When Rain Matters! Investments and Value Relevance

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ABSTRACT

We study whether firms, whose operational performance is highly sensitive to rainfall conditions (rain-sensitive firms), follow differential investment strategies to generate value in response to diverse extreme rainfall conditions. Using Indian monsoon data, we find that rain-sensitive firms suffer a significant decline in their market value in the immediate aftermath of excess and deficit rainfall conditions. Results show that the investment response by rain-sensitive firms depends on the saliency of extreme rainfall conditions. While excess rain-sensitive firms boost their investments following excess rainfall, deficit rain-sensitive firms shrink investments following deficit rainfall. However, these alternative investment strategies appear to be effective as both groups of affected firms experience positive growth in their market values following the differential investment strategies. Our results indicate that saliency theory can bridge the theoretical tensions between the real-options and risk-shifting theories resulting in differential corporate investment behavior in the face of two extreme rainfall conditions.

JEL Codes : G30; G32; Q54; Q51; D81
Key Words : Climate change; Abnormal rainfall; Salience theory; Investment strategy; Firm value

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1. Introduction

Studies focusing on weather-related anomalies have been attracting global attention in both practice and academia. An overwhelming weight of accumulated research corroborates that changing climatic conditions in recent years have led to the widespread dislocation of the population (Black et al., 2011; Perch-Nielsen et al., 2008), along with lower agricultural income arising from loss of crop and livestock, higher unemployment and poverty (Carter et al., 2006; Cohen et al., 2013; de Sherbinin et al., 2011). These ramifications of climate change carry significant negative consequences for economic growth and development (Barrios et al., 2010; Brown et al., 2011; Dell et al., 2012, 2009).[1]

Worldwide statistics show that in recent decades the frequencies of disasters, such as floods and droughts, have been distressingly intensifying, particularly in Asia. For example, between the years 2000 and 2018, flooding and drought conditions in India have incurred losses of around USD 48.04 billion and USD 5.60 billion respectively.[2] Since macroeconomic outputs are directly linked to the performance of the corporate sector, we extend the literature on corporate climate finance by investigating the economic impact of extreme climatic conditions, specifically extreme rainfall deviations, from their expected normal (hereinafter referred to as rainfall-departures), on corporate investments and market-based valuations.

Evidence suggests that higher precipitation levels, which are directly linked to escalating atmospheric temperature, are one of the major factors contributing to climate change

[1] The IPCC (Intergovernmental Panel on Climate Change) published its special report entitled "Global Warming of 1.5°C" in October 2018. Panmao Zhai, Co-Chair of IPCC stated the following "*One of the key messages that comes out very strongly from this report is that we are already seeing the consequences of 1°C of global warming through more extreme weather, rising sea levels and diminishing Arctic sea ice, among other changes*" (https://www.orano.group/en/unpacking-nuclear/all-about-the-ipcc-report-on-climate-change).

[2] *Source*: EM-DAT: The Emergency Events Database - Université Catholique de Louvain (UCLouvain) - CRED, D. Guha-Sapir - www.emdat.be, Brussels, Belgium

conditions (Hardwick Jones et al., 2010). Studies document that the exponential increase in the water-holding capacity of air with rising temperature, as supported by the theoretical modeling of the 'Clausius–Clapeyron' relation, results in the intensification of rainwater cycles (Lenderink and van Meijgaard, 2008). Such phenomena further lead to extreme rainfall conditions causing severe floods and droughts (Henderson et al., 2016).[3] Given the rising extremities in rainfall conditions, the key focus of our study is to examine the impact of two extreme rainfall-departure conditions, i.e. the excess and the deficit conditions, on managerial responses to corporate investment strategies. Additionally, we also investigate the market-based value relevance of such investment strategies.

Corporate finance theories offer an inconclusive view on the direction of investment intensity following both the excess/deficit rainfall conditions, which creates a heightened environment of uncertainties. While the risk-shifting theory suggests that investments among rain-sensitive firms should increase in the face of abnormal rainfall conditions, the real-options view envisages shrinkage in investments among rain-sensitive firms (Aretz et al., 2018; Ioulianou et al., 2017). Reconciling these opposite views, our study draws on the 'salience theory of choice under risk', which predicts that firms pursue differential investment strategies based on differential saliency encountered by the managers.

Within our context of rainfall-departures, salience theory suggests that managers, principally of firms whose operational performance is highly sensitive to rainfall conditions (hereafter referred to as rain-sensitive firms), are salient to the impacts of rainfall-departure conditions. These saliencies arise from managers witnessing different ramifications of extreme rainfall conditions, such as partial destruction of operating assets, underutilization of production capacity, cash shortages stemming from the drop in local demand, increased

[3] A recent study by NASA's Jet Propulsion Laboratory found that for every 1 degree Celsius rise in ocean surface temperature, 21% more storms are formed, which means a substantial increase in extreme rainfall (NASA, 2019).

operating costs, etc. (Dessaint and Matray, 2017). However, the two different rainfall-departure conditions may lead to different saliency experiences. For example, while partial destruction of operating assets is more likely in the case of excess rainfall conditions, underutilization of production capacity is highly probable in deficit conditions. This implies that rain-sensitive firm managers, who are differentially salient to heterogeneous rainfall-departure conditions, may adopt different investment strategies to generate positive market-based valuation.

We investigate the above-stated conjectures in our empirical set-up using data that captures extreme unexpected changes in the Indian rainfall (monsoon rains). Specifically, we examine the following three issues: (i) market-based firm valuation effects of rain-sensitive firms in the immediate aftermath of extreme rainfall-departures, (ii) investment strategies of rain-sensitive firms following extreme rainfall-departures, and (iii) market-based valuation response after these investment strategies are initiated.

The Indian empirical set-up suits our study well for two key reasons. First, we observe a rising trend of extreme variations and intensities of rainfall-departures in India when compared to other countries. For example, Table A1 of the Appendix shows a simple comparison between the rainfall-departures of India and the USA. It is evident that the average rainfall-departures in each decile for the study period of 2001 to 2017 for India are much greater than for the USA. While the USA's rainfall-departures range is between -17.39% to +22.33%, India's extreme rainfall-departures range is between -73.7% to +126%. Such extreme variations provide us with an excellent empirical set-up to credibly test our hypotheses. Second, the contribution of the rain-sensitive primary sectors' gross value added to the Indian gross domestic product (GDP) is estimated to be 17.1% for the year 2017-18.[4] This translates into approximately USD 466.48 billion per year, as per World Bank GDP data on India.

[4] The primary sectors are agriculture, forestry, fishing, and mining & quarrying See the link: https://pib.gov.in/newsite/PrintRelease.aspx?relid=186413 : Government of India, Ministry of Finance.

In terms of empirical investigation, drawing on empirical evidence offered by the extensive literature, we identify firms belonging to those industries whose operational performance is most negatively affected by rainfall-departure conditions. We refer to them as rain-sensitive firms or, in our quasi-experimental set-up, treated group firms. Moreover, given that firms even within the treated group are likely to be differentially affected by excess and deficit rainfalls, we further sub-classify them into two sub-groups. If firms' operational performance is negatively affected by excess rainfall conditions, we group them as 'excess-rain-sensitive firms' and those negatively affected by deficit rainfall conditions as 'deficit-rain-sensitive firms'. The remaining firms whose operational performance is least likely to be negatively affected by rainfall-departure conditions are classified as control group firms.

In terms of data, we estimate the intensity of rainfall-departures, relative to the 'normal' expected rainfall intensity, using the rainfall deviation data provided by the Indian Meteorological Department (IMD). Since we only employ extreme deviations, our rainfall-departure measure reflects exogenous variations in rainfall conditions. We use different empirical methods, including an approach similar to difference-in-differences (DiD), to establish potential causal links between extreme rainfall-departures and the following investment strategies initiated by rain-sensitive firms.

The empirical investigations reveal the following findings. First, relative to control group firms, rain-sensitive firms suffer a market-based value drop in the immediate aftermath of the rainfall-departures. Under both excess and deficit conditions, the firm value declines significantly in the immediate September quarter which marks the end of the monsoon season, with the decline continuing until the end of the fourth quarter of the same fiscal year.[5] In economic terms, the decline in firm value (using market-to-book measure) of rain-sensitive

[5] In India, fiscal year begins on 1 April and ends on 31 March of the following year. The monsoon season is the months of June, July, August and September. The immediate value effect of extreme rainfall-departure is tested at the end of the second fiscal quarter, i.e. September and fourth fiscal quarter, i.e. March.

sectors is in the range of -10 to -17.7 units in the excess and the range of -1.6 to -5.9 units in the deficit rainfall conditions.

Second, the investigation linking rainfall-departure and the post-rainfall-departure investment strategies reveals several interesting outcomes. We find that under the excess rainfall scenario, the excess-rain-sensitive firms significantly increase their capital expenditure (on average, in the range of 3.4% to 4.8%) compared to control group firms. Conversely, in the deficit conditions, the deficit-rain-sensitive firms reduce their capital expenditure (on average by 3%) when compared to control group firms. These results are further supported by a battery of additional tests, including the use of alternative investment proxies, single-year pair DiD approach, and sensitivity analyses employing different levels of rainfall-departure intensities (i.e., ±15% to ±30% rainfall deviations).

We also find evidence that the growth in corporate investments among rain-sensitive firms continues to persist for almost three years following the excess conditions, particularly when rainfall-departure conditions are 20% above the normal level. However, for deficit conditions, the impact is seen only in the immediate year following rainfall-departure. Taken together, our empirical findings lend strong support to the proposition that the two diverse rainfall-departure conditions (excess vs. deficit) are associated with differential responses in terms of corporate investments (increase vs. decrease).

Finally, evidence suggests a significant increase in market value, in the year following the rainfall-departure conditions, not only for the excess-rain-sensitive firms (average of 2 units) but even for the deficit-rain-sensitive firms (average 9 units). These results imply that managers' diverse post-rainfall-departure investment decisions (to invest or not to invest) under the saliency of differential exogenous conditions (excess or deficit) can lead to value generation. This also indicates that firms can recoup the value lost in the immediate aftermath of rainfall-departure through their post-rainfall-departure investment strategies. Such outcomes support the conjecture that investment strategies induced by rainfall-departures are associated with increased market valuations of rain-sensitive firms.

Our study makes the following important contributions. First, we add to the literature that investigates the impact of climate and environmental changes on corporate behavior and market performance. For example, a sizeable number of studies relate climate change to overall stock market returns, market sentiment, liquidity, and volatility (Cao and Wei, 2005; Hirshleifer and Shumway, 2003; Kamstra et al., 2003; Rehse et al., 2019). Although these studies provide useful insights that corporates are not immune to changing climatic conditions, they mostly focus on the implications for stock markets.

In terms of operational and financial performance, using data from the US market, Barrot and Sauvagnat (2016) show that natural disasters negatively affect revenue growth, while Dessaint and Matray (2017) document that hurricanes lead to a reduction in firm value. Similarly, studies also document that extreme temperature drops can increase the usage of credit lines by corporates (Brown et al., 2017) resulting in a sharp decline in productivity (Chen and Yang, 2019; Zhang et al., 2018). However, unlike the above-mentioned studies linking extreme weather conditions to operational and financial performance, the key focus of our study is to examine corporate investment decisions in the wake of significant climate events. Specifically, we add to the literature on corporate climate finance by presenting evidence on the association between extreme rainfall-departure conditions and firm-level investment strategies, and how such post-rainfall-departure investment strategies may influence market valuations.

Second, our study also adds to the literature on risk-taking by contributing to the ongoing debate of theoretical tensions between the real-options approach and the risk-shifting theory of corporate investments (Eisdorfer, 2008; Ioulianou et al., 2017; Jensen and Meckling, 1976; McDonald and Siegel, 1986). As a reconciling approach, we propose a plausible economic intuition exploiting the salience theory to explain a unique and previously unexplored investment behavior of firms whose operational performance is sensitive to extreme rainfall conditions. Thus, our paper contributes to the line of literature that uses the impact of past experiences on subsequent risk-taking and corporate investment policy choices (Bordalo et al., 2012; Dessaint and Matray, 2017; Malmendier et al., 2011).

The rest of the paper is organized as follows. Section 2 reports a survey of relevant literature and develops testable hypotheses. We discuss the data and identification strategy in Section 3. Section 4 reports and discusses the findings of the empirical examinations and finally, Section 5 concludes the paper.

2. Literature and hypotheses development

In this section, we develop testable hypotheses to address the three issues discussed above, i.e. (i) market-based firm valuation effects in the immediate aftermath of extreme rainfall-departures, (ii) investment strategies following extreme rainfall-departures, and (iii) market-based valuation implications of the post-rainfall-departure investment strategies.

2.1 Rainfall-departure and immediate market-based value effect

Studies note that the socio-economic impacts of climate change are beset with uncertainty due to the fat tail probabilities of extreme climate events (Heal and Millner, 2014; Pindyck, 2007). Extreme rainfall-departures, generally associated with full or partial destruction of physical assets and/or significant economic distress conditions, substantially dampen economic activities and outputs (Fuss, 2016). While excess rainfall conditions cause significant damage to the physical infrastructure, deficit rainfall conditions are no less detrimental, with a substantial impact on outputs and income (de Sherbinin et al., 2011; Huang et al., 2018; Mall et al., 2006).

The literature offers extensive empirical evidence of extreme rainfall-departures creating conditions of uncertainty and distress across several rain-sensitive industries such as agriculture (Ahmed et al., 2018; Guan et al., 2015; Läderach et al., 2013; Okom et al., 2017), chemicals & fertilizer, electricity generation & transmission, mining & quarrying sectors (Chang and Brattlof, 2015; Cronin et al., 2018; Golombek et al., 2012; Larsbo et al., 2016) and tourism & leisure (Fukushima et al., 2002; Peeters and Dubois, 2010; Wall, 1998), among others. In summary, the extant literature provides sufficient evidence in support of the fact that rainfall-departures have a substantial impact on earnings, costs, and operational productivity of various societal stakeholders including firms, households, government, and financial markets (Freire-González et al., 2017; Huang et al., 2018).

Given that a firm's market price reflects information on future cash flows, any rainfall-departure that impairs a firm's normal production and operation creates greater uncertainty for its future cash flows. This implies market investors encounter a higher cost of capital for these rain-sensitive industries leading to the lower market price of their securities. Further, as the market awaits the strategic response to address cash flow uncertainty from the affected firms, the information asymmetry triggered by extreme rainfall-departure should result in lower market prices (Diamond and Verrecchia, 1991; Johnstone, 2016). From the investors' viewpoint, the bigger the uncertainty the greater the stock's risk premium, and the higher the cost of capital of the firm (Easley and O'Hara, 2004). Thus, in the wake of higher uncertainty of cash flows and managerial actions, investors demand a higher rate of return, which should dampen the firm's market value in the immediate aftermath of rainfall-departure.

As noted above, since extreme rainfall-departure conditions negatively impact firms' productive and operative performance, the market is likely to discount the future expected cash flows and escalate the associated discount rate of rain-sensitive firms in the immediate aftermath of such abnormal conditions. This notion is also consistent with prior theoretical and empirical evidence on stock market reactions to other weather phenomena, such as extreme temperature (Cao and Wei, 2005; Hirshleifer and Shumway, 2003). We thus hypothesize a decline in the firm value of rain-sensitive firms, relative to non-rain-sensitive firms, in the immediate aftermath of extreme rainfall-departure conditions:

H_1: Following excess (deficit) rainfall conditions, firms belonging to excess (deficit) rain-sensitive industries should experience a greater immediate decline in their firm values, relative to non-rainfall-sensitive firms.

2.2 Rainfall-departure and investments

In the immediate aftermath of extreme rainfall-departure, managers of rain-sensitive firms face a 'capacity investment' decision scenario, whereby they need to respond in managing uncertainties and future demands (Fine and Freund, 1990). Importantly, as investments are generally irreversible, firms must carefully assess their investment strategies following the uncertainty and distress caused by extreme rainfall-departures. Considering corporate investment decisions are a measure of risk-taking, two competing views in the traditional corporate finance literature examine the issue of risk-taking under uncertainty and distress.

