestScore represents the standardized reading or math test scores for child *i* in time *t*. α_d represents district fixed effects; it controls for time-invariant district specific characteristics. $Time_t$ is a dummy variable with eight versions, each designed to facilitate the construction of an event study framework. Across these versions, it assumes a value of 0 for the base year 2008 and subsequently takes the value 1 for each year from 2009 to 2018 (excluding 2015 and 2017, as our primary dataset lacks data for these years). $Drought_{ds}$ is a dummy variable indicating whether the individual belongs to the drought-prone subdivision of state *s*. In the context of Maharashtra, this subdivision corresponds to Marathwada, while in Karnataka, it is NIK. As we know that drought is non-permanent in nature and is not restricted by administrative boundaries, to avoid contamination in the control group, we excluded the districts in state *s* that faced severe drought during the period of study but are not a part of the drought-prone meteorological subdivision in state *s*. Demographic controls represented by *X* encompass the child's age, the child's gender, the family size, and the mother's education. Standard errors are adjusted for district-level clustering.

The interpretation of the coefficient β_1 yields the difference in mean test scores for time t compared to the base year, differentiating between children from the drought-prone subdivisions and those from other regions of the state s. The identifying assumption implies that in the counterfactual scenario, the estimated coefficient would be statistically insignificant. This is demonstrated in the results section.

5 Results

In this section, we employ an event study difference-in-differences framework, as described in the methodology section (subsection 4.2), to present the outcomes of our analysis regarding drought incidents in the drought-prone areas of Maharashtra and Karnataka, starting from the year 2011.

5.1 Validating the Treatment Status

To confirm that our identification of drought-prone regions is reasonable, we use rainfall data from our primary dataset as the dependent variable in the main empirical equation (Equation 1), discussed in the methodology section (subsection 4.2). This is executed for both states, encompassing all years starting from 2009 with respect to the base year 2008 in the event study setup. Figures A1 and A2 plot the estimated coefficients for the difference in the average annual rainfall for each time period compared to the base year,

distinguishing between the Marathwada region and the rest of the regions in Maharashtra, as well as the NIK region and the rest of the regions in Karnataka, respectively.

These figures indicate that prior to 2011, the difference in the average annual rainfall between the droughtprone subdivisions and the rest of the regions in their respective states was not statistically significant when compared to the base year. However, in 2011, a statistically significant decline in the average annual rainfall is observed in the drought-prone subdivisions compared to the rest of the regions, as indicated by the negative coefficients. However, in the year 2012, a marginal positive coefficient is observed for the Marathwada region in comparison to the rest of Maharashtra when compared to the base year. However, this observed increase is not statistically significant and does not indicate an actual rise in rainfall. Instead, Marathwada experienced a decline in rainfall for the second consecutive year, and the positive coefficient is influenced by other regions in Maharashtra also facing shortages in rainfall during that year (refer to Figure A2 of the online appendix). A similar pattern is noted for Karnataka in 2012, where a non-significant positive coefficient is observed, and the raw means of the rainfall data align with the actual scenario (Figure A3 of the online appendix).

5.2 Main Findings

As discussed in the background section (Section 2), the Maharashtra government lacked preventive schemes to address drought. Despite the implementation of the Jalyukt Shivar scheme after consecutive drought years in 2014–2015, its effectiveness was questioned.

This circumstance offers an opportunity to investigate the impact of drought in the absence of preventive measures. To accomplish this, we employ the difference-in-differences regression for Maharashtra in an event study framework outlined in Equation 1, as detailed in the methodology section (subsection 4.2), to examine the causal impact of drought on learning outcomes. Equation 1 is separately applied to reading and math scores for the various years considered in our study, with 2008 as the base year. The results for child math scores are presented in Figure 1 and those for child reading scores are reported in Figure 2 based on the estimation of our regression equation. Panels 1 and 2 of Table A1 of the appendix contain the full regression table corresponding to these figures.