First, the risk-shifting view posits that firms are more likely to take riskier investment decisions during times of distress (Black and Scholes, 1973). As per this view, since excessive risk-taking enhances the possibility of disproportionately benefiting shareholders in the wake of firms facing uncertainty and financial distress, managers tend to move away from safer to riskier assets (Aretz et al., 2018; Eisdorfer, 2008; Jensen and Meckling, 1976). Since extreme rainfall-departure conditions generate uncertainties and enhance financial distress, the risk-shifting view implies that investments among rain-sensitive firms should increase.

Second, the real options approach to investments posits a trade-off between making immediate investments and delaying them in order to gain more information (Cooper and Priestley, 2011; Ioulianou et al., 2017; McDonald and Siegel, 1986; Tserlukevich, 2008). As the value of delaying investment decisions increases with higher uncertainty, as would be the case following extreme rainfall-departure conditions, the real-options framework conjectures a decrease in investments.

As is evident, both the above mentioned traditional corporate finance views do not provide a unified framework to examine investments when firms experience heterogeneous conditions of the excess and deficit rainfall-departure. The possibility of firms pursuing different investment strategies in the aftermath of heterogeneous rainfall conditions is, to a considerable extent, addressed by the 'salience theory of choice under risk' (hereafter referred to as salience theory), which predicts investment strategies based on the saliencies of past experiences encountered by the managers.

Proposed by Bordalo et al. (2012), salience theory states that decision-makers are risk-seeking when they see the upside pay-offs from such decisions to be salient and risk-averse when its downside is salient. In our context, it is reasonable to argue that local firms, particularly the rain-sensitive ones, would be more attentive to the saliency of the rainfall-departures. This arises due to the fact that these firms experience significant adverse operating issues such as cash shortages, destruction of operating assets, increased operating costs, or the necessity for new investments (Dessaint and Matray, 2017). Moreover, as different rainfall-departure conditions (excess or deficit) have a differential impact on the firm's operations, we argue that managers of rain-sensitive firms are likely to pursue different investment strategies in the aftermath of the excess or deficit rainfall conditions.

Since salience theory dictates that investment choices are context-dependent, the excess and deficit rainfall-departure conditions present a differential risk-return frontier to rain-sensitive firms, presenting a rational manager with differential opportunities of pursuing investment strategies. A utility-maximizing manager should respond to such differential investment opportunities with the ultimate objective function of maximizing the firm value. In other words, managers should boost (deter) investments when the rainfall-departure triggered opportunity is favorable (unfavorable) to do so. However, both strategies are followed with the same objective function of maximizing firm value.

It is well established in the literature that the production and operational activities of the excess-rain-sensitive firms are negatively impacted not only by the aggregate demand and production conditions of a sluggish economy but also by the damages suffered by its own physical infrastructure (Huang et al., 2018).[6] Thus, economic logic dictates that the 'excess-rain-sensitive' firms should, therefore, make additional investments, in the aftermath of the excess rainfall-departure conditions, at a level to at least recover the lost production capacity and recoup the lost market value. This post excess rainfall period, however, may also provide opportunities to undertake additional investments to expand firms' current capacity and implement better technologies, thereby providing a 'favorable opportunity window' to undertake capital investments.

In contrast, in the deficit rainfall condition, deficit-rain-sensitive firms are negatively impacted by the fall in aggregate demand and potential underutilization of operational and production capacity (Gadgil and Gadgil, 2006; Saha et al., 1979). Despite not incurring damages to tangible assets, the increase in the cost of operations due to lower production and higher opportunity cost of underutilized capacity should impact the firms' value, at least in the immediate aftermath of the deficit rainfall. In such a scenario of underutilized capacity, we argue that any additional investments following deficit rainfall-departure periods may only add to the already existing unused capacity, creating deadweight costs. As such, we also argue that the deficit condition provides an 'unfavorable window' for making any further investments for

[6] See Subsection 3.5 for more on the classification of 'excess-rain-sensitive' and 'deficit-rain-sensitive' firms.

the deficit-rain-sensitive firms.

Given the aforesaid arguments and in line with the salience theory, we conjecture that firms that are in rain-sensitive industries undertake capital investments to align with the excess or deficit rainfall conditions. In the case of the excess condition, they should boost investments and in the case of the deficit, they should either maintain or shrink investments. We assess such conjectures testing the following hypothesis.

H_2: Following excess (deficit) rainfall conditions, firms belonging to excess-rain-sensitive (deficit-rain-sensitive) industries increase (decrease) their investments.

2.3 Rainfall-departure, investments, and firm value

In this section, we discuss how differential investment strategies adopted by firms in the wake of rainfall-departures may affect their market-based valuation. The standard shareholder value maximization hypothesis posits that the stock market should reward firms positively (negatively) if corporate investment strategies are perceived to be value-enhancing (destroying) (see Woolridge and Snow, 1990). As noted in Section 2.2, following extreme rainfall conditions, firms belonging to rain-sensitive industries may adopt different investment strategies as suggested by salience theory. However, whether the firms do indeed adopt those strategies is an empirical question. Given the evidence, particularly following the agency theories of managerial self-interest (Seth et al., 2002), that managers do not always make rational investment decisions that are in the best interest of shareholders, we posit two alternative hypotheses on investments and firm value.

First, in line with shareholder theory (Friedman, 1970; Shleifer and Vishny, 1997), one could argue that corporate actions by rain-sensitive firms following the rainfall-departures call for closer scrutiny by shareholders who expect managers to make decisions that maximize their wealth. Furthermore, while it is the fiduciary duty of managers to pursue investment strategies that maximize shareholders' return (Becker and Strömberg, 2012), this duty becomes even more important in the wake of distress conditions caused by unforeseen events such as rainfall abnormalities. If rain-sensitive firms do indeed adopt value-enhancing alternative coping strategies, then in line with the traditional valuation and stockholder maximization theories, we should expect the market to positively reward these firms. This is consistent with the literature which suggests that the market value of the firm increases with value-maximizing corporate investment strategies (Brav et al., 2008; Faccio et al., 2011; Koirala et al., 2018). Based on these arguments, investments by rain-sensitive firms, as prescribed by the salience theory following rainfall-departures, should lead to a positive response from the stock market. We thus hypothesize the following proposition.

H_{3A}: Following excess (deficit) rainfall conditions, firms belonging to excess (deficit) rain-sensitive industries, that increase (decrease) their investments, experience higher firm value.

Second, the literature also suggests that irrational investments due to managerialism and agency problems can be value-destroying as managers tend to maximize their own utility at the expense of the firm's shareholders (Seth et al., 2002). For example, Malmendier and Tate (2008) show that overconfident CEOs take value-destroying risks, as they overestimate their ability to generate returns. It is evident from prior literature that not all corporate investments are rational or lead to value maximization. Consistent with the idea of value-destructive investments, Woolridge and Snow (1990) empirically show that the stock market reacts negatively to a firm's investment decisions, particularly when the timing of those investments is inappropriate (i.e., sub-optimal). Thus, if managers do not follow the prescribed investment strategies (increasing or decreasing investments) as dictated by salience theory, we should expect the market to react negatively. We thus hypothesize the following alternative proposition for firm value.

H_{3B}: Following excess (deficit) rainfall conditions, firms belonging to excess (deficit) rain-sensitive industries that either decrease (increase) their investments are associated with lower firm value.

3. Data and empirical strategy

3.1 Sample dataset

The time-varying rainfall data is obtained from the IMD, Ministry of Earth Sciences website.[7] We use the subdivision level rainfall-departure data of the Indian monsoon season (June-July-August-September months) for this study.[8] IMD computes the actual monthly, seasonal and annual rainfall statistics for 36 meteorological subdivisions belonging to the different States of India based on the daily rainfall data obtained from 3,500 rain-gauge stations spread across India. For each of the 36 subdivisions, IMD also calculates 'normal' or 'expected' rainfall using records of 50 years (1951-2000) from a network of 2,412 stations all over India. This normal value is the independent 50-year Long Period Average (LPA) rainfall recorded during the monsoon seasons.

For each subdivision, based on the difference between actual rainfall recorded and the expected normal figures, IMD computes the percentage of rainfall deviation (referred to as rainfall-departure hereafter). IMD considers rainfall-departure above 19% or below -19%, relative to the expected normal, to be the excess or deficit rainfall condition. This implies

[7] http://imd.gov.in

[8] Rainfall data available from the IMD shows that around 85% of the annual rainfall is received during the monsoon season. Table A3 in the Appendix indicate a high correlation between monsoon and annual rainfall-departure. IMD identifies different seasons as Winter (Jan-Feb), Pre-Monsoon (Mar-May), Monsoon (June-Sept) and Post-Monsoon (Oct-Dec)

rainfall-departures within the range of ±19% are normal conditions. We use a slightly different approach of classifying the excess and the deficit conditions to capture extreme variations in our investigations (see Subsection 3.4).

Firm-level annual data, as of fiscal year-end 31 March, are obtained from the standard Prowess database, maintained by the Centre for Monitoring Indian Economy (CMIE). Prowess provides detailed annual financial data of both listed and unlisted Indian firms. Our sample consists of all non-financial listed firms from 2001 to 2017.[9] We integrate the rainfall data from the IMD with firm-level data of Prowess based on the location of the firm. Upon integration of the data, 32 of the 36 rainfall subdivisions remain associated with each listed firm under study. This ensures that firms belonging to a particular rainfall subdivision are exposed to the same rainfall conditions. Our panel dataset consists of 71,728 firm-year observations of 5,639 non-financial firms listed on the Bombay Stock Exchange Ltd (BSE) or the National Stock Exchange of India Ltd. (NSE) for the sample period. Of the 71,728 observations, the rain-sensitive firms, i.e. firms whose operational performance is highly sensitive to rainfall conditions, are 20,718 firm-year observations.

3.2 Investment and firm value measures

Drawing on the existing literature, we use the ratio of the firm's yearly actual capital expenditure to the stock of long-term assets (property, plant, and equipment) as the core measure of corporate investments (Black et al., 2014; Holderness, 2009; Villalonga and Amit, 2006). We refer to this measure as *Capex.* In line with industry convention, we calculate the actual capital expenditure as the sum of the yearly change in property, plant, and equipment (PP&E) and current depreciation. In addition, for robustness checks, we consider two

[9] Since IMD calculates the 'normal rainfall' measure using the rainfall periods ranging from 1951-2000, we begin our analysis from the year 2001. Also, some of the key control variables used in the study, such as the ownership data, are maintained by Prowess only from 2001. The rainfall data report for 2018 has not yet been officially released by the IMD at the time of this study. Thus, for these reasons, we conduct our analysis for the sample period of 2001 to 2017.

alternative measures of investment. First, we use the sum of the firm's PP&E and research and development (R&D) spending for the year scaled by the lagged book value of PP&E (*Capex_RD*) (Bhandari and Javakhadze, 2017; Tsoutsoura, 2015). Second, following Koirala et al. (2018), we take the ratio of year-on-year changes in long-term tangible fixed assets, reflecting the size of tangible investments (*Capex_LT*).

In terms of firm value (*Firm_value*) we use the market-to-book value (*M/B*) of a firm's equity (Baker and Wurgler, 2002; Koirala et al., 2018) as the main proxy of market-based shareholder wealth valuation. In order to calibrate with our analyses of immediate and more medium-to-long term examinations of rainfall conditions, we use *M/B* at the end of the monsoon quarter, i.e., end of September (Q2) and at the end of the fiscal year, i.e. end of the fourth quarter (Q4). As an alternative measure of *Firm_value*, we use Tobin's q (*Tobin's q*), defined as the sum of the book value of debt, preference stock, and market value of equity scaled by the book value of assets (Desai and Dharmapala, 2009).

3.3 Control variables

In line with existing studies, we take into account a number of variables that could also explain the cross-sectional and temporal changes in our dependent variables. The size of a firm can play a key role in a firm's ability and appetite to make investment decisions (Whited and Wu, 2006). We control for size by taking the natural logarithm of total assets (*Size*). We expect a positive relationship between *Size* and investments. The literature, however, offers an inconclusive prediction on the association between *Size* and firm value. Studies note that *Size* reflects firm visibility and maturity, implying a positive association between the two (Koirala et al., 2018). In contrast, to the extent M/B (the proxy of firm value) gauges future growth expectation, *Size* could relate negatively with the M/B.

Further, a firm's investment decisions are directly influenced by its capital structure

(Almeida and Campello, 2007; Campello et al., 2010). We control for leverage (*Leverage*) by taking the ratio of the book value of total debt to equity. Two opposing views on leverage exist in the emerging market literature. First, leverage can be negatively associated with investments because the creditors of the firm, in enjoying a fiduciary stake and concave payoff, have interests that are different from those of shareholders when it comes to a firm's risky investment appetite (Acharya et al., 2011). Second, to the extent that leverage measures a firm's access to external financing, higher leverage should be positively associated with a firm's valuation (Beck and Demirgüç-Kunt, 2008). Notwithstanding, higher leverage could invite more debtholder-shareholder agency issues, increasing investment conservatism, and hurting firm performance (Acharya et al., 2011). Thus, the relationship between leverage and investment is inconclusive and is an empirical question in our set-up.

Operational liquidity is shown to influence corporate investments as a hedge against future possible credit shocks (Koirala et al., 2018). Thus, firms that expect financing uncertainty can build up operational liquidity in the form of higher cash reserves or liquid assets. Following Bargeron et al. (2010), we control for operational liquidity (*Liquidity*) by including the total cash holdings, measured as the sum of year-end cash and short-term securities, scaled by total sales. Similarly, since higher operational liquidity is inversely factored in the determination of the cost of equity, we should expect a positive link between operational liquidity and firm value (Lang et al., 2012).

Evidence suggests that firms with highly concentrated ownership having dominant shareholders may hold the authority and incentives to reduce the discretion enjoyed by managers of pursuing aggressive investment policies (Shleifer and Vishny, 1986). We, therefore, expect a negative link between concentrated ownership and the level of corporate investments (John et al., 2008). In terms of influencing value, studies offer an inclusive verdict on the link between ownership concentration and the firm's financial performance, and hence, it is an open empirical issue. For example, Singal and Singal (2011) note that concentrated ownership could improve firms' financial performance by better aligning insiders' and outsiders' interests. However, Anderson et al. (2009) argue that increased firm's opacity, associated with more closely held firms, could escalate information asymmetry, thereby deterring the firm's financial performance. We control for ownership concentration (*OwnCon*) as the proportion of total shares held by promoters (Koirala et al., 2018).

Further, extant literature provides mixed evidence of the impact of firm value on investment. While some studies show that value-maximizing firms will invest as long as the market value of the firm is greater than the book value of the firm (Shin and Kim, 2002), others show that firms with a low market-to-book ratio spend relatively more on investments than firms with high valuations (Kim and Weisbach, 2008). In the regression of explaining investments, we, therefore, control for the ratio of market-to-book value of its equity (*M/B*). Finally, following Maccini and Yang (2009) we include a linear time trend (*Time*) to absorb any long-running trends. *Time* is a continuous variable starting from the value of 1 for the first year of the sample, i.e., 1 for the year 2001, 2 for 2002, and so on. All control variables are winsorized at 2% and 98% levels and lagged by one year (Bena et al., 2017).

3.4 Normal and rainfall-departure periods

Studies strongly advocate that weather-shock set-ups offer credible identification properties as extreme rainfall events vary randomly over time for a given spatial area (Dell et al., 2014). Evidence also strongly suggests that unexpected variations in rainfall conditions present credible exogenous shocks as they cannot be accurately predetermined, which implies that endogeneity issues of reverse-causations and self-selection bias plaguing corporate finance empirical estimations are unlikely to be a major concern (see Auffhammer et al., 2013; Bhomia et al., 2017; Dell et al., 2014). In our panel set-up, the identification emanates from rainfall deviations from its expected values. Thus, for each rainfall data point, we take the deviations from their expected mean (average) values to identify the extreme rainfall conditions (rainfall-departure). For each period, a deviation above a certain positive threshold (in %) indicates an excess rainfall period and a deviation below a certain negative threshold (in %) signifies a deficit rainfall period. If the deviations are within the positive and negative thresholds then these are considered normal periods. Accordingly, we have three distinct periods of rainfall conditions. The first two are the extreme excess and deficit rainfall-departure, and the third is the normal condition.

For our empirical purpose, we first sort the rainfall deviation data obtained from the IMD into quintiles (from highest to lowest) and classify the rainfall-departure falling in the uppermost quintile as excess rainfall condition, which in our case is above the deviation figure of +20.1% rainfall-departure. In a similar approach, the rainfall-departure falling in the lowest quintile, i.e., below -23%, is classified as the deficit rainfall condition. The mid-quintile (i.e. the third quintile) observations falling in the rainfall-departure range of -7.5% to +3% are identified as the normal rainfall condition. This implies that we discard the potentially noisy 2nd and 4th quintiles, thus only incorporating the extreme excess and deficit rainfall-departures in our sample dataset. It must be noted that such a classification strategy to define the excess, deficit, and the normal rainfall conditions is more conservative than that defined by IMD which simply takes an arbitrary value above +19% as excess, below -19% as the deficit, and between ±19% as normal.

Every year, each of the 32 rainfall subdivisions experiences either the excess, deficit or normal rainfall condition. In terms of estimation purpose, for each subdivision and year combination, we define $RDyr$ as a dummy variable that takes the value of one for the panel observations belonging to either the excess or the deficit rainfall years and zero for the panel observations belonging to the years where rainfall condition is considered as normal.[10]

3.5 Treated (rain-sensitive) and control (non-rain-sensitive) firms

Several studies document that extreme rainfall-departure conditions (excess or deficit) can have a differential impact on the operational performance of different industries. From an extensive set of literature, we first identify those industries whose operational performance could be highly sensitive to different extreme climatic conditions. We report this extensive literature in Table A2 in the Appendix. Each broad category of industry identified in Table A2 is drawn from multi-disciplinary literature[11], such as natural science, geology, environmental economics, agricultural economics, energy economics, etc. These studies offer theoretical and empirical evidence on the differential adverse impact of extreme climatic conditions on firms' sales, earnings, and operating costs of these sectors.[12]

As some sectors' operational performance is negatively affected by the excess rainfall condition, whereas for others by the deficit rainfall conditions, we identify two types of affected (treated) groups. For empirical estimation purposes, we construct two *treated* categorical variables. The first takes the value of one for the firms whose operational performance is negatively affected by the excess rainfall condition (excess-rain-sensitive)[13]. The second *treated* categorical variable takes the value of one for firms whose operational performance is negatively affected by the deficit rainfall condition (deficit-rain-sensitive).[14] All other non-

[10] Econometrically, the $RDyr$ dummy variable not only captures the rainfall-departure but also the location-specific effect of the firm. Since we interact $RDyr$ with the dummy variable 'treated' in our empirical set-up (see Section 4), the variable $RDyr$ ensures that we are only using firms in the same subdivision as our control group firms and this takes into consideration any subdivision-specific differences in spending/investments.

[11] Based on journals with high H-index rating in https://www.scimagojr.com/journalrank.php

[12] To corroborate the evidence from literature, we regress 'sales to total assets' on different specifications of the rain-departure for both excess (deficit) rain-sensitive industries. The results, not presented here for brevity, show that the regression coefficients carry negative signs and are generally statistically significant.

[13] Excess-rain-sensitive sectors include agricultural machinery, agriculture & processed food, air transport services, tourism, hotels & restaurants, auto sector, construction & allied activities, courier services, transport services, electricity generation & transmission, fertilizers & pesticides, and mining & quarrying.

[14] Deficit-rain-sensitive sectors include agricultural machinery, agriculture & processed food, auto sector,

rain-sensitive sectors in the sample are considered as the control group.[15]

In summary, our empirical strategy thus has two sets of periods, i.e. 'normal' and 'rainfall-departure' periods (excess and deficit). Similarly two sets of firms, i.e. rain-sensitive firms (treatment group, excess- and deficit-rain-sensitive) and non-sensitive firms (control). Our empirical identification is a shock-based set-up, similar to DiD.

4 Empirical results

4.1 Descriptive statistics and complexity of rainfall-departure

We report the descriptive statistics of the *rainfall-departure, Capex, Size, Leverage, Liquidity, OwnCon,* and *M/B* variables for the sample period 2001 to 2017 in Panel A of Table 1. The variable *rainfall-departure* has a standard deviation of 24.6% with the maximum deficit rainfall-departure of an extreme of -73.7% and maximum excess rainfall-departure of 126%. Clearly, as the Indian setting manifests extreme variations in rainfall-departure, it provides an ideal experimental set-up to undertake our study investigating the impact of such extreme rainfall conditions on investment strategies.

The average *Capex* is around 24% of the total assets for the firms over the sample period with a fairly high mean of 3.11 for leverage, perhaps indicating that the real investments could be driven by debt financing. However, statistics also reveal a high variation in leverage across firms indicated by the high standard deviation of 10.71%. While average cash holdings (*Liquidity*) are around 11% of the total sales, the median value is 1%, indicating that at least half of the firms in our observations maintain low operating liquidity. While the mean of the

electricity generation & transmission, fertilizers & pesticides and mining & quarrying. In the deficit treatment analysis, we do not include firms belonging to air transport services, tourism, hotels & restaurants, construction & allied activities, courier services, transport services sectors in the subsample of the study as these are purely excess-rain-sensitive sectors and including them in the deficit analysis subsample study may yield biased estimates.

[15] Banking and insurance sectors are also impacted by extreme rainfall conditions. While lending activities are impacted in the banking sector, the insurance sector faces large scale pay-outs (Linnerooth-Bayer and Hochrainer-Stigler, 2015; Surminski et al., 2016). However, since only non-financial sectors are considered in this study, we do not include the banking & insurance sectors as these are highly regulated and policy driven.

variable *OwnCon* for the firms in our sample is 33.46% indicating a high concentration of insiders, we see that the median value of *OwnCon* is 36.86%, which suggests more than half of the firms in our sample have high promoter ownership concentration. This statistic reinforces the potential of dominant promoter ownership influence on investment decision arguments (Shleifer and Vishny, 1986). Finally, the descriptive statistics of *M/B* indicate that on average the market value of the equity is 19 times that of its book value with more than half of the firms within the sample having an *M/B* ratio of at least 6.6. The high variance of 40.26% indicates extreme outliers; this is managed through winsorization, as indicated in Section 3.3

[**Table 1 about here**]

Panel B of Table 1 shows that we have 13,804 observations for the excess-rain-sensitive treatment, 6,914 for the deficit-rain, and 57,924 for the common control group firm-year observations in the overall sample period. Panel C of Table 1 reports the average difference between the treated (excess and deficit-rain-sensitive firms) and the control group firms (firms that are not or least-sensitive to rainfall conditions). Relative to the control firms, we observe *Capex* is significantly higher (lower) among the excess-rain-sensitive firms (deficit-rain-sensitive firms). Further, treated firms are relatively bigger, have greater leverage and higher ownership concentration when compared to control group firms. We, therefore, control for these variables in our empirical analysis.

Table 2 Panel A shows the complexity of the rainfall-departure during the monsoon season in 32 rainfall subdivisions of India (listed in Panel B) from the years 2000 to 2017. As evident, the intensification of rainfall-departure significantly varies across years and subdivisions, whereby the extreme rainfall-departure figures provide us with credible exogenous variations. We present the rainfall-departures using different shades of red and blue to provide a visual perspective of the complexity and changes in the intensity of extremity. The different shades of red cells represent subdivisions with the deficit rainfall-departures (below -15%) and shades of blue cells represent subdivisions with excess rainfall-departures (above 15%). Uncolored cells represent subdivisions with normal rainfall conditions. The four different shades of blue and red cells, changing at every 5% deviation, indicate the varying intensity of rainfall-departures.

[**Table 2 about here**]

4.2 Rainfall-departure and immediate impact on firm value

The monsoon season receives almost 85% of the annual rainfall in India. Generally, by the end of the September quarter, it becomes apparent whether rainfall conditions are the deficit, excess, or normal. As such, we begin examining the impact of rainfall-departures on firm value (proxied by *M/B*) at the end of Q2 and Q4 of the same fiscal year. Accordingly, we run the following specification:

$$Firm\_value_{it} = \alpha + \beta.(RDyr_{\boldsymbol{t}} \times treated_{\boldsymbol{i}}) + \boldsymbol{X_{i,t-1}}.\boldsymbol{\delta} + \tau.Time + \gamma_i + e_{it} \quad (1)$$

where depending on the specification $Firm\_value_{it}$ is *M/B*, calculated at the end of the Q2 or Q4. The interaction term $(RDyr_{\boldsymbol{t}} \times treated_{\boldsymbol{i}})$ is the main variable of interest. $RDyr$ and *treated* are dummy variables, as defined in Subsections 3.4 and 3.5. $\boldsymbol{X_{it}}$ is a vector of control variables that includes *Size, Leverage, Liquidity,* and *OwnCon,* as defined in Subsection 3.3, all lagged by one fiscal year. The *Time* variable absorbs long-running trends in rainfall conditions. γ_i controls for firm fixed effects and e_{it} is the error term.[16] The results are reported in Table 3

[**Table 3 about here**]

[16] Since the rainfall-departure is a time varying variable, we do not include time fixed effects because by doing so the temporal variations in the rainfall-departure are neutralised. Instead, to control for any long run trends in rainfall conditions, we introduce the *Time* control variable in our specification.

The results in Table 3 shows that under both excess and deficit rainfall conditions, we observe a significant decline in *M/B* of treated firms, relative to control firms, both at the end of Q2 and Q4. The firm value (*M/B*) for the excess (deficit) rain-sensitive firms reduces in the range of 10 to 17.7 units (1.6 to 5.8 units) in the immediate aftermath (i.e. end of Q2 and Q4) of excess (deficit) rainfall conditions. The fall in firm value is greater in the case of excess, relative to deficit conditions as well as in Q4 relative to Q2, indicating that the market fully captures the extent of the damage only after the end of the monsoon period. These results support the conjecture of hypothesis H_1, implying rain-sensitive firms suffer value decline in the immediate aftermath of encountering the excess and the deficit rainfall conditions.

4.3 Rainfall-departure and investments

As noted above, our main identification strategy resembles a DiD approach, where firms (treated & control) are exposed each year to either the excess, deficit, or normal rainfall conditions, depending on the firm's location in one of the 32 rainfall subdivisions. We first undertake a univariate analysis using our core investment measure (*Capex*), whereby we observe the difference between the treated and control group firms between the normal (before) and the excess/deficit (after) periods for both the excess rainfall-departure and the deficit rainfall-departure conditions. The results are reported in Panel A of Table 4.

[**Table 4 about here**]

As evident from the last row and the columns named Capex [1] and Capex [4] of Table 4, panel A, we observe a statistically significant difference in *Capex* between the treated and control group firms following both excess and deficit rainfall-departures (5% significance level). Specifically, we find approximately a 2.6% differential increase in *Capex* for the treated group, relative to control group firms, in the excess rainfall-departure condition. This indicates a strategy of boosting investment in the post-excess-rainfall condition period. However, the differential value of -3.3% in *Capex* for the treated group firms, reflects the strategy of reducing investments in the case of the deficit rainfall-departure condition. These univariate results offer support to the conjecture of hypothesis H_2.

Further, to test our hypothesis H_2 in a more robust econometric framework and separately on the excess and the deficit rainfall subsamples, we estimate the following general specification:

$$Investment_{it} = \alpha + \beta.(RDyr_{\boldsymbol{t}} \times treated_{\boldsymbol{i}}) + \boldsymbol{X_{i,t-1}}.\boldsymbol{\delta} + \tau.Time + \gamma_i + e_{it} \qquad (2)$$

In specification (2), $Investment_{it}$ is the proxy for investments (*Capex)* for firm *i* in year *t*, as defined in Section 3.2. The interaction term ($RDyr_{\boldsymbol{t}} \times treated_{\boldsymbol{i}}$) is the main variable of interest, as defined earlier. $\boldsymbol{X_{it-1}}$ is a vector of control variables including *Size, Leverage, Liquidity, OwnCon,* and *M/B,* all lagged by one year. γ_i controls for firm fixed effects and e_{it} is the error term. The outcomes of the estimations are reported in Panel B of Table 4.

Columns [1] to [4] in Table 4 (Panel B) present the results of the multivariate specification (2) for the full sample, which includes all the industries pooled together. We find that the coefficients of the interaction term (*RDyr* × *treated*) carry positive signs for the excess and negative signs for deficit-rainfall conditions, all statistically significant at least at a 5% significance level. These results for the full sample indicate that following the excess rainfall-departure, treated firms increase their *Capex* in the range of 3.4% to 4.8% more than the control group firms. Conversely, in the deficit rainfall-departure, treated firms reduce their *Capex* on average by 3.2% compared to control group firms.[17]

[17] 372 firms have a fiscal year ending other than 31 March. When we drop these firms and rerun the specification (2) our results remain qualitatively unchanged.

4.4 Robustness checks

4.4.1 Location-based issues

Our identification is based on the rainfall conditions of the subdivision where the company headquarters is located. However, it is plausible that the company headquarters may be located away from the location of its actual business operations and the headquartered location may potentially experience a different rainfall condition when compared to those encountered at the location of its business.

Hence, we perform a robustness test using different subsamples to address this location issue. We use the business geographic segment information available from the Capita IQ database to conduct a subsample analysis and retain only those listed Indian firms that have operations/revenue bases solely in India. This ensures that we remove all those Indian multinational firms which may be obtaining their revenues from outside India. [18]

From this subsample of Indian firms, we further exclude firms having multiple office locations across India and which generate revenues from more than one business segment, i.e. type of business. This implies that in this final subsample we only include those Indian firms which have only one office location/revenue base and which generate their revenue from only one type of business and are not into multi-business segments. This conservative filtering process generates 1,131 distinct firms, whose revenues/operational performance are entirely dependent on that particular sub-division's rainfall condition where they are located. We rerun specification (2) on this subsample and present the results in columns [5] and [7] of Table 4 (Panel B). As shown, our results indicate a 4.6% (3.1%) increase (decrease) in *Capex* of the excess (deficit) rainfall-departure firms compared to control firms and are in line with the main

[18] All multinational companies (MNCs) may have differential or low sensitivity to local rainfall conditions due to their multi-country locations and revenue bases, and this could be an interesting future research avenue, but is beyond the scope of our study. However, when we run a regression on those Indian MNCs that have their revenue base only from outside India, we find no significant impact of rain extremities on investments.

results as presented in columns [1] to [4].

As a further robustness test, we rerun our specification (2) on the above subsample by further excluding group-affiliated firms. This is because investments in business group-affiliated firms are usually influenced by the overall group level strategy. Furthermore, as business group firms operate in several different industries and geographic locations, it is highly improbable that all its affiliated firms operate in the same rainfall subdivision. The results of this subsample analysis are shown in columns [6] and [8] of Table 4 (Panel B) and are also in line with the general findings. Overall, these results provide evidence in support of hypothesis H_2.

4.4.2 Alternative measures of investment

We also use two alternative measures of $Investment_{it}$, i.e. *Capex_RD* (capital expenditure with R&D) and *Capex_LT (*change in long-term tangible assets) and present the results of specification (2) with these new measures in Table 5. We observe that the results using these alternative investment proxies are consistent with the general findings, as shown in Table 4. Our results show that the excess (deficit) rainfall-departure treated firms increase (decrease) their investments in the range of 3.5% to 4.5% (3.6% to 6.7%) compared to the control group firms for the full sample, as presented in columns [1] to [4]. As shown in columns [5] to [12], we obtain similar results for our other subsamples (single location and non-business group firms). These robustness results lend further confidence in support of hypothesis H_2.

[**Table 5 about here**]

4.4.3 Sequential one-year pair observations

One concern with our analysis may be that the experimental DiD set-up in Section 4.3 may have a limitation. In the sense that a cleaner DiD would normally require a set-up with sequential pre- and post-rainfall-departure periods. However, in our case, and as evident from Table 2, each subdivision has an equal probability of experiencing all three types of rainfall conditions (excess, normal, or deficit) every year. In order to alleviate this concern, we generate pairs of years for each subdivision in which the normal periods are sequentially followed by rainfall-departure periods (either excess or deficit).