We observe a statistically significant drop in math scores following consecutive drought years in 2011– 2012. In 2012, the decline in math scores is approximately 0.22 σ points compared to the base year, as compared to the base year between the average child in Marathwada and the rest of Maharashtra after accounting for time-invariant district-specific effects. This learning loss in math scores gradually begins to recover during the normal year of 2013, only to be followed by another consecutive drought affecting the exposed group in 2014–2015. A similar impact is discernible in reading scores, with a notable drop in the year 2012. Subsequently, recovery is observed until the next consecutive drought in 2014–2015 impacts the exposed group.

The impact of drought on the academic performance of exposed groups, specifically in mathematics and reading scores, exhibits a similarity in magnitude. However, given that mathematics scores are lower than reading scores in Maharashtra, and particularly in Marathwada, the negative impact is more pronounced in mathematics. Furthermore, the recovery from the impact of drought appears to be swifter in reading scores than in mathematics scores. This disparity indicates that children may already possess weaker mathematical skills compared to reading skills, amplifying the detrimental effects of drought on mathematics performance.

Moreover, we observe that despite drought occurring in both 2011 and 2012, the effects on academic performance begin to manifest from 2012 onwards. This suggests a temporal lag of one year between the onset of drought and its discernible influence on learning outcomes. Given this hypothesis, for the second consecutive drought (which occurred in 2014–2015), we would anticipate observing its substantial impact on test scores in the year 2015. However, since ASER data for 2015 and 2017 are not publicly available, we were unable to comprehensively assess the effects of the second consecutive drought. Despite incomplete data, we still observe a slight decrease in math scores, hindering recovery from prior drought years, alongside a significant decline in reading scores.

5.2.1 Effectiveness of Drought Preventive Strategies by the Public Sector¹⁶

As discussed earlier, Karnataka, being a neighboring state, shares a similar climate and climatic challenges with Maharashtra, especially in the neighboring meteorological subdivisions (Marathwada and NIK). However, unlike Maharashtra, Karnataka had existing drought preventive programs before a series of consecutive droughts starting in 2011. This presents an opportunity to assess the effectiveness of Karnataka's preventive strategies. With both states facing comparable climatic conditions, this analysis of the neighboring meteorological division (NIK) allows us to evaluate the impact of drought on learning outcomes with preventive measures in place.

To achieve this objective, we employ the difference-in-differences regression for Karnataka in an event study framework outlined in Equation 1, as detailed in the methodology section (subsection 4.2), to assess the influence of drought on learning outcomes with preventive measures implemented. Equation 1 is independently applied to reading and math scores for the different years under examination in our study for Karnataka, with 2008 serving as the reference year. The outcomes for child math scores are depicted in

 $^{^{16}}$ We also examine the role of the private sector in drought-prone areas to address water scarcity; unlike government efforts, the private sector often targets localized areas. Given the constraints of data and the time lag in educational outcomes, we analyze expenditure patterns. However, the main focus of our paper on educational outcomes leads us to place this analysis of private sector drought prevention effectiveness in the online appendix.

Figure 4 and the results for child reading scores are illustrated in Figure 5 derived from the estimation of our regression equation. The full regression table corresponding to these figures is provided in panels 1 and 2 of Table A2 of the appendix.

In contrast to Maharashtra, the academic achievement of an average child in the exposed group within Karnataka, i.e., the NIK meteorological subdivision, appears resilient to the impact of successive meteorological droughts. While there is a slight downturn in the reading scores in 2011 following consecutive drought years in 2011–2012, this dip is neither economically nor statistically significant. Moreover, the recovery from this dip is swift when compared to the baseline scenario.

However, there could have been a potential issue with interpreting our findings if Karnataka inherently excelled in education compared to Maharashtra, beyond drought mitigation efforts. However, our summary statistics indicate that Maharashtra slightly outperforms Karnataka in education, with the reverse not holding true. Therefore, Maharashtra cannot be characterized as a poor performer in terms of learning outcomes compared to Karnataka. In fact, Marathwada, within Maharashtra, also outperforms the NIK subdivision of Karnataka. Additionally, Maharashtra and Marathwada receive slightly more rainfall than Karnataka and NIK, respectively (refer to Figures A2 and A3 in the online appendix).