We subdivide the departure-rainfall periods into the case of excess (presented in Table 6, Panel A) and the deficit (reported in Table 6, Panel B) rainfall-departure years, both preceded only by the normal rainfall years. Thus, we now have a set-up of pre (normal condition) and post (either excess or deficient condition). Following this sequential classification, we rerun specification (2) by defining $RDyr$ as an indicator variable that takes the value of one for years with the excess or the deficit rainfall-departure and the value of zero for preceding years which received the normal rainfall. In other words, for each subdivision, we code the normal years as pre-shock years and excess/deficit rainfall-departure years as the post-shock years to run the DiD analysis.

We present the results of this analysis in Panel C of Table 6. The DiD interaction (RD_{yr} × *treated*) coefficient is positive and significant at 1% in columns [1], [2], and [3]. The size of the coefficient indicates that on average the excess-rain-sensitive firms differentially increase their *Capex* in the range of 10.4% to 14.3% compared to control group firms in the excess-rainfall-departure years. Further, in support of hypothesis H_2, the DiD interaction coefficient is significantly negative in columns [4], [5] and [6] with the size of the coefficient indicating that the deficit-rain-sensitive firms differentially shrink their investments in the range of 5.7% to 7.7% in the deficit rainfall-departure years.

[**Table 6 about here**]

4.4.4 Rainfall-departure sensitivity analysis

Following the results in Subsections 4.3 that indicate a strong positive (negative) relationship between *Capex* and the excess (deficit) rainfall-departure conditions, it would be interesting to examine if this pattern holds at different intensities of rainfall-departures. Accordingly, we conduct a sensitivity analysis of specification (2) and create several $RDyr$ dummy variables as having a value of one in different years with a 1% incremental rainfall-departure from equal to or greater than +15% for the excess condition and equal to or lesser than -15% for the deficit conditions, and zero for rainfall-departure falling within the range of -15% to +15%. The results of 32 different regression estimations are presented in Table 7 for both the excess and the deficit rainfall-departures.

[**Table 7 about here**]

In Table 7 we observe that the coefficients of the interaction term are positive for each excess rainfall-departure condition. However, they are only statistically significant when the excess rainfall-departure is 20% or more, with economic implications being in the range of a 4.5% to 7.7% boost in investments. For the deficit rainfall-departure conditions, the coefficients of interaction terms are significant for the rainfall-departure conditions below -18%, with economic effects being in the range of 4.3% to 10% decline in investments. The results of rainfall sensitivity analysis further corroborate our investment increase (decrease) conjecture during the excess (deficit) conditions. Also, these results indicate that our 20% (-18%) cut-off for identifying excess (deficit) condition aligns with the IMD's ±19% rainfall deviation.

4.4.5 Impact persistence

Given the significant impact of rainfall-departure on investment strategies, we investigate the persistence of the nexus over time. We run specification (3) for four different scenarios, where the dummy variable $RDyr$ takes the value of one if the excess (deficit) rainfall-departure is 15% (-15%) or greater (lower), 20% (-20%) or greater (lower), 25% (-25%) or greater (lower), and 30% (-30%) or greater (lower), and the value of zero otherwise. Further, for each intensity of both rainfall-departure conditions, we interact the variable $Rain_{\boldsymbol{t-n}}$, which is the percentage of rainfall-departure, with the treated groups (excess and deficit-rain-sensitive). Here, *'t-n'* represents the lag length at which we are investigating the persistence of the rainfall on investments, as shown in the following specification.

$$Investment_{it} = \alpha + \beta.(RDyr_{\boldsymbol{t}} \times treated_{\boldsymbol{i}}) + \sum_{n=1}^{5} \lambda_n.(Rain_{\boldsymbol{t-n}} \times treated_{\boldsymbol{i}}) + \boldsymbol{X_{i,t-1}}.\boldsymbol{\delta} + \tau.Time + \gamma_i + e_{it} \quad (3)$$

where, $Rain_{\boldsymbol{t-n}}$ is lagged up to five years. All other variables in these specifications are as defined for specification (2) earlier. The results of specification (3) are reported in Table 8.

[**Table 8 about here**]

Consistent with our previous results, we find that following excess (deficit) rainfall-departure conditions, *Capex* significantly increases (decreases) in the excess (deficit) rain-sensitive firms, as noted by the (*RDyr* × *treated*) variable. We observe that the impact of excess rainfall-departure [represented by ($Rain_{t-n}$ × *treated*)] on investments seems to persist for up to three years following the rainfall-departure conditions – specifically when the rainfall-departure is in the range of 20-25% and above. However, the persistence of the deficit rainfall-departure seems to be weaker, with results suggesting that it loses its significance beyond one year.

It is interesting to note that excess rainfall-departures are more persistent than deficit rainfall-departures. Intuition dictates that the excess rainfall-departure results in the destruction of infrastructure and other physical tangible damages that warrant additional investments to re-build the capacity. It is highly possible that the additional investments needed to restore the capacity to follow a project-investment pattern in different phases over a long period of time, resulting in the longer persistence observed for excess rainfall-departures. Deficit rainfall-departures, on the other hand, do not result in the destruction of tangible assets. As a result, reduced investment strategies could exist as long as these assets are underutilized. In Table 8, we observe that the deficit DiD coefficients lose their significance in the second year suggesting no further investment contraction as these firms begin utilizing their previously underutilized capacity. Additionally, it is highly probable that normal rainfall conditions, that follow deficit rainfall-departure, bring in an additional spurt in product demand, thus leading to demand-driven renewed investments. Our results in Table 8 support this argument as the DiD coefficient sign for deficit conditions flip to positive indicating a significant increase in investments from the third year. These results reinforce our arguments made in hypothesis H2.

4.4.6 Other Robustness checks

We conduct a host of other robustness checks and sub-sample analyses. For brevity we do not discuss these in detail, however, we provide a brief outline of these analyses in this sub-section.

The treated group in our main analysis included pooling all rain-sensitive industries together. In an additional subsample robustness analysis, we re-run the specification (2) separately on Agriculture, Mining & Quarrying, Construction, Auto/Transportation sector firms taken as treated group. The results presented in Appendix Table A4 and consistent with the general findings that following excess (deficit) rainfall conditions, firms belonging to excess-rain-sensitive (deficit-rain-sensitive) industries increase (decrease) their investments.

It can be argued that managers make investment decisions based on rainfall forecasts and do not wait until actual rainfall-departure data is available. If this is indeed the case, our results of the impact of rainfall-departures on firm investments are likely to be biased. We believe that managers are unlikely to rely on rainfall forecasts to make investment decisions for two reasons. First, prior research shows rainfall varies both temporally and spatially. These geological complexities affect the performance of rainfall prediction models, thus making 10-day or longer forecasts highly unreliable (French et al., 1992; Toth et al., 2000; Zhang et al., 2019). Second, we run our main regression for the excess and deficit rainfall conditions to investigate the immediate investment effects using the quarterly data available from the Prowess database for our sample period. We do not find any materially significant change in investments in the immediate quarter following monsoon season.

Some empirical studies using extreme weather events as exogenous shocks, classify firms in the extreme weather affected geographic regions as treated firms and those in unaffected geographic regions as control firms (Aretz et al., 2018; Dessaint and Matray, 2017). Results tabulated in Table A5 of the appendix mostly indicate that geographic location-based treatment classification does not capture the impact of rainfall extremities on corporate investments in our empirical setup. This may perhaps indicate that not all firms located in the same geographic location exposed to extreme rainfall conditions are affected. These results thus provide support to our treatment classification based on the rainfall sensitivity of the firms.

Prior studies show that some industries such as construction, fertilizer & pesticides, health & pharmaceuticals, and timber (referred here as positively rain-sensitive industries) are more likely to experience increased sales and revenue growth in the years following excess rainfall-departure (Hsiang, 2010). We have 732 positively rain-sensitive firms in our sample of analysis. As an extended investigation, the results tabulated in Table A6 of the appendix, indicate that compared to other firms, positively rain-sensitive firms show an increase in revenue (*Sales/total assets*), operating performance (*EBITDA/total assets* and *PAT/total assets*), investments (*Capex*) and firm value (*M/B*) in the post excess-rainfall-departure year.

4.5 Rainfall-departure, investments, and firm value

Hitherto, we have shown that firms experience a negative impact on their market value, by the end of the second and fourth quarters of the same fiscal year, following episodes of the extreme rainfall-departure condition. We also provide empirical evidence in support of hypothesis H_2 that firms' investment policies, following extreme rainfall, depends on the nature of rainfall-departures (excess and deficit) experienced by the managers.

Next, we examine whether the differential investment strategies pursued by the managers are rewarded by the market. We use the standard approach to unveil the effects of investment on firm value by repeating the baseline specification (2) and simply replacing the main dependent variable with *M/B* and *Tobin's q*. This equates to an intention-to-treat (ITT) specification, wherein, through the "treatment on *Capex*" firm value is ultimately affected.[19] To this end, we perform empirical tests using the following specification.

$$Firm\_value_{it+1} = \alpha + \beta.(RDyr_{\boldsymbol{t}} \times treated_{\boldsymbol{i}}) + \boldsymbol{X_{i,t}}.\boldsymbol{\delta} + \tau\,.Time + \gamma_i + e_{it} \qquad (4)$$

We use two different proxies of $Firm\_value_{it+1}$ for the firm 'i' and fiscal year '$t+1$': (i) *M/B* and (ii) Tobin's q (*Tobin's q*). Our main variable of interest is the $(RDyr_{\boldsymbol{t}} \times treated_{\boldsymbol{i}})$ interaction term. $\boldsymbol{X_{it}}$ is a vector of control variables *Size, Leverage, Liquidity,* and *OwnCon.* All other variables are defined under specification (2) and the results of using *M/B* and using *Tobin's q* are reported in Table 9.[20]

[19] Thapa et al. (2020) use a similar approach to unveil the effects of borrowing on capital expenditure, return on assets (ROA) and M/B. Further see Belloni et al. (2017) and Berger et al. (2019), among others, for ITT method for establishing causal inference.

[20] Our results are in line with the main findings when we run specifications (1), (2) and (4) using industry fixed effects.

[**Table 9 about here**]

As shown in Table 9, we find that the value of the rain-sensitive firms increases significantly in the lead years following the rainfall-departure conditions. For instance, using *Tobin's q* as a proxy (columns [5] to [8]), we find that in the year following the year of excess rainfall-departure, the market value of the excess-rain-sensitive firms increases in the range of 0.14 to 0.165 units when compared to the control group firms (significant at the 1% significance level). Further, we also find that in the year following the year of deficit rainfall-departure conditions, market values of the deficit-rain-sensitive firms also significantly increase in the range of 0.062 to 0.064 units when compared to the control group firms. Both of these results are in support of hypothesis H_{3A}.[21]

We run further tests to support the above findings. Although on average, the above-stated results hold, we could expect significant variations in the actual increase or decrease in rain-sensitive firms' investments. Thus, there may still be a handful of excess (deficit)-rain-sensitive firms that may not increase (decrease) investments in post excess (deficit) rainfall-departure conditions. The rain-sensitive firms who actually increased (decreased) investments in the excess (deficit) conditions should experience a higher increase (decrease) in value relative to firms who do not actually increase (decrease) their investments. Thus, we exploit such cross-sectional heterogeneity among the same group of rain-sensitive firms and run the following regression on a subsample of excess and deficit-rain-sensitive firms.

$$Firm\_value_{it+1} = \alpha + \beta.(RDyr_{\boldsymbol{t}} \times Cap_{\boldsymbol{i}}) + \boldsymbol{X_{i,t}}.\boldsymbol{\delta} + \tau\,.Time + \gamma_i + e_{it} \qquad (5)$$

[21] We use *Capex* data at the end of the same monsoon quarter and run our regression analysis on investments to test the immediate effect of rainfall-departures on investments. Any statistically significant results of *Capex* at the end of the monsoon quarter would undermine our saliency investment strategy argument and could indicate that the value gain in the lead period is a result of confounded investment decisions contemporaneous to the rain-deviation period. Using about 3,569 distinct firms at quarterly level, we run our main regression for excess and deficit rainfall conditions to investigate the immediate investment effect. The coefficient of the key independent variable in the monsoon quarter is insignificant. This reinforces our investment strategy and value relevance argument.

It must be noted that in the specification (5) the categorical variable $Cap_{\boldsymbol{i}}$ represents firms from the same group of rain-sensitive firms. Thus, for the excess (deficit) rain-sensitive firms, the dummy Cap_i takes the value of one if the *Capex* increases (decreases) for the firm 'i' in the post extreme rainfall-periods or takes the value of zero otherwise. All other variables are as defined for specification (4).

In an alternative specification, whereby we attempt to capture extreme variations in the investments of the firms following the excess (deficit) conditions, the dummy variable $Cap_{\boldsymbol{i}}$ takes the value of one for the excess (deficit) rain-sensitive firms with capital expenditure falling in the top-most (lower-most) tercile and zero for the lower-most (top-most) tercile. In all of the four specifications of equation (5) above, if our conjecture on investment value relevance is valid then we should expect the regression coefficient to be positive and statistically significant. We present the results of the two models in Table 10.

[**Table 10 about here**]

For both the excess and deficit-rain-sensitive firms, we find a significant increase in market value for treated firms in the lead period. The market value of excess-rain-sensitive-firms that document increased *Capex* or whose *Capex* falls in the upper tercile increases in the range of 0.13 to 0.21 units (1% significance level) when compared to excess-rain-sensitive-firms that exhibit decreased *Capex* or whose *Capex* falls in the lower tercile. Similarly, the value of deficit-rain-sensitive-firms that experience a reduction in *Capex,* or whose *Capex* falls in the lower tercile, increases in the range of 0.07 to 0.25 units (1% significance level) when compared to deficit-rain-sensitive-firms that experience growth in *Capex* or whose *Capex* falls in the upper tercile. Thus, the results of Table 10 further provide strong evidence in support of hypothesis H_{3A}, the conjecture that the investment strategy adopted in the post-rainfall-departure and the size of such investments are value relevant.

5 Conclusion and discussion

Recent statistics indicate a significant negative impact of extreme climatic conditions on economic activities. As macroeconomic outputs are directly associated with the corporate sector, we examine the economic impact of extreme climatic conditions, specifically extreme rainfall deviations from the expected normal, on corporate investments and valuations. Using the extreme rainfall-departure of the excess or deficit conditions, we investigate whether corporate managers follow differential investment strategies, depending on the experience of the excess or deficit conditions, to mitigate the negative effects of extreme rainfall conditions and if these investment strategies carry value implications.

While the real-option theory of the traditional corporate finance literature argues that in the wake of heightened uncertainties caused by extreme rainfall-departures, firms should reduce their current investments, the other school contends that firms facing such conditions should display 'risk-shifting' behavior and therefore increase investments. However, these two opposing views on corporate investments do not fit well in the heterogeneous conditions of the excess and deficit rainfall, both of which create severe uncertainty. Accordingly, we draw on the salience theory of choice under risk, which argues that the two different rainfall-departure conditions may lead to different saliency experiences, and hence the manager responds with different investment strategies.

Using Indian monsoon data, our results show that the market-based valuations of rain-sensitive firms significantly decline in the immediate aftermath of extreme rainfall deviations. Consistent with the saliency argument that managers follow differential investment strategies under different rainfall conditions, our results show that relative to the normal rainfall conditions, firms whose operational performance is negatively affected by the extremely high level of rainfall conditions, seem to boost their investments following the excess rainfall periods. In contrast, following the deficit rainfall periods, we witness a reduction in investments of firms whose operational performance is negatively affected under extremely low levels of rainfall. However, in both cases, firms through their investment strategies regain the lost market-based values in the lead periods of extreme rainfall deviations.

Although we conduct our analysis using the salience theory in the Indian monsoon context, we argue that our evidence could be generalized to other forms of weather/climate conditions as well as in both developed and developing economies. As managers are salient to the impacts of weather extremities, it is plausible to assume that they would make differential investment decisions (expansion, contraction, or even deferral) in the aftermath of weather conditions, depending on the saliency of expected payoff. It is natural to relate the findings of our study to economies that predominantly depend on rain-sensitive sectors (such as the primary sector).[22]

However, the growing number of episodes of climate change-induced natural disasters such as hurricanes, floods, extreme temperature, landslides, and bush fires (Alok et al., 2020; Barrot and Sauvagnat, 2016; Dessaint and Matray, 2017) even in developed countries, such as the US, means that firms in these economies will also be presented with differential risk-return frontiers, thus availing the utility-maximizing managers to respond in a manner that would be consistent with the salience theory of choice under risk (Bordalo et al., 2012). Overall, while our paper makes an important contribution to the ongoing debate on the approach to investment/risk-taking in the face of uncertainty, our results also have important implications from a practice point of view. We show that in the face of extreme uncertainty, managers need to ascertain the saliency of the condition relevant in their context to take decisions accordingly.

[22] We provide some additional statistics using one of the important rain-sensitive sectors (i.e., primary sector) to see how our findings could also impact other countries and why studying extreme rainfall conditions is relevant to the world economy. From Table A7 in the appendix it is quite apparent that across countries, based on per capita income, primary sector contribution to GDP and amount of rainfall received by different countries, the impact of rainfall conditions on the world economy would be quite significant.

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Table 1: Descriptive statistics

Panel A reports descriptive statistics of the variables *rainfall-departure*, *Capex*, *Size*, *Leverage*, *Liquidity*, *OwnCon*, *M/B*. The rainfall-departure variable is the percentage deviation of the monsoon rainfall from the long-term normal mean rainfall computed between the period 1952-2000, *Capex* is the ratio of actual capital expenditure to long-term assets, *Size* is the natural logarithm of the total assets, *Leverage* is the debt to equity ratio, *Liquidity* is the cash holdings scaled by total sales, *OwnCon* is the percentage of promoter (founder/insider) ownership and *M/B* is the market to book value of shareholders' equity. The total sample period ranges from 2001 to 2017. Panel B reports the number of treatment and control groups' observations for the *rainfall-departure* variable for the sample period. Panel C reports the statistical differences between treated and control group firms for different variables. Figures in parenthesis represent the number of observations. Data source: Indian Metrological Department (IMD) and Centre for Monitoring Indian Economy (CMIE) databases.

Panel A

Variable	No. of Obs.	Mean	Std. Dev.	Minimum	Median	Maximum
Rainfall-departure	71,728	-1.41	24.6	-73.7	-0.7	126
Capex	71,728	0.24	0.48	-0.31	0.07	2.19
Size	71,552	6.21	2.34	0.26	6.12	12.38
Leverage	69,462	3.11	10.71	0	0.71	107.58
Liquidity	55,340	0.11	0.4	0	0.01	3
OwnCon	71,728	33.46	28.5	0	36.86	89.02
M/B	43,152	19.05	40.26	-0.19	6.6	243.62

Panel B

Rainfall-departure	Treatment	Control	Total Observations
Excess	13,804	57,924	71,728
Deficit	6,914	57,924	64,838

Panel C

	Excess-rain-sensitive firms					Deficit-rain-sensitive firms			
Variables	Control firms	Treated firms	Diff	t-stat	p-value	Treated firms	Diff	t-stat	p-value
Capex	0.1625 (57,924)	0.1750 (13,804)	0.0125	2.2997	0.0215	0.1290 (6914)	-0.0334	-4.6391	0.0000
Size	6.1227 (57,772)	6.5522 (13,780)	0.4295	19.4097	0.0000	6.4315 (6895)	0.3089	10.4174	0.0000
Leverage	2.9920 (56,053)	3.5954 (13,409)	0.6035	5.8629	0.0000	4.5045 (6734)	1.5125	10.7729	0.0000
Liquidity	0.1115 (44,413)	0.1178 (10,927)	0.0063	1.4714	0.1412	0.0721 (5445)	-0.0394	-6.9838	0.0000
OwnCon	48.8299 (39,344)	52.0176 (9201)	3.1877	13.6194	0.0000	51.5729 (4479)	2.7431	8.6176	0.0000
M/B	20.9330 (36,637)	22.3329 (8502)	1.3999	2.5610	0.0104	21.2190 (4103)	0.2860	0.3858	0.6997

Table 2: Rainfall-departure and rainfall subdivisions of India

Panel A shows the rainfall-departure from the normal expected rainfall during the monsoon season months of June-July-August-September in 32 rainfall subdivisions of India from the years 2000 to 2017. While deficit rainfall-departure in the matrix indicated by red cells is below -15%, excess rain with departure above 15% is indicated by blue cells. Other uncolored cells indicate normal rainfall condition. Each rainfall-departure is then indicated with different shades of red and blue with a 5% range as indicated in the legend. Panel B lists the rainfall subdivisions of India as classified by the IMD.

Legends of *Rainfall-departure*

-15% to -20%	15% to 20%
-20% to -25%	20% to 25%
-25% to -30%	25% to 30%
Below -30%	Above 30%

Panel A: Subdivision-wise rainfall-departure

Sub-division	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
2000	-3.6	2.3	-26.4	17.4	-2.4	-19.8	-30.8	-0.5	2.2	-42.1	-29.7	-18	-5.5	-3.3	-14.1	1.8
2001	-18.2	-7.2	20.9	-8.7	-10.5	-5.6	-15.6	-1.3	-1.9	-8	-15	-20.3	6.2	-5.3	-6.5	-20
2002	-8	-7.9	-32.9	-33.6	-25.9	-20.1	-57.2	-32.2	10.3	-28.3	-45.4	-37.7	-5.1	-17.2	-32.9	-12.3
2003	-9	5.7	22.6	-3.2	-5.3	25.2	-0.8	16.5	-17.8	30.6	19.4	-21.4	-5	-20.2	-23.8	-0.7
2004	7	-6.6	-16	-12.8	-14.2	-16.6	-5.9	-24.9	5.6	11	-21.5	-40.1	-35.5	-15.2	-17.5	3.4
2005	-11.8	-22.2	-8.9	13.5	5.8	12.7	-8.7	-20.3	-11.2	49	-3.1	-18	18.6	-28.4	6.6	26.2
2006	-30.1	-8.5	1	16.4	6.3	-22.8	20.1	-34.1	24.8	66.1	-40.7	-6.2	59	17.6	8.4	8.8
2007	14.3	33.8	-3.3	36.2	19.9	-46.7	-9.9	-28.7	43.9	33.4	-29.1	-19.2	-1.6	13.3	32.8	20.8
2008	-2.6	5.8	-14	17.7	-5.6	-10.8	1.3	5.3	12.7	1.3	37	-4	19	10.9	-17.4	5.7
2009	-14.8	-30.9	-29.4	-19.3	9.1	-30.2	-35.5	-43.1	-13.7	-31.3	-21.8	-29.5	10.35	-24.2	-3.2	-18.2
2010	-2.2	-47.6	-2.9	45.6	0.5	-15.9	4.8	-26	-31.7	17.3	35.7	9	1.7	-46.9	-4.7	24.3
2011	-28.5	-5.8	0.9	-4.1	17.9	16.7	31	-15.1	23.4	0.9	-0.6	2	-30.5	15.5	9.1	32.5
2012	8.5	-9.7	4.8	19.8	-5.4	-8.1	13.1	-34.3	-14.1	-19.9	-18.5	-12.1	1.7	-16.6	-24.1	1.8
2013	-32.1	-29.5	-3.9	-16.8	25.3	23	29.5	-0.9	2	20.1	-17.9	-4.2	-9.4	-22.5	26.5	19.9
2014	-1.3	-17.1	-8.7	-20.7	6.3	-30.8	3.2	-40.7	-10.2	-21.5	-54.8	-37.7	21.2	-14.6	7	-6.5
2015	0	-27.5	-16.3	21.1	-15.9	-30.9	-7.1	-45.9	15.6	-31.3	-33.3	-22.2	19.4	-13.8	-25.2	-31.6
2016	-26	-3	2	15	-21	19	32	-12	-1	-24	-26	-24	-10	1	-34	22
2017	-3	-9	-10	15	-16	-24	-8	-28	-2	9	-23	-13	2	-9	-9	10

Sub-division	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32
2000	-16.5	-5.8	5.7	-19.1	-29.3	32.7	-39.2	24.7	2.3	21.5	23.7	29.4	8.8	-32.2	-11.8	-2.5
2001	-14.2	-18.6	-17	23.6	-22.8	-3.8	8.6	-6.8	-19.1	-55	-11.1	8.7	-2.6	-18.5	-4.7	-18.5
2002	-10.2	-3.4	-33.9	-19.8	-50.6	-29.7	-33.5	-33.5	-11.3	-71.7	-22	-1.8	-9.6	-24.8	-73.7	-27.6
2003	-3.5	-2.3	-34.7	6.6	-29.9	20.3	47.8	-29.1	-11.4	-58.9	1.8	16.3	-0.3	7.2	33.7	31.5
2004	25	-17.2	-11.8	-10.4	-49.4	-15.3	-2.9	4.9	-7.4	24.3	-34.8	-15.7	-31	-9.1	-36	-29.1
2005	53.2	21.3	19.1	-0.5	-10.6	4.5	36.3	24.5	-9	0.7	13.8	-6.3	7.3	-16.9	-15.6	-9.1
2006	70.2	13.9	-6.9	30.1	9.1	-13.7	51.1	1.7	-22	-15.6	10.5	-27.3	11.4	25.2	27.1	-38.1
2007	38.3	4	35	23.2	-3	66	91.8	35.7	-4.5	20.3	-0.1	31.7	17.3	-10.9	-3.3	-38
2008	12.9	-11.5	-10.4	20.2	36	-15.2	28.4	11.8	-1	-3.3	9.5	-4.4	-15.5	-11.2	5.6	4.1
2009	-4.2	-20.8	18.5	-3.2	-35.1	-3.6	28.2	21.1	-27.5	-15.6	-30	-46.2	-32	-19.6	-45.2	-39
2010	16.9	34.3	24.9	-16.3	-14.6	43.2	126	8.7	-10.2	9.9	38.4	10.7	26.8	-12.7	72.1	5.7
2011	5.5	-6.1	-6.3	0.7	33.5	1.9	60.2	1	-13.1	-7.8	-12.2	17.3	-8.7	23.2	55.2	-0.6
2012	-20.6	-32	-28.8	-0.5	-18	-6.1	-30.7	-17.6	-3.8	-21.9	9.8	-5.2	10.2	19.3	19.3	-49.9
2013	19.1	11.5	6	-3.8	3.7	10.6	39.1	21	-19.7	-3.3	35.7	21.3	41.2	49.3	32.9	4.6
2014	-7.8	-40.4	-4.4	8.3	-47.1	-17.3	-19.2	16.2	-12.9	-5.2	-28.2	-20.7	-15.1	-10	2.9	-53.5
2015	-32.1	-38.3	-29.2	-10.8	-27.3	-6.2	-6.9	-7.6	-11.9	-14	-11.6	-22.1	-11.9	6.7	50.5	-40.3
2016	13	21	4	-10	-25	-2	-13	-22	0	-20	19	-10	10	19	20	-17
2017	17	-6	3	-8	-21	27	35	1	2	31	-12	-2	-23	-16	39	-30

Source: Reconstructed from data obtained from the IMD, Government of India

Panel B: Rainfall subdivisions in India

Code	Rainfall subdivision	Code	Rainfall subdivision	Code	Rainfall subdivision	Code	Rainfall subdivision
1	Assam & Meghalaya	9	Gangetic West Bengal	17	Madhya Maharashtra	25	Sub Himalayan West Bengal
2	Bihar	10	Gujarat Region	18	Marathwada	26	Tamil Nadu
3	Chhattisgarh	11	Haryana Delhi & Chandigarh	19	North Interior Karnataka	27	Telangana
4	Coastal Andhra Pradesh	12	Himachal Pradesh	20	Orissa	28	Uttarakhand
5	Coastal Karnataka	13	Jammu & Kashmir	21	Punjab	29	Vidarbha
6	East Madhya Pradesh	14	Jharkhand	22	Rayalaseema	30	West Madhya Pradesh
7	East Rajasthan	15	Kerala	23	Saurashtra & Kutch	31	West Rajasthan
8	East Uttar Pradesh	16	Konkan & Goa	24	South Interior Karna	32	West Uttar Pradesh

Table 3: Rainfall-departure and immediate value decline

This table reports the regression results of the following general equation:

$$Firm\_value_{it} = \alpha + \beta.(RDyr_{\boldsymbol{t}} \times treated_{\boldsymbol{i}}) + \boldsymbol{X_{i,t-1}}.\boldsymbol{\delta} + \tau.Time + \gamma_i + e_{it}$$

where $Firm\_value_{it}$ is market-to-book value of equity (*M/B*) as calculated at the end of the September quarter (Q2) which marks the end of the monsoon season in India, or fiscal year end (Q4) *M/B* value. $RDyr$ is a dummy variable which takes the value of one for years with rainfall-departure (excess/deficit) and zero for normal years. *treated* is a categorical variable that takes the value of one for the firms belonging to the excess-rain-sensitive industries or deficit-rain-sensitive industries and zero otherwise for control firms. $(RDyr_{\boldsymbol{t}} \times treated_{\boldsymbol{i}})$ is an interaction term which is the main variable of interest. $\boldsymbol{X_{it}}$ is a vector of control variables including *Size, Leverage, Liquidity, OwnCon* all lagged by one year, as defined in Section 3.3. The *Time* variable absorbs long-running trends. γ_i controls for firm fixed effects and e_{it} is the error term. Standard errors are clustered at firm level. *, ** and *** denote statistical significance at 10%, 5% and 1% significance levels respectively. The study period is 2001 to 2017. Source: IMD and CMIE databases.

	Excess rainfall-departure				Deficit rainfall-departure			
	MB_Q2	MB_Q2	MB_Q4	MB_Q4	MB_Q2	MB_Q2	MB_Q4	MB_Q4
(RDyr × treated)	**-12.685****	**-10.099****	**-13.179****	**-17.698****	**-2.099****	**-4.622****	**-1.609****	**-5.858*****
	(-2.67)	**(-3.01)**	**(-2.24)**	**(-2.37)**	**(-2.55)**	**(-2.76)**	**(-3.25)**	**(-4.46)**
Size		-30.414**		-22.232***		-12.756***		-11.467***
		(-2.50)		(-9.96)		(-4.57)		(-7.91)
Leverage		3.039*		0.785*		1.496***		1.647***
		(1.98)		(1.92)		(8.88)		(6.21)
Liquidity		-12.274**		-8.606***		-5.348***		3.782***
		(-2.57)		(-4.91)		(-10.16)		(7.09)
OwnCon		-0.045		0.177		0.049***		0.182**
		(-0.14)		(0.95)		(3.89)		(2.54)
Time		2.175		1.114		0.386		0.146
		(1.25)		(1.57)		(0.77)		(0.28)
R^2 (adjusted)	0.31	0.42	0.32	0.37	0.36	0.51	0.45	0.46
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Firms	3,823	3,638	3,823	3,638	4,587	4,197	4,587	4,197
No. of Obs.	23,988	21,291	23,988	21,291	40,579	34,444	40,579	34,444

Table 4: Capex & rainfall-departure

Panel A of Table 4 shows the univariate *Capex* based DiD for the treated and control group firms comparing the normal rainfall period with the excess and the deficit rainfall-departure periods. *Capex* is the ratio of actual capital expenditure to long-term assets. *, ** and *** denote statistical significance at 10%, 5% and 1% significance levels respectively. The study period is 2001 to 2017. Source: IMD and CMIE databases.