Furthermore, as the latter half of the decade unfolds, discernible positive trends emerge, indicating that the initiatives implemented in drought-prone areas of the state are yielding results. The academic performance of children from the drought-prone division (NIK) exhibits an upward trajectory compared to the baseline year of 2008.

5.3 Effect on School Dropout Rates

The primary focus of this study is to assess the effects of drought on learning outcomes. One significant pathway through which drought may influence learning outcomes is by compelling children to withdraw from school. In the context of climate-related disasters such as droughts, households facing water scarcity encounter increased opportunity costs associated with maintaining their children's enrollment in school (Glory and Nsikak-Abasi, 2013).

To investigate this phenomenon and to provide additional support for our primary findings about learning outcomes, we employ the event study framework delineated in Equation 1 (see subsection 4.2) to examine the causal impact of drought on school dropout rates. We apply Equation 1 separately to dropout rates in Maharashtra and Karnataka, presenting the corresponding results in Figures 3 and 6 for Maharashtra and Karnataka, respectively. The full regression tables corresponding to these figures are provided in panel 3 of Appendix Tables A1 and A2.

Our analysis reveals a statistically significant increase in dropout rates during consecutive drought years in 2011–2012 in the drought-prone regions of Maharashtra, namely the Marathwada meteorological subdivision, followed by a recovery in subsequent years. In contrast, the school participation in the exposed group within Karnataka, namely the NIK meteorological subdivision, appears resilient to the impact of successive meteorological droughts. Moreover, positive trends emerge in the latter years, indicating the effectiveness of initiatives implemented in drought-prone areas of the state. These findings regarding the impact of drought on school participation complement our primary results on learning outcomes, providing additional support and confidence in our conclusions.

5.4 Results from an Alternative Identification Strategy

In our main event study framework (Equation 1), we employed difference-in-difference regression equations to assess the impact of drought in comparison to regions less prone to drought within a state over time. Specifically, we conducted separate analyses for Maharashtra and Karnataka to examine the effects of drought with and without public sector preventive measures in place. By running two distinct event studies for each state, we avoided assuming that Maharashtra and Karnataka were identical in their counterfactual conditions.

In this subsection, we propose an alternative identification strategy utilizing triple difference regression equations within the same event study framework. This approach allows for a more comprehensive comparison between states and facilitates the comparison of the drought-prone regions with their corresponding non-drought-prone regions within a single equation. Additionally, it allows us to test the robustness of our estimates.

The proposed alternative identification strategy for each child i from district d in state s during the time period t is as follows:

$$Y_{idst} = \alpha_d + \beta_1 \cdot (Drought_d * State_s * Time_t) + \beta_2 \cdot (Drought_d * State_s) + \beta_3 \cdot (State_s * Time_t) + \beta_4 \cdot (Drought_d * Time_t) + \beta_5 \cdot (State_s) + \beta_6 \cdot (Time_t) + \beta_i \cdot (X_i) + \mu_{idst},$$

$$(2)$$

where Y_{idst} denotes the outcome variable for child *i* at time *t*. $Time_t$ is a dummy variable, varying across eight versions to create an event study framework. It assumes a value of 0 for the base year 2008 and a value of 1 for each subsequent year from 2009 to 2018, excluding 2015 and 2017 due to data unavailability in our primary dataset. $Drought_d$ is a dummy variable indicating whether a child belongs to the drought-prone subdivisions or not, taking the value 1 for individuals from either Marathwada or NIK. $State_s$ is a dummy variable that is assigned the value 1 for Maharashtra and 0 for Karnataka. Control variables consistent with Equation 1 are included, denoted by X_i . α_d represents district fixed effects, and standard errors are clustered at the district level.

The results of the above-mentioned alternative identification strategy, depicted in Figures 7 8 and 9 for the math score, reading score, and dropout rates, respectively, provide a combined picture of the earlier findings presented separately for both states. The triple difference point estimates illustrated in these figures reveal that, over time, prior to consecutive drought years, there existed no significant disparity between the two states concerning learning outcomes and school attendance. However, following the consecutive drought years of 2011–2012, the trends indicate that the drought-prone regions of Maharashtra face learning losses and higher school dropout rates, while the drought-prone regions of Karnataka display resilience and progress due to public sector interventions in drought-prone areas.

5.5 Results from an Alternative Reference Year

In our primary empirical framework, we established 2008 as the baseline year for our event study, as our primary dataset starts from that year. However, in this particular subsection, for the robustness of our estimates, we shift the baseline year to 2010, the year immediately preceding a series of consecutive drought events. Like the year 2008, the year 2010 was also not marked by severe drought conditions. Consequently, Equation 1, as elaborated in the methodology section (subsection 4.2), remains unchanged except for the modification of the $Time_t$ dummy variable.

In this analysis, the $Time_t$ variable serves as a dummy variable with eight versions, each designed to construct an event study framework. Across these versions, it is assigned a value of 0 for the year 2010, which serves as the baseline year for all versions. Subsequently, for each version, the dummy variable takes on a value of 1 for one year at a time, namely 2008, 2009, 2011, 2012, 2013, 2014, 2016, and 2018.

The outcomes of this analysis utilizing the alternative base year for the states of Maharashtra and Karnataka are depicted in Figures 10, 15, where Figures 10, 11, and 12 pertain to math scores, reading scores, and dropout rates for Maharashtra, and Figures 13, 14, and 15 correspond to the same outcome variables for Karnataka. Notably, these findings for both states align closely with the primary results obtained with 2008 as the baseline year. Thus, it is evident that our conclusions remain consistent irrespective of the choice of the baseline year.

6 Discussion

In our study, we examine the effects of drought and its recovery with and without preventative measures, using an event study approach. Since droughts are temporary and their impact areas may vary with each occurrence, we focus on meteorological subdivisions prone to drought. Specifically, we concentrate on the semi-arid regions of the Deccan Plateau in two neighboring states, Maharashtra and Karnataka, which experience frequent severe droughts in India. We provide empirical evidence supporting the relevance assumption for our strategy that the drought-prone subdivisions experienced severe drought compared to other areas within their respective states during the study period.

We compare the occurrence of drought in these drought-prone subdivisions between the two states. In Maharashtra, we observe learning losses in its drought-prone subdivisions following drought events, while in Karnataka, such losses are not evident. We hypothesize that this discrepancy is due to the presence of drought-preventative measures in one state and their absence in the other.

However, one concern may arise regarding the interpretation of our findings if Karnataka simply provides better education. Our analysis, employing a triple difference setup to compare both states and their drought-prone regions with a baseline year, disproves this concern. In fact, our summary statistics indicate that, on average, Maharashtra performed slightly better in educational outcomes compared to Karnataka. Additionally, drought-prone regions within Maharashtra also demonstrated superior academic performance compared to those in Karnataka. Another concern could relate to the drought intensity and the timeline of drought occurrence in the drought-prone regions of both states. However, despite being administratively distinct, the meteorological subdivisions in both states share borders and belong to the same arid zone, experiencing similar climatic conditions and encountering comparable drought incidents. Moreover, we also demonstrate using our dataset and through secondary sources that both regions experienced similar drought incidents in terms of intensity and timing during the study period.

Thus, our main findings regarding test scores and school participation support the hypothesis that preventive measures in one state contribute to education resilience in its drought-prone regions. These preventive measures were primarily targeting agriculture, a crucial pathway through which meteorological drought affects human capital investment in agriculture-dependent economies. Therefore, our study suggests that with such preventive measures in place, the drought-prone regions in agriculture-dependent economies may still face meteorological droughts, but the severity of their impact may be mitigated.