Panel B of Table 4 reports the results of multivariate regression results of the following general equation:

$$Investment_{it} = \alpha + \beta.(RDyr_{\boldsymbol{t}} \times treated_{\boldsymbol{i}}) + \boldsymbol{X_{i,t-1}}.\boldsymbol{\delta} + \tau.Time + \gamma_i + e_{it}$$

where $Investment_{it}$ is the investment proxy *Capex* of firm *i* for the year *t*. $RDyr$ is a dummy variable which takes the value of one for years with rainfall-departure (excess/deficit) and zero for normal years. *treated* is a categorical variable that takes the value of one for the firms belonging to the excess-rain-sensitive industries or deficit-rain-sensitive industries and zero otherwise for control firms. $(RDyr_{\boldsymbol{t}} \times treated_{\boldsymbol{i}})$ is an interaction term which is the main variable of interest. $\boldsymbol{X_{it}}$ is a vector of control variables including *Size*, *Leverage*, *Liquidity*, *OwnCon*, *M/B* all lagged by one year, as defined in Section 3.3. The *Time* variable absorbs long-running trends. γ_i controls for firm fixed effects and e_{it} is the error term. Standard errors are clustered at the firm level. *, ** and *** denote statistical significance at 10%, 5% and 1% significance levels respectively. The study period is 2001 to 2017. Columns [1] to [4] report the results for the full sample. Columns [5] and [7] report the results for subsample firms with a single location. Columns [6] and [8] report the results for subsample of non-business group-affiliated firms with a single location, as specified in Section 4.4.1. Source: IMD and CMIE databases.

Panel A

		Excess rainfall-departure				Deficit rainfall-departure		
Variable	No. of Obs.	Capex [1]	t-value [2]	p-value [3]	No. of Obs.	Capex [4]	t-value [5]	p-value [6]
Before								
Control group firms	11,097	0.121			10,383	0.235		
Treated group firms	2,642	0.130			1,328	0.243		
Difference	13,739	0.009	0.96	0.335	11,711	0.008	0.57	0.565
After								
Control group firms	13,237	0.148			19,939	0.190		
Treated group firms	2,891	0.182			2,680	0.165		
Difference	16,128	0.035	4.13	0.000***	22,619	-0.025	2.68	0.007***
Difference-in-Differences		**0.026**	**2.04**	**0.041****		**-0.033**	**1.97**	**0.049****

Panel B

	Full sample				Subsample			
	Excess rainfall-departure		Deficit rainfall-departure		Excess rainfall-departure		Deficit rainfall-departure	
Variables	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
(RDyr × treated)	**0.048*****	**0.034****	**-0.0318*****	**-0.032****	**0.046****	**0.070****	**-0.031***	**-0.048****
	(4.98)	**(2.21)**	**(-4.58)**	**(-2.23)**	**(2.04)**	**(2.17)**	**(-2.09)**	**(-2.27)**
Size		0.064***		0.075***	0.060**	0.064**	0.102***	0.114***
		(4.81)		(4.30)	(2.26)	(2.56)	(4.16)	(4.88)
Leverage		-0.003**		-0.007***	-0.001	-0.002	-0.003	-0.005
		(-2.35)		(-4.54)	(-0.55)	(-0.82)	(-1.03)	(-1.80)
Liquidity		0.030**		0.000	0.005	0.009	0.000	0.001
		(2.35)		(1.13)	(0.37)	(0.78)	(1.20)	(0.71)
OwnCon		0.001***		0.001**	0.001**	0.001*	0.000	0.001
		(4.68)		(2.87)	(2.19)	(1.82)	(1.13)	(1.77)
M/B		0.001***		0.001***	0.000	0.000	0.001	0.001
		(6.46)		(5.47)	(1.39)	(1.15)	(1.31)	(0.82)
Time		-0.012***		-0.011***	-0.01***	-0.011***	-0.014***	-0.017***
		(-7.10)		(-4.77)	(-2.95)	(-3.92)	(-3.84)	(-3.32)
R^2(within)	0.001	0.014	0.001	0.009	0.006	0.007	0.013	0.014
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Firms	5,299	3,408	4,887	3,443	1,131	824	1,115	845
No. of Obs.	29867	15996	34330	20106	5,216	3,554	6,550	4,557

Table 5: Capex & rainfall-departure using alternative measures

This table reports the results of multivariate regression results of the following general equation:

$$Investment_{it} = \alpha + \beta.(RDyr_{\boldsymbol{t}} \times treated_{\boldsymbol{i}}) + \boldsymbol{X_{i,t-1}}.\boldsymbol{\delta} + \tau.Time + \gamma_i + e_{it}$$

where $Investment_{it}$ is the investment proxy using alternative measures of *Capex_RD* and *Capex_LT* of firm *i* for the year *t*. $RDyr$ is a dummy variable which takes the value of one for years with rainfall-departure (excess/deficit) and zero for normal years. *treated* is a categorical variable that takes the value of one for the firms belonging to the excess-rain-sensitive industries or deficit-rain-sensitive industries and zero otherwise for control firms. $(RDyr_{\boldsymbol{t}} \times treated_{\boldsymbol{i}})$ is an interaction term which is the main variable of interest. $\boldsymbol{X_{it}}$ is a vector of control variables including *Size, Leverage, Liquidity, OwnCon, M/B* all lagged by one year, as defined in Section 3.3. The *Time* variable absorbs long-running trends. γ_i controls for the firm fixed effects and e_{it} is the error term. Standard errors are clustered at firm level. *, ** and *** denote statistical significance at 10%, 5% and 1% significance levels respectively. The study period is 2001 to 2017. Columns [1] to [4] report the results for the full sample. Columns [5] [6] [9] [10] report the results of subsample firms with a single location and Columns [7] [8] [11] [12] report the results of the non-business group-affiliated firms subsample as specified in Section 4.4.1 Source: IMD and CMIE databases.

	Excess rainfall		Deficit rainfall		Excess rainfall-departure				Deficit rainfall-departure			
	Full Sample				Single location firms		Non-business group firms		Single location firms		Non-business group firms	
	Capex_RD	Capex_LT	Capex RD	Capex_LT	Capex_RD	Capex_LT	Capex RD	Capex_LT	Capex RD	Capex_LT	Capex RD	Capex_LT
Variables	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
(RDyr × treated)	**0.035****	**0.045*****	**-0.067***	**-0.036****	**0.046****	**0.067*****	**0.069****	**0.076****	**-0.033***	**-0.016***	**-0.051****	-0.011
	(2.27)	**(4.07)**	**(-1.86)**	**(-2.86)**	**(2.04)**	**(3.07)**	**(2.19)**	**(2.27)**	**(-2.02)**	**(-1.88)**	**(-2.24)**	(-0.72)
Size	0.064***	0.088***	0.096*	0.121***	0.060**	0.085***	0.064***	0.094***	0.105***	0.086***	0.115***	0.095***
	(4.82)	(8.56)	(1.84)	(14.74)	(2.29)	(8.06)	(2.63)	(4.84)	(4.34)	(7.97)	(4.93)	(5.20)
Leverage	-0.003**	-0.004***	-0.002	-0.004**	-0.001	-0.003**	-0.002	-0.006***	-0.003	-0.002	-0.005	-0.004
	(-2.41)	(-4.18)	(-0.53)	(-2.53)	(-0.58)	(-2.17)	(-0.80)	(-2.97)	(-1.04)	(-1.80)	(-1.75)	(-1.73)
Liquidity	0.033***	0.073***	0.220**	0.064***	0.005	0.051***	0.009	0.039**	0.007	0.067***	-0.004	0.000
	(2.66)	(5.73)	(2.72)	(4.05)	(0.38)	(2.87)	(0.81)	(2.07)	(0.37)	(7.92)	(-0.20)	(0.47)
OwnCon	0.001***	0.002***	0.001	0.001***	0.001**	0.002***	0.001*	0.003***	0.000	0.001***	0.001	0.001***
	(4.67)	(9.74)	(1.05)	(6.20)	(2.25)	(4.22)	(1.85)	(4.77)	(0.97)	(6.62)	(1.69)	(4.34)
M/B	0.001***	0.001***	0.001**	0.001***	0.000	0.000***	0.000	0.000**	0.001	0.000***	0.001	0.000**
	(6.47)	(10.44)	(2.38)	(7.95)	(1.43)	(2.69)	(1.16)	(2.12)	(1.32)	(4.72)	(0.82)	(2.97)
Time	-0.012***	-0.017***	-0.015*	-0.024***	-0.010***	-0.015***	-0.011***	-0.018***	-0.014***	-0.010***	-0.017***	-0.009***
	(-7.11)	(-17.12)	(-2.15)	(-12.85)	(-2.97)	(-9.28)	(-3.95)	(-8.00)	(-4.04)	(-5.53)	(-3.45)	(-5.13)
R^2(within)	0.015	0.057	0.005	0.029	0.007	0.042	0.007	0.047	0.013	0.050	0.014	0.042
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Firms	3,408	3,477	3,443	3,447	1,131	1,176	824	865	1,115	1,124	845	852
No. of Obs.	15,997	16,214	20,106	20116	5,216	5,355	3,554	3,678	6,550	6,535	4,557	4,557

Table 6: Capex & rainfall (one-year pair difference-in-differences)

Panel A of Table 6 is a matrix that indicates the pairs of years in each rainfall subdivision in which a normal rainfall year is succeeded by excess rainfall-departure of +19% and above following the IMD's definition of excess rainfall-departure. The study period is 2001 to 2017 for 32 subdivisions of India. We observe that the pairing is not possible for years 2001 and 2002 and for subdivisions 1, 3, 8, 11, 12, 14 and 32 as no values fall under the criteria mentioned above. Source: IMD.

Year	2	4	5	6	7	9	10	13	15	16	17	18	19	20	21	22	23	24	26	27	28	29	30	31
2003											-3.5													
2004							11			3.4	25	-17.2	-11.8				-2.9	4.9						
2005					-8.7	-11.2	49	18.6		26.2		21.3	19.1	-0.5			36.3	24.5					-16.9	-15.6
2006	-8.5	16.4	6.3		20.1	24.8		59	8.4	8.8			-6.9	30.1		-13.7		1.7	-15.6				25.2	27.1
2007	33.8	36.2	19.9					-1.6	32.8	20.8			35		-3	66		35.7	20.3					
2008								19							36			11.8						
2009										-18.2			18.5			-3.6		21.1						
2010					4.8					24.3			24.9		-14.6	43.2							-12.7	
2011		-4.1			31										33.5								23.2	
2012		19.8	-5.4	-8.1	13.1					1.8								-17.6		9.8	-5.2	10.2		
2013			25.3	23	29.5			-9.4		19.9								21		35.7	21.3	41.2		
2014								21.2																2.9
2015					-7.1																		6.7	50.3
2016					32											-2	-13						19	
2017																27	35							

Source: Reconstructed from data obtained from the IMD, Government of India

Panel B of Table 6 is a matrix that indicates the pairs of years in each rainfall subdivision in which a normal rainfall year is succeeded by deficit rainfall-departure of -19% and above following the IMD's definition of deficit rainfall-departure. The study period is 2001 to 2017 for 32 subdivisions of India. We observe that the pairing is not possible for subdivision 20 as no values fall under the criteria mentioned above. Source: IMD

Year	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	21	22	23	24	25	26	27	28	29	30	31	32
2001				-8.7	-10.5	-5.6	-15.6	-1.3		-8	-15				-6.5				-17		-3.8	8.6	-6.8			-11.1			-18.5	-4.7	-18.5
2002				-34	-26	-20	-57	-32		-28	-45			-17.2	-33				-34		-30	-34	-34			-22			-25	-74	-28
2003								16.5						-20												1.8		-0.3			
2004		-6.6						-25						-15.2												-35		-31			
2005	-11.8	-22				12.7					-3.1			-28										-9			-6.3				-9.1
2006	-30					-23					-41	-6.2												-22			-27				-38
2007												-19																			
2008		5.8	-14	17.7		-10.8	1.3	5.3		1.3		-4		10.9				-11.5						-1		9.5	-4.4	-15.5	-11.2	5.6	4.1
2009		-31	-29	-19		-30	-36	-43	-13.7	-31		-30		-24				-21						-28		-30	-46	-32	-20	-45	-39
2010	-2.2								-32				1.7																		
2011	-29							-15.1		0.9			-31		9.1		5.5	-6.1	-6.3						-7.8						-0.6
2012	8.5	-9.7						-34		-20				-16.6	-24		-21	-32	-29					-3.8	-22						-50
2013	-32	-30		-16.8				-0.9			-17.9	-4.2		-23				11.5		3.7				-20							
2014		-17.1		-21				-41			-55	-38			7	-6.5	-7.8	-40	-4.4	-47											
2015	0	-28			-15.9										-25	-32	-32		-29				-7.6		-14						
2016	-26				-21			-12															-22		-20			10			-17
2017								-28																				-23			-30

Source: Reconstructed from data obtained from the IMD, Government of India

Panel C of Table 6 reports the results of one-year pair DiD regression results of the following general equation:

$$Investment_{it} = \alpha + \beta.(RDyr_{\boldsymbol{t}} \times treated_{\boldsymbol{i}}) + \boldsymbol{X_{i,t-1}}.\boldsymbol{\delta} + \tau.Time + \gamma_i + e_{it}$$

where $Investment_{it}$ is the investment proxy *Capex* of firm *i* for the year *t*. $RDyr$ is a dummy variable which takes the value of one for years with rainfall-departure (excess/deficit) and zero for normal years. *treated* is a categorical variable that takes the value of one for the firms belonging to the excess-rain-sensitive industries or deficit-rain-sensitive industries and zero otherwise for control firms. $(RDyr_{\boldsymbol{t}} \times treated_{\boldsymbol{i}})$ is an interaction term which is the main variable of interest. $\boldsymbol{X_{it}}$ is a vector of control variables including *Size, Leverage, Liquidity, OwnCon, M/B* all lagged by one year, as defined in Section 3.3. The *Time* variable absorbs long-running trends. γ_i controls for firm fixed effects and e_{it} is the error term. Standard errors are clustered at the firm level. *, ** and *** denote statistical significance at 10%, 5% and 1% significance levels respectively. The study period is 2001 to 2017. Source: IMD and CMIE databases.

	Excess rainfall-departure			*Deficit rainfall-departure*		
	[1]	[2]	[3]	[4]	[5]	[6]
(RDyr × treated)	**0.104*** **	**0.143*** **	**0.141** **	-0.025	**-0.057** **	**-0.077*** **
	(2.66)	**(2.76)**	**(2.50)**	(-0.71)	**(-2.07)**	**(-2.76)**
Size		-0.312***	-0.004		-0.056	0.008
		(-3.23)	(-0.36)		(-1.40)	(1.09)
Leverage		-0.001	-0.005***		-0.001**	-0.002***
		(-0.24)	(-2.99)		(-2.29)	(-5.59)
Liquidity		-0.052	-0.077***		0.043	-0.044
		(-1.03)	(-3.07)		(0.57)	(-0.96)
OwnCon		0.003	0.001		0.002	0.002
		(0.73)	(1.56)		(1.28)	(1.15)
M/B		0.001*	0.001***		0.001***	0.001**
		(1.68)	(2.73)		(3.07)	(2.36)
Time		0.019**	-0.008		-0.015**	-0.019***
		(2.30)	(-1.35)		(-2.07)	(-4.90)
R (within)	0.03	0.03	0.01	0.06	0.04	0.01
Firm FE	Yes	Yes	No	Yes	Yes	No
Industry FE	No	No	Yes	No	No	Yes
No. of Firms	3,980	2,151	2,151	4,483	2,488	2,488
No. of Obs.	18,440	7,805	7,805	15,406	5,534	5,534

Table 7: Capex & rainfall sensitivity analysis

This table reports the results of the excess and deficit rainfall sensitivity analysis using the following general equation:

$$Investment_{it} = \alpha + \beta.(RDyr_{\boldsymbol{t}} \times treated_{\boldsymbol{i}}) + \boldsymbol{X_{i,t-1}}.\boldsymbol{\delta} + \tau.Time + \gamma_i + e_{it}$$

where $Investment_{it}$ is the investment proxy *Capex* of firm *i* for the year *t*. $RDyr$ is a dummy variable which takes the value of one for years with rainfall-departure in excess of 15%, 16% (in deficit of -15%, -16%) and so on and zero for normal years. *treated* is a categorical variable that takes the value of one for the firms belonging to the excess-rain-sensitive (deficit-rain-sensitive) industries and zero otherwise for control firms. $(RDyr_{\boldsymbol{t}} \times treated_{\boldsymbol{i}})$ is an interaction term which is the main variable of interest. $\boldsymbol{X_{it}}$ is a vector of control variables including *Size, Leverage, Liquidity, OwnCon, M/B* all lagged by one year, as defined in Section 3.3. The *Time* variable absorbs long-running trends. γ_i controls for firm fixed effects and e_{it} is the error term. Standard errors are clustered at firm level. *, ** and *** denote statistical significance at 10%, 5% and 1% significance levels respectively. The study period is 2001 to 2017. Source: IMD and CMIE databases.

Rainfall in excess of →	**+15%**	**+16%**	**+17%**	**+18%**	**+19%**	**+20%**	**+21%**	**+22%**	**+23%**	**+24%**	**+25%**	**+26%**	**+27%**	**+28%**	**+29%**	**+30%**
(RDyr × treated)	0.224	0.039	0.044	0.038	0.038	**0.046****	**0.045***	**0.040***	**0.062****	**0.065****	**0.073****	**0.069****	**0.077****	**0.077****	**0.077****	**0.076****
	(0.92)	(1.32)	(1.36)	(1.26)	(1.26)	**(2.04)**	**(1.92)**	**(1.65)**	**(2.39)**	**(2.37)**	**(2.30)**	**(2.28)**	**(2.34)**	**(2.34)**	**(2.34)**	**(2.32)**
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Firms	3,600	3,598	3,595	3,589	3,589	3,562	3,545	3,541	3,534	3,534	3,529	3,526	3,526	3,525	3,525	3,525
No. of Obs.	24,105	23,915	23,687	23,299	23,293	21,958	20,888	20,663	19,917	19,693	18,736	18,615	18,085	18,076	18,039	17,974

Rainfall in deficit of →	**-15%**	**-16%**	**-17%**	**-18%**	**-19%**	**-20%**	**-21%**	**-22%**	**-23%**	**-24%**	**-25%**	**-26%**	**-27%**	**-28%**	**-29%**	**-30%**
(RDyr × treated)	-0.040	-0.067	-0.069	**-0.043***	**-0.050***	**-0.052***	**-0.042***	**-0.048***	**-0.087***	**-0.097***	**-0.097****	**-0.095***	**-0.086***	**-0.079***	-0.086	**-0.100***
	(-1.64)	(-1.08)	(-1.10)	(-1.74)	(-1.86)	(-1.94)	(-1.78)	(-1.85)	(-2.06)	(-2.04)	(-2.24)	(-2.18)	(-2.04)	(-1.86)	(-1.78)	(-2.14)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Firms	3,184	3,179	3,162	3,143	3,123	3,098	3,078	3,184	3,057	2,984	2,961	2,917	2,914	2,898	2,896	2,811
No. of Obs.	14,642	14,243	14,111	13,541	12,685	12,329	11,958	14,642	10,980	10,617	10,280	9,916	9,840	9,510	9,415	9,007

Table 8: Persistence effects of rainfall-departure

This table reports the results of persistence of excess (deficit) rainfall on investment using the following equation:

$$Investment_{it} = \alpha + \beta.(RDyr_{\boldsymbol{t}} \times treated_i) + \sum_{n=1}^{5} \lambda_n.(Rain_{\boldsymbol{t-n}} \times treated_{\boldsymbol{i}}) + \boldsymbol{X_{i,t-1}}.\boldsymbol{\delta} + \tau.Time + \gamma_i + e_{it}$$

where $Investment_{it}$ is the investment proxy *Capex* of firm *i* for the year *t*. We conduct a sensitivity analysis using the specification with a 5% incremental rainfall-departure from 15% up to 30% with $RDyr$ as a dummy variable which takes the value of one for years with the excess/deficit rainfall-departure and zero for normal years. *treated* is a categorical variable that takes the value of one for the firms belonging to the excess/deficit-rain-sensitive industries and zero otherwise for the control firms. $(RDyr_{\boldsymbol{t}} \times treated_{\boldsymbol{i}})$ is an interaction term. $Rain_{\boldsymbol{t-n}}$ is the percentage of rainfall-departure (excess/deficit) lagged up to five years. $\boldsymbol{X_{it}}$ is a vector of control variables including *Size*, *Leverage*, *Liquidity*, *OwnCon*, *M/B* all lagged by one year, as defined in Section 3.3. The *Time* variable absorbs long-running trends. γ_i controls for firm fixed effects and e_{it} is the error term. Standard errors are clustered at the firm level. *, ** and *** denote statistical significance at 10%, 5% and 1% significance levels respectively. The study period is 2001 to 2017. Source: IMD and CMIE databases.

	Excess rainfall-departure				Deficit rainfall-departure			
	15%	20%	25%	30%	15%	20%	25%	30%
(RDyr × treated)	**0.0497****	**0.0599*****	**0.0778****	**0.0720****	**-0.104****	**-0.129***	**-0.107***	-0.105
	(2.44)	**(2.69)**	(2.49)	(2.22)	**(-2.01)**	**(-1.87)**	**(-1.67)**	(-1.54)
($Rain_{t-1}$ × treated)	**0.00177*****	**0.00146****	0.00107	0.000987	-0.0000241	-0.00775	-0.0104	-0.00962
	(2.67)	**(2.26)**	(1.47)	(1.34)	(-0.02)	(-1.10)	(-1.12)	(-0.81)
($Rain_{t-2}$ × treated)	**0.00180****	**0.00174*****	**0.00151***	**0.00152***	0.00376***	0.00632	0.0120*	0.00128
	(2.26)	**(6.04)**	**(1.82)**	(1.78)	(3.92)	(0.72)	(1.67)	(0.56)
($Rain_{t-3}$ × treated)	0.000991	**0.00178****	**0.00200****	0.00104	0.00184	0.0212*	-0.00200	-0.00113
	(1.16)	**(2.10)**	**(2.05)**	(1.04)	(1.12)	(1.70)	(-0.66)	(-0.61)
($Rain_{t-4}$ × treated)	0.00036	0.0012	0.00047	0.00096	0.00023	0.0029	0.00081	0.00131
	(0.47)	(1.51)	(0.50)	(0.96)	(0.26)	(0.78)	(0.39)	(0.46)
($Rain_{t-5}$ × treated)	0.00047	0.00024	0.00076	0.00014	0.00045	0.0061*	0.0028	0.00481
	(0.71)	(0.38)	(1.09)	(0.20)	(0.34)	(1.73)	(1.15)	(1.38)
Size	0.118***	0.116***	0.118***	0.119***	0.285***	0.275**	0.259**	0.282***
	(10.47)	(10.32)	(10.53)	(10.54)	(6.36)	(2.24)	(2.56)	(2.63)
Leverage	-0.00366***	-0.00362***	-0.00366***	-0.00366***	-0.0132*	0.00446	0.000114	0.0241
	(-6.26)	(-6.19)	(-6.23)	(-6.27)	(-1.92)	(0.11)	(0.56)	(0.57)
Liquidity	0.0361	0.0349	0.0368	0.0366	-0.125	0.0385	0.986	1.000
	(1.46)	(1.42)	(1.49)	(1.48)	(-0.22)	(0.04)	(1.14)	(1.06)
OwnCon	0.00138**	0.00146**	0.00138**	0.00138**	-0.000953	-0.0170	-0.0143	-0.00402
	(2.16)	(2.29)	(2.16)	(2.17)	(-0.39)	(-1.23)	(-1.22)	(-1.13)
M/B	0.00109***	0.00106***	0.00109***	0.00110***	0.00528***	0.0159	0.00593	0.00523
	(5.77)	(5.58)	(5.80)	(5.82)	(3.22)	(1.36)	(1.30)	(1.05)
Time	-0.0309***	-0.0308***	-0.0308***	-0.0309***	-0.0512***	-0.0642***	-0.0358**	-0.0410***
	(-21.83)	(-21.90)	(-21.72)	(-21.79)	(-7.27)	(-4.75)	(-2.50)	(-2.73)
R^2 (within)	0.0332	0.0350	0.0334	0.0330	0.0048	0.001	0.0003	-0.0001
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Firms	3600	3562	3529	3525	3393	3375	3320	3261
No. of Obs.	24,105	21,958	18,736	17,974	23108	20743	18413	17092

Table 9: Implications of rainfall-departure

This table reports the regression results of the following general equation:

$$Firm\_value_{it+1} = \alpha + \beta.(RDyr_{\boldsymbol{t}} \times treated_{\boldsymbol{i}}) + \boldsymbol{X_{i,t}}.\boldsymbol{\delta} + \tau.Time + \gamma_i + e_{it}$$

where $Firm\_value_{it}$ is the market-to-book value of equity (*M/B)* or Tobin's q (*Tobin's q*) which is equal to the sum of book value of debt, preference stock and market value of equity as a ratio of the book value of assets as calculated at the fiscal year end for firm *i* and lead year t+1. $RDyr$ is a dummy variable which takes the value of one for years with rainfall-departure (excess/deficit) and zero for normal years. *treated* is a categorical variable that takes the value of one for the firms belonging to the excess-rain-sensitive industries or deficit-rain-sensitive industries and zero otherwise for control firms. $(RDyr_{\boldsymbol{t}} \times treated_{\boldsymbol{i}})$ is an interaction term which is the main variable of interest. $\boldsymbol{X_{it}}$ is a vector of control variables including *Size, Leverage, Liquidity, OwnCon,* as defined in Section 3.3. The *Time* variable absorbs long-running trends. γ_i controls for firm fixed effects and e_{it} is the error term. Standard errors are clustered at the firm level. Columns [1] to [4] present the results for *M/B* and columns [5] to [8] present the results for *Tobin's q*. *, ** and *** denote statistical significance at 10%, 5% and 1% significance levels respectively. The study period is 2001 to 2017. Source: IMD and CMIE databases.

	M/B				Tobin's q			
	Excess rainfall-departure		Deficit rainfall-departure		Excess rainfall-departure		Deficit rainfall-departure	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
(RDyr × treated)	**2.061****	**2.045*****	**8.689***	**9.235****	**0.140****	**0.165*****	**0.0625****	**0.0644***
	(3.08)	**(3.66)**	**(2.22)**	**(2.49)**	**(2.25)**	**(3.84)**	**(2.76)**	**(1.82)**
Size		-7.473***		-17.048***		-0.111**		-0.00171
		(-21.85)		(-12.80)		(-2.84)		(-0.11)
Leverage		0.231***		2.012***		0.0078**		-0.00026
		(5.56)		(4.48)		(2.37)		(-0.21)
Liquidity		-1.329		-0.622		-0.0499**		-0.0069
		(-1.26)		(-0.31)		(-2.83)		(-0.45)
OwnCon		0.164***		0.373***		-0.00014		0.00047
		(26.77)		(6.91)		(-0.12)		(0.58)
Time		0.069		0.912		0.0298**		0.000572
		(1.15)		(1.65)		(2.83)		(0.40)
R^2 (adjusted)	0.52	0.56	0.31	0.34	0.57	0.58	0.45	0.46
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Firms	3,620	3,358	3,500	3,373	4427	3029	4712	2766
No. of Obs.	22,387	19,251	28,406	25,761	22025	13993	29926	12975

Table 10: Implications of rainfall-departure and subsequent investment strategies

This table reports the regression results of the following general equation:

$$Firm\_value_{it+1} = \alpha + \beta.(RDyr_{\boldsymbol{t}} \times Cap_{\boldsymbol{i}}) + \boldsymbol{X_{i,t}}.\boldsymbol{\delta} + \tau.Time + \gamma_i + e_{it}$$

where Tobin's q (*Tobin's q*) is the proxy for $Firm\_value_{it}$ and future growth opportunities of firm '*i*' for the year '*t+1*' and is equal to the sum of book value of debt, preference stock and market value of equity as a ratio of the book value of assets. $RDyr$ is a dummy variable which takes the value of one for years with rainfall-departure (excess/deficit) and zero for normal years. For columns [1] to [4] under the excess (deficit) rain-sensitive firms, the dummy variable Cap_i takes the value of one if the capital expenditure increases (decreases) for the firm 'i' in the post extreme rainfall-periods or takes the value of zero otherwise. For columns [5] to[8], the dummy variable Cap_i takes the value of one for the excess (deficit) rain-sensitive firms with capital expenditure falling in the top-most (lower-most) tercile and zero for the lower-most (top-most) tercile. ($RDyr_{\boldsymbol{t}} \times Cap_{\boldsymbol{i}}$) is an interaction term which is the main variable of interest. $\boldsymbol{X_{it}}$ is a vector of control variables including *Size, Leverage, Liquidity, OwnCon,* as defined in Section 3.3. The *Time* variable absorbs long-running trends. γ_i controls for the fixed effects of firm/industry and e_{it} is the error term. Standard errors are clustered at firm level. *, ** and *** denote statistical significance at 10%, 5% and 1% significance levels respectively. The study period is 2001 to 2017. Source: IMD and CMIE databases.

	Based on increase/decrease Capex				Based on tercile of Capex			
	Excess		Deficit		Excess		Deficit	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
(RDyr × treated)	**0.136*** **	**0.128*** **	**0.254*** **	**0.094***	**0.160** **	**0.209*** **	**0.088** **	**0.070** **
	(5.10)	**(3.14)**	**(3.39)**	**(2.00)**	**(2.18)**	**(3.22)**	**(2.26)**	**(2.18)**
Size		0.012		0.084		-0.111		-0.022
		(0.42)		(1.10)		(-1.33)		(-0.27)
Leverage		0.004		0.005		0.000		0.003
		(1.48)		(1.49)		(0.05)		(1.43)
Liquidity		0.019		0.581*		-0.091		-0.002
		(0.25)		(2.05)		(-1.15)		(-0.01)
OwnCon		0.002		-0.003		0.001		-0.003
		(1.12)		(-1.35)		(0.60)		(-0.93)
Time		0.016		0.037**		0.030***		0.050***
		(1.45)		(2.30)		(3.20)		(4.17)
R^2 (within)	0.01	0.01	0.01	0.07	0.01	0.03	0.00	0.09
Industry FE	Yes	Yes	Yes	Yes	No	No	No	No
Firm FE	No	No	No	No	Yes	Yes	Yes	Yes
No. of Obs.	4,237	2,712	5,216	2,530	3,242	1,961	3,499	1,771

Appendix

Table A1: Rainfall-departure comparison of India and USA

This table provides a comparison of the overall rainfall-departures in India and the USA at each decile for the study period of 2001 to 2017. Source: IMD for India and NCEI (NOAA National Centre for Environmental Information) for the USA

Decile	India	USA
1	**-40.94**	-9.45
2	**-25.52**	-4.32
3	**-17.59**	-2.33
4	-9.70	-0.85
5	-2.80	0.53
6	2.27	1.53
7	7.86	2.99
8	**16.02**	4.51
9	**23.45**	7.06
10	**41.30**	12.28
Mean rainfall-departure	-0.80	1.16
Standard deviation.	**23.84**	5.94
Maximum deficit rainfall-departure	**-73.7**	-17.39
Maximum excess rainfall-departure	**126**	22.33

Table A2: Industry classification into rain-sensitive sectors

This table provides the grouping and classification of industries into the excess-rain-sensitive, deficit-rain-sensitive, and positively rain-sensitive industries. Source: industry names from the CMIE database.