Furthermore, we acknowledge the role of corporate initiatives in combating water crises in droughtprone regions. While private sector efforts complement those of the public sector, they often operate on a smaller scale and with limited geographic coverage. Recognizing the potential limitations of district-level observation and the time required for test scores to manifest, we shift our focus to expenditure patterns. Since the main focus of our paper is on educational outcomes, we place this analysis of private sector drought prevention effectiveness and the associated results in the online appendix, highlighting increased educationrelated expenses in regions with a higher density of private sector drought prevention projects. However, we caution against drawing causal conclusions due to limitations in data granularity and the potential influence of other private sector projects on our comparison group.

Moving forward, primary research focusing on collecting data at lower administrative levels could provide more targeted insights into the effectiveness of private sector drought preventive measures. Our study highlights the importance of collective efforts involving all stakeholders in addressing water scarcity. While our findings demonstrate the positive impacts of government measures on education resilience, they also indicate the need for further research to assess the causal impact of private sector initiatives. Such efforts would contribute to a comprehensive understanding of the collective actions needed to address water scarcity effectively.

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Tables and Figures

	Maharas	htra	Karnata	ıka
Variables	Observations	Mean	Observations	Mean
Outcomes:				
Math Score	249123	2.487	209425	2.393
(Ranges from $0-4$)		(1.266)		(1.210)
Reading Score	249550	2.951	209879	2.664
(Ranges from $0-4$)		(1.347)		(1.398)
Dropout Rate	341271	0.0132	287136	0.0244
(Yes = 1, No = 0)		(0.114)		(0.154)
Explanatory Variables:				
Child's Age	303169	9.740	258388	9.759
(yrs)		(3.760)		(3.703)
Child's Gender	302480	0.474	258542	0.497
(Female = 1, Male = 0)		(0.499)		(0.499)
Family Size	337988	5.835	284815	6.028
(No. of members in the household)		(2.712)		(3.115)
Mother's Education	320041	1.328	270819	1.450
(Grade up to which she had attended school)		(0.469)		(0.497)
Rainfall Data:				
Average Annual Rainfall	299,310	100.57	250,361	101.04
		(74.64)		(90.18)
Average Monsoon Rainfall	298,206	262.52	250,360	221.17
		(207.77)		(247.94)

Table 1: Summary statistics

Note: The table contains summary statistics for the outcome variable and all the explanatory variables used in the study. We have reported the summary statistics for the primary data used in our main analysis for both states under consideration for our study from the years 2008 to 2018, excluding the years 2015 and 2017. Each state's first and second columns represent the number of observations and the variable's mean value for that state, respectively. Standard deviations are reported in parentheses.



Figure 1: Results for math scores from baseline scenario

Note: The figure is based on Equation 1, comparing Marathwada and the rest of Maharashtra in the event study framework with 2008 as the reference period. All points represent coefficients from different regressions of math test scores and include demographic controls and district fixed effects. Vertical lines represent 90% confidence intervals.



Figure 2: Results for reading scores from baseline scenario

Note: The figure is based on Equation 1, comparing Marathwada and the rest of Maharashtra in the event study framework with 2008 as the reference period. All points represent coefficients from different regressions of reading test scores and include demographic controls and district fixed effects. Vertical lines represent 90% confidence intervals.



Figure 3: Results for dropout rate from baseline scenario

Note: The figure is based on Equation 1, comparing Marathwada and the rest of Maharashtra in the event study framework with 2008 as the reference period. All points represent coefficients from different regressions of the dropout rate and include demographic controls and district fixed effects. Vertical lines represent 90% confidence intervals.

Figure 4: Results for math scores with public sector drought preventive measures



Note: The figure is based on Equation 2, comparing NIK and the rest of Karnataka in the event study framework with 2008 as the reference period. All points represent coefficients from different regressions of math test scores and include demographic controls and district fixed effects. Vertical lines represent 90% confidence intervals.



Figure 5: Results for reading scores with public sector drought preventive measures

Note: The figure is based on Equation 2, comparing NIK and the rest of Karnataka in the event study framework with 2008 as the reference period. All points represent coefficients from different regressions of reading test scores and include demographic controls and district fixed effects. Vertical lines represent 90% confidence intervals.



Figure 6: Results for dropout rate with public sector drought preventive measures

Note: The figure is based on Equation 2, comparing NIK and the rest of Karnataka in the event study framework with 2008 as the reference period. All points represent coefficients from different regressions of the dropout rate and include demographic controls and district fixed effects. Vertical lines represent 90% confidence intervals.





Note: The figure is based on Equation 2, comparing drought-prone regions against those not prone to drought in two states, namely Maharashtra and Karnataka, over time. This analysis is conducted within an event study framework, with the year 2008 as the reference period. All points represent coefficients from different regressions of math test scores and include demographic controls and district fixed effects. Vertical lines represent 90% confidence intervals.

Figure 8: Results for reading scores using alternative identification strategy



Note: The figure is based on Equation 2, comparing drought-prone regions against those not prone to drought in two states, namely Maharashtra and Karnataka, over time. This analysis is conducted within an event study framework, with the year 2008 as the reference period. All points represent coefficients from different regressions of reading test scores and include demographic controls and district fixed effects. Vertical lines represent 90% confidence intervals.



Figure 9: Results for dropout rates using alternative identification strategy

Note: The figure is based on Equation 2, comparing drought-prone regions against those not prone to drought in two states, namely Maharashtra and Karnataka, over time. This analysis is conducted within an event study framework, with the year 2008 as the reference period. All points represent coefficients from different regressions of dropout rates and include demographic controls and district fixed effects. Vertical lines represent 90% confidence intervals.



Figure 10: Results using alternative reference year for math scores from baseline scenario

Note: The figure is based on Equation 1, comparing Marathwada and the rest of Maharashtra in the event study framework with 2010 as the reference period. All points represent coefficients from different regressions of math test scores and include demographic controls and district fixed effects. Vertical lines represent 90% confidence intervals.

Figure 11: Results using alternative reference year for reading scores from baseline scenario



Note: The figure is based on Equation 1, comparing Marathwada and the rest of Maharashtra in the event study framework with 2010 as the reference period. All points represent coefficients from different regressions of reading test scores and include demographic controls and district fixed effects. Vertical lines represent 90% confidence intervals.

Figure 12: Results using alternative reference year for dropout rate from baseline scenario



Note: The figure is based on Equation 1, comparing Marathwada and the rest of Maharashtra in the event study framework with 2010 as the reference period. All points represent coefficients from different regressions of the dropout rate and include demographic controls and district fixed effects. Vertical lines represent 90% confidence intervals.

Figure 13: Results using alternative reference year for math scores with public sector drought preventive measures



Note: The figure is based on Equation 1, comparing NIK and the rest of Karnataka in the event study framework with 2010 as the reference period. All points represent coefficients from different regressions of math test scores and include demographic controls and district fixed effects. Vertical lines represent 90% confidence intervals.





Note: The figure is based on Equation 1, comparing NIK and the rest of Karnataka in the event study framework with 2010 as the reference period. All points represent coefficients from different regressions of reading test scores and include demographic controls and district fixed effects. Vertical lines represent 90% confidence intervals.

Figure 15: Results using alternative reference year for dropout rate with public sector drought preventive measures



Note: The figure is based on Equation 1, comparing NIK and the rest of Karnataka in the event study framework with 2010 as the reference period. All points represent coefficients from different regressions of the dropout rate and include demographic controls and district fixed effects. Vertical lines represent 90% confidence intervals.

Appendix



Figure A1: Results for rainfall using primary empirical framework

Note: The figure is based on Equation 1, comparing rainfall (in millimeters) in Marathwada and the rest of Maharashtra in the event study framework with 2008 as the reference period. All points represent coefficients from different regressions of average annual rainfall. Vertical lines represent 90% confidence intervals.





Note: The figure is based on Equation 2, comparing rainfall (in millimeters) in NIK and the rest of Karnataka in the event study framework with 2008 as the reference period. All points represent coefficients from different regressions of average annual rainfall. Vertical lines represent 90% confidence intervals.

Table A1: Regression results from baseline scenario

Score
Math
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anel

Panel 1: Math Score								
				Yee	urs			
	2009	2010	2011	2012	2013	2014	2016	2018
$Marathwada_{d}*Reference_period_{2008}$	-0.0811	-0.0429	-0.0093	-0.2167**	-0.1800	-0.1059	-0.1463	-0.1434
	(0.1306)	(0.1068)	(0.1303)	(0.0992)	(0.1276)	(0.1175)	(0.1192)	(0.1109)
Observations	55,517	56,118	51,683	48,259	49,700	47,694	46,389	45,923
R-squared	0.535	0.535	0.513	0.515	0.514	0.506	0.485	0.478
Controls	$\mathbf{Y}_{\mathbf{es}}$	$\mathbf{Y}_{\mathbf{es}}$	\mathbf{Yes}	$\mathbf{Y}_{\mathbf{es}}$	\mathbf{Yes}	$\mathbf{Y}_{\mathbf{es}}$	$\mathbf{Y}_{\mathbf{es}}$	$\mathbf{Y}_{\mathbf{es}}$
District Fixed Effects	\mathbf{Yes}	\mathbf{Yes}	\mathbf{Yes}	\mathbf{Yes}	\mathbf{Yes}	\mathbf{Yes}	\mathbf{Yes}	\mathbf{Yes}
Panel 2: Reading Score								
				Yea	urs			
	2009	2010	2011	2012	2013	2014	2016	2018
$Marathwada_{d}*Reference_period_{2008}$	0966	0238	0034	1501*	0513	0761	1736**	0741
	(.0942)	(.0692)	(0260.)	(.0872)	(2060.)	(.0848)	(.0788)	(.0878)
Observations	55,588	56,189	51,778	48,298	49,730	47,709	$46,\!427$	45,981
R-squared	0.497	0.501	0.482	0.492	0.488	0.482	0.461	0.470
Controls	$\mathbf{Y}_{\mathbf{es}}$	\mathbf{Yes}	\mathbf{Yes}	\mathbf{Yes}	\mathbf{Yes}	\mathbf{Yes}	\mathbf{Yes}	\mathbf{Yes}
District Fixed Effects	\mathbf{Yes}	\mathbf{Yes}	\mathbf{Yes}	$\mathbf{Y}_{\mathbf{es}}$	\mathbf{Yes}	$\mathbf{Y}_{\mathbf{es}}$	$\mathbf{Y}_{\mathbf{es}}$	$\mathbf{Y}_{\mathbf{es}}$
Panel 3: Dropout Rate								
				Yea	urs			

This table reports the results from regression Equation 1 described in the methodology section. It compares Marathwada with the rest of Maharashtra using the event study framework with 2008 as the base year after including demographic controls and district fixed effects. Panel 1 contains the results for math test scores, Panel 2 for reading test scores, and Panel 3 for dropout rates, across different years. Each panel's first row represents the estimated coefficient $(\beta 1)$ for the interaction term (Marathwada_d * Time_t) from various regressions. Robust standard errors clustered at the district level are reported in parentheses on the second row. The number of observations used is reported in the third row. Significance levels are denoted by ***, **, and *, indicating p < 0.01, p < 0.05, and p < 0.1, respectively.

-0.0091(0.0066)56,5370.041

(0.0073)-0.0056

(0.0059)-0.0053

(0.0065)-0.004

> (0.0079)57,799

(0.0081)-0.0036

(0.0065)-0.0062

65,6140.038

64,5760.038

Observations R-squared Controls

57, 514

58, 321

60, 3400.043

0.041 \mathbf{Yes} Yes

0.044 \mathbf{Yes} Yes

0.04 \mathbf{Yes} Yes

 $\mathbf{Y}_{\mathbf{es}}$ $\mathbf{Y}_{\mathbf{es}}$

 $\mathbf{Y}_{\mathbf{es}}$ \mathbf{Yes}

 $\mathbf{Y}_{\mathbf{es}}$ Yes

Yes Yes

 $\mathbf{Y}_{\mathbf{es}}$ \mathbf{Yes}

District Fixed Effects

2018

2016

2014

2013

2012

2010

2009

 0.0102^{*} (0.0057)58,6630.045

0.00632011

 $Marathwada_d * Reference_period_{2008}$

Table A2: Regression results with public sector drought preventive measures

				,	Years			
	2009	2010	2011	2012	2013	2014	2016	2018
$NIK_d * Reference_period_{2008}$	-0.0483	0.0151	-0.0036	0.0924	0.1033	0.1569^{*}	0.2023^{***}	0.1917^{**}
	(0.0536)	(0.0713)	(0.0741)	(0.0682)	(0.0628)	(0.0816)	(0.0705)	(0.0769)
Observations	44,711	43,181	41,955	40,957	41,205	39,429	42,488	45,135
R-squared	0.430	0.440	0.435	0.443	0.445	0.431	0.426	0.429
Controls	\mathbf{Yes}	\mathbf{Yes}	$\mathbf{Y}_{\mathbf{es}}$	Yes	\mathbf{Yes}	$\mathbf{Y}_{\mathbf{es}}$	$\mathbf{Y}_{\mathbf{es}}$	Yes
District Fixed Effects	\mathbf{Yes}	Yes	$\mathbf{Y}_{\mathbf{es}}$	\mathbf{Yes}	\mathbf{Yes}	\mathbf{Yes}	\mathbf{Yes}	Yes
Panel 2: Reading Score								
				,	Years			
	2009	2010	2011	2012	2013	2014	2016	2018
$NIK_d * Reference_period_{2008}$	0.0297	0.0543	-0.0283	0.1144^{*}	0.0848	0.1421^{**}	0.1985^{***}	0.2548^{***}
	(0.0459)	(0.0656)	(0.0663)	(0.0613)	(0.0646)	(0.0581)	(0.0495)	(0.0900)
Observations	44,866	43,360	42,010	40,974	41,228	39,450	42,527	45,146
R-squared	0.421	0.436	0.430	0.436	0.448	0.446	0.445	0.453
Controls	\mathbf{Yes}	\mathbf{Yes}	\mathbf{Yes}	Yes	\mathbf{Yes}	\mathbf{Yes}	Yes	Yes
District Fixed Effects	\mathbf{Yes}	Yes	\mathbf{Yes}	Yes	\mathbf{Yes}	\mathbf{Yes}	\mathbf{Yes}	Yes
Panel 3: Dropout Rate								
				,	Years			
	2009	2010	2011	2012	2013	2014	2016	2018
$NIK_d * Reference_period_{2008}$	-0.0047	-0.0141^{**}	-0.0129	-0.0246^{**}	-0.0145	-0.0259^{***}	-0.0252***	-0.0309***
	(0.0065)	(0.0061)	(0.0102)	(0.0119)	(0.0087)	(0.0076)	(0.0061)	(0.0089)
Observations	53,093	53,260	48, 399	50,247	$49,\!680$	48,192	51,364	54, 336
R-squared	0.070	0.065	0.068	0.061	0.063	0.063	0.064	0.059
Controls	Yes	Yes	\mathbf{Yes}	Yes	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	$\mathbf{Y}_{\mathbf{es}}$	Yes	Yes	Yes	Yes	Yes

This table reports the results from regression Equation 2 described in the methodology section. It compares NIK with the rest of Karnataka using the event study framework with 2008 as the base year after including demographic controls and district fixed effects. Panel 1 contains the results for math test scores, Panel 2 for reading test scores, and Panel 3 for dropout rates, across different years. Each panel's first row represents the estimated coefficient (β 1) for the interaction term ($NIK_d * Time_t$) from various regressions. Robust standard errors clustered at the district level are reported in parentheses on the second row. The number of observations used is reported in the third row. Significance levels are denoted by ***, **, **, and *, indicating p < 0.01, p < 0.05, and p < 0.1, respectively.