Industry Name	Rain-sensitive Sector group	Literature evidence	Excess	Deficit
Agricultural machinery	Agriculture & processed food	Ahmed et al. (2018); Ahmed and Stepp, (2013); Browne et al. (2013); Campbell et al. (2016); Creighton et al. (2016); Fain et al. (2018); Guan et al. (2015); Henderson et al. (2016); Läderach et al. (2013); Mendelsohn et al. (1994, 2000); Mueller et al. (2012); Niang et al. (2017); Okom et al. (2017); Porter et al. (2014); Rao and Veena (2018); Ray et al. (2016); Schroth et al. (2016); Yu et al. (2014)	Yes	Yes
Milling products			Yes	Yes
Tea			Yes	Yes
Poultry & meat products			Yes	Yes
Starches			Yes	Yes
Vegetable oils & products			Yes	Yes
Processed foods			Yes	Yes
Floriculture			Yes	Yes
Marine foods			Yes	Yes
Cocoa products & confectionery			Yes	Yes
Tobacco products			Yes	Yes
Bakery products			Yes	Yes
Sugar			Yes	Yes
Dairy products			Yes	Yes
Other agricultural products			Yes	Yes
Coffee			Yes	Yes
Hotels & restaurants	Tourism, hotels & restaurants	Fukushima et al. (2002); Peeters and Dubois (2010); Wall (1998)	Yes	-
Tourism			Yes	-
Two & three wheelers	Auto sector	Busse et al. (2015); See news articles: https://www.standard.co.uk/news/uk/yorkshire-dales-flash-flooding-roads-destroyed-and-bridge-collapses-after-shocking-rainfall-a4201981.html ; https://www.telegraph.co.uk/news/2019/08/10/uk-weathertravellers-face-chaos-heavy-rain-shuts-railways-england/	Yes	Yes
Passenger vehicles			Yes	Yes
Diversified automobile			Yes	Yes
Commercial vehicles			Yes	Yes
Commercial complexes	Construction & allied activities	Ballesteros-Pérez et al. (2015); Damtoft et al. (2008); Kaming et al. (1997); Kazaz et al. (2012); Tatum (1987)	Yes	-
Industrial construction			Yes	-
Infrastructural construction			Yes	-
Glass & glassware			Yes	-
Other construction & allied activities			Yes	-
Housing construction			Yes	-
Ceramic products			Yes	-
Air transport services	Transport services	Chang et al. (2010); Hong et al. (2015); Ishfaq (2013); Pregnolato et al. (2017); Burbidge (2018)	Yes	-
Railway transport services			Yes	-
Road transport services			Yes	-
Transport logistics services			Yes	-
Electricity distribution	Electricity generation & transmission	Cronin et al. (2018); Golombek et al. (2012).	Yes	Yes
Renewable electricity			Yes	Yes
Electricity transmission			Yes	Yes
Pesticides	Fertilizers & pesticides	Chang and Brattlof (2015); Larsbo et al. (2016).	Yes	Yes
Fertilizers			Yes	Yes
Coal & lignite	Mining & quarrying	Marmer and Slade (2018); See online articles : https://www.reuters.com/article/us-australia-floods/australia-floods-cause-catastrophic-damage-idUSTRE6BU09620110105 ; https://www.ausimmbulletin.com/feature/climate-impacts-mining-risk-materiality-actions/	Yes	Yes
Minerals			Yes	Yes
Mining & construction equipment			Yes	Yes
Wood & wood products	Other sectors	Cline (1992); McMichael et al. (2009); Sohngen et al. (2000, 2001); Sohngen and Sedjo (2005); Sohngen and Mendelsohn (1998); WHO (2007)	-	-
Drugs & pharmaceuticals			-	-
Health services			-	-
All Other industries			-	-

**Reference list for this table is available in the online appendix.*

Table A3: Correlation matrix of rainfall-departures of seasons with the annual departure

This table reports a correlation matrix of rainfall-departure between various seasons in India. The monsoon season is during the months of June-July-August-September. Source: IMD database.

Departures	Annual	Monsoon Season	Jan-Feb	March-April-May
Monsoon Season	**0.9262*** 0.0000**	1		
Jan-Feb	0.0186*** 0.0000	-0.0266*** 0.0000	1	
March-April-May	-0.0296*** 0.0000	-0.148*** 0.0000	-0.0101*** 0.0017	1
Oct-Nov-Dec	0.2717*** 0.0000	0.0586*** 0.0000	-0.0242*** 0.0000	0.0278*** 0.0000

Table A4: Capex & rainfall-departures (robustness tests)

$$Investment_{it} = \alpha + \beta.(RDyr_{\boldsymbol{t}} \times treated_{\boldsymbol{i}}) + \boldsymbol{X_{i,t-1}}.\boldsymbol{\delta} + \tau.Time + \gamma_i + e_{it}$$

where $Investment_{it}$ is the risk-taking investment proxy *Capex* of firm *i* for the year *t*. $RDyr$ is a dummy variable that takes the value of one for years with rainfall-departure (either excess or deficit depending on the empirical study) and zero for normal years. *treated* is a categorical variable that takes the value of one for the firms belonging to the excess-rain-sensitive industries or deficit-rain-sensitive industries and zero otherwise for control firms. $(RDyr_{\boldsymbol{t}} \times treated_{\boldsymbol{i}})$ is an interaction term which is the main variable of interest. $\boldsymbol{X_{it}}$ is a vector of control variables including *Size*, *Leverage*, *Liquidity*, *OwnCon*, *M/B* all lagged by one year, as defined in Section 3.3. The *Time* variable absorbs long-running trends. *Time* captures trends. γ_i controls for firm fixed effects and e_{it} is the error term. *, ** and *** denote statistical significance at 10%, 5% and 1% significance levels respectively. The study period is 2001-2017. Source: IMD and CMIE databases.

	Agriculture		Mining & Quarrying		Construction§	Auto/Transportation	
	Excess rainfall-departure	Deficit rainfall-departure	Excess rainfall-departure	Deficit rainfall-departure	Excess rainfall-departure	Excess rainfall-departure	Deficit rainfall-departure
Variables	**[1]**	**[2]**	**[3]**	[4]	[5]	[6]	[7]
(RDyr× treated)	**0.046****	**-0.026****	**0.320***	**-0.058**	**0.062*****	**0.054***	**0.051**
	(2.27)	**(-2.06)**	**(2.04)**	**(-0.71)**	**(3.21)**	**(1.71)**	**(1.19)**
Size	0.121***	0.080***	-0.045	0.188**	0.114***	0.063	0.085*
	(4.08)	(4.89)	(-0.42)	(2.45)	(4.92)	(1.31)	(1.67)
Leverage	-0.009***	-0.003	-0.099	-0.036*	-0.010*	-0.093***	-0.015*
	(-3.46)	(-1.30)	(-1.22)	(-1.78)	(-1.95)	(-5.55)	(-1.83)
Liquidity	0.045	0.150*	-0.195	-0.091	0.065***	0.531***	0.728**
	(0.66)	(1.77)	(-0.06)	(-1.36)	(3.69)	(2.75)	(2.48)
OwnCon	0.002***	0.002***	-0.004	0.008	0.005***	0.001	-0.001
	(2.93)	(3.86)	(-0.60)	(1.36)	(4.85)	(0.92)	(-1.08)
M/B	0.001***	0.001***	0.096	0.001	0.001***	0.004***	0.006***
	(2.79)	(3.11)	(1.53)	(1.30)	(2.73)	(3.26)	(2.75)
Time	-0.018***	-0.014***	0.035	-0.032*	-0.035***	-0.016***	-0.016**
	(-5.10)	(-6.58)	(1.06)	(-1.97)	(-8.82)	(-2.70)	(-2.42)
R^2 (within)	0.079	0.050	0.344	0.046	0.126	0.202	0.224
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	903	1,550	19†	235	1,129	169	137.000

†We acknowledge that the number of observations on Mining & Quarrying is very low in excess rainfall condition, severely compromising efficiency. Due to a similar issue, we do not conduct a test for every sector.

§ Since the Construction sector is an excess-rain-sensitive industry (see Table A2), we do not present results for deficit rainfall-departure.

Table A5: Capex & rainfall-departure with geographic treatment and control group firms

This table reports the results of excess and deficit rainfall sensitivity analysis using the following general equation:

$$Investment_{it} = \alpha + \beta.(RDyr_{\boldsymbol{t}} \times geo\_treated_{\boldsymbol{i}}) + \boldsymbol{X_{i,t-1}}.\boldsymbol{\delta} + \tau.Time + \nu_i + e_{it}$$

where, $Investment_{it}$ is the investment proxy *Capex* of firm *i* for the year *t*. $geo\_treated$ is a categorical variable that takes the value of one for the firms located in the subdivision with excess rainfall-departure and zero for control firms, $(RDyr_{\boldsymbol{t}} \times geo\_treated_{\boldsymbol{i}})$ is a dummy variable (DiD_{Geo}) which is an interaction of *RDyr* with *geo_treated.* In pairs of years, *RDyr* is a dummy variable that takes the value of zero for the first year which receives normal rain and value of one for the second year which has excess/deficit rainfall. $\boldsymbol{X_{it}}$ is a vector of control variables including *Size, Leverage, Liquidity, OwnCon, M/B* all lagged by one year, as defined in Section 3.3. The *Time* variable absorbs long-running trends. ν_i controls for industry fixed effects and e_{it} is the error term. Standard errors are clustered at firm level. *, ** and *** denote statistical significance at 10%, 5% and 1% significance levels respectively. The total sample period of study is 2001 to 2017 (for excess 2001-2002 and 2002-2003 and for deficit 2007-2008 year pairs have no observations). Source: IMD and CMIE databases.

Year Pair	Excess (RDyr × geo_treated)	(t-stat)	Excess rainfall-departure Subdivisions	Normal rainfall Subdivisions	Deficit (RDyr × geo_treated)	(t-stat)	Deficit rainfall-departure Subdivisions	Normal rainfall Subdivisions	Control Variables	Industry FE
2001-2002	-	-	No Observations	No Observations.	-0.885	(-1.51)	4 , 5 , 6 , 7 , 8 , 10 , 11 , 15 , 19 , 22 , 23 , 24 , 27 , 30 , 31 , 32	1 , 2 , 9 , 14 , 17 , 18 , 28 , 29	Yes	Yes
2002-2003	-	-	No Observations.	No Observations.	0.0736	(0.33)	14	1 , 2 , 9 , 16 , 17 , 18 , 25 , 28 , 29	Yes	Yes
2003-2004	0.0671	(0.98)	17	1 , 2 , 4 , 5 , 7 , 9 , 16 , 18 , 20 , 25 , 28 , 30	**0.0638***	**(1.88)**	8 , 27 , 29	1 , 2 , 4 , 5 , 7 , 9 , 16 , 18 , 20 , 25 , 28 , 30	Yes	Yes
2004-2005	0.0272	(1.27)	10 , 16 , 18 , 19, 23 , 24	1 , 3 , 4 , 5 , 6 , 7 ,9 , 15 , 20 , 22 , 25 , 28 , 30	-0.0301	(-0.99)	2 , 14	1 , 3 , 4 , 5 , 6 , 7 , 9 , 15 , 20 , 22 , 25 , 28 , 30	Yes	Yes
2005-2006	0.0209	(0.55)	7 , 9 , 13 , 20 , 30 , 31	3 , 4 , 5 , 12 , 15 , 21 , 22 , 26 , 27 , 29	0.0617	(0.89)	1 , 6 , 11 , 25 , 28 , 32	3 , 4 , 5 , 12 , 15 , 21 , 22 , 26 , 27 , 29	Yes	Yes
2006-2007	-0.0088	(-0.34)	2 , 4 , 5 , 15 , 16 , 19 , 22 , 24 , 26	3 , 14 , 18 , 21 , 27 , 29	-0.122	(-1.19)	12	3 , 14 , 18 , 21 , 27 , 29	Yes	Yes
2007-2008	-0.0839	(-1.52)	13 , 21	1 , 3 , 7 , 14 , 18 , 25 , 27 , 29 , 30 , 31	-	-	No Observations.	No Observations.	Yes	Yes
2008-2009	-0.0755	(-1.33)	24	1 , 5 , 9 , 15 , 16 , 17 , 19 , 22 , 26 , 24	-0.0259	(-1.21)	2 , 3 , 4 , 6 , 7 , 8 , 10 , 12 , 14 , 18 , 25 , 27 , 28 , 29 , 30	1 , 5 , 9 , 15 , 16 , 17 , 19 , 22 , 26	Yes	Yes
2009-2010	0.0078	(0.2)	16 , 19 , 22	1 , 5 , 13 , 15 , 17 , 20 , 26	0.0166	(0.37)	9	1 , 5 , 13 , 15 , 17 , 20 , 26	Yes	Yes
2010-2011	**-0.09*****	**(-3.51)**	7 , 21 , 30	3 , 5 , 6 , 10 , 12 , 15 , 17 , 20 , 24 , 25 , 26 , 28 , 32	0.0173	(0.18)	1 , 13	3 , 5 , 6 , 10 , 12 , 15 , 17 , 20 , 24 , 25 , 26 , 28 , 32	Yes	Yes
2011-2012	-0.0648	(-0.87)	4	2 , 3 , 5 , 6 , 11 , 12 , 14 , 20 , 22 , 24 , 25 , 27 , 28 , 29	0.00769	(0.37)	8 , 10 , 15 , 17 , 18 , 19 , 26 , 32	2 , 3 , 5 , 6 , 11 , 12 , 14 , 20 , 22 , 24 , 25 , 27 , 28 , 29	Yes	Yes
2012-2013	-0.00672	(-0.35)	5 , 6 , 7 , 16 , 24 , 27 , 28 , 29	3 , 9 , 11 , 12 , 13 , 20 , 21 , 22	-0.362	(-1.08)	3 , 9 , 11 , 12 , 13 , 20 , 21 , 22	1 , 2 , 14 , 25	Yes	Yes
2013-2014	-0.00672	(-0.35)	13	3 , 9 , 19 , 20 , 22 , 26	0.0309	(1.15)	3 , 9 , 19 , 20 , 22 , 26	4 , 8 , 11 , 12 , 18 , 21 , 32	Yes	Yes
2014-2015	-0.0202	(-0.97)	31	1 , 3 , 5 , 7 , 9 , 14 , 20 , 22 , 24 , 25 , 26 , 29 , 30	**-0.0283***	**(-1.66)**	2 , 15 , 16 , 17 , 19	1 , 3 , 5 , 7 , 9 , 14 , 20 , 22 , 24 , 25 , 26 , 29 , 30	Yes	Yes
2015-2016	0.0197	(0.43)	7 , 27 , 30	3 , 9 , 14 , 20 , 22 , 23 , 25 , 29	0.413	(0.29)	1 , 5 , 24 , 26	3 , 9 , 14 , 20 , 22 , 23 , 25 , 29	Yes	Yes
2016-2017	0.122	(1.39)	22 , 23	2 , 3 , 4 , 9 , 13 , 14 , 17 , 19 , 20 , 25 , 28	-0.00402	(-0.06)	8 , 29 , 32	2 , 3 , 4 , 9 , 13 , 14 , 17 , 19 , 20 , 25 , 28	Yes	Yes

Table A6: Positively rain-sensitive industries and excess rainfall-departure

This table reports the results of the general equation in Table 9 with dependent variables as *Sales/total assets*, *EBITDA/total assets*, *PAT/total assets*, $Investment_{it}$ proxied by *Capex* and $Firm\_value_{it}$ proxied by market-to-book value of equity (*M/B)* in columns [1] to [5] respectively. $RDyr$ is a dummy variable that takes the value of one for years with excess rainfall-departure and zero for normal years. *treated* is a categorical variable that takes the value of one for the firms belonging to the positively rain-sensitive industries and zero otherwise for control firms. $(RDyr_t \times treated_i)$ is an interaction term which is the main variable of interest. $\boldsymbol{X_{it}}$ is a vector of control variables including *Size*, *Leverage*, *Liquidity*, *OwnCon*, *M/B*, as defined in Section 3.3. The *Time* variable absorbs long-running trends. γ_i controls for firm fixed effects and e_{it} is the error term. Standard errors are clustered at the industry level. *, ** and *** denote statistical significance at 10%, 5% and 1% significance levels respectively. The study period is 2001 to 2017. Source: IMD and CMIE databases.

	Sales/total assets	*EBITDA/total assets*	*PAT/total assets*	*Capex*	*M/B*
Variables	[1]	[2]	[3]	[4]	[5]
(RDyr × treated)	**0.093***	**0.008****	**0.006***	**0.055*****	**2.735*****
	(1.89)	**(2.01)**	**(1.96)**	**(3.48)**	**(5.92)**
Size	0.069	-0.042***	0.001	0.061***	-5.690***
	(0.45)	(-16.49)	(0.45)	(5.21)	(-11.62)
Leverage	-0.016*	-0.001	-0.002***	-0.002	0.704***
	(-1.81)	(-1.01)	(-4.55)	(-1.52)	(5.87)
Liquidity	-0.008	-0.035***	-0.009*	0.024	-0.105
	(-0.12)	(-4.87)	(-1.71)	(1.50)	(-0.23)
OwnCon	0.003**	0.001***	0.000***	0.000	0.109***
	(2.44)	(4.72)	(3.29)	(0.45)	(9.01)
M/B	0.000***	0.000	0.000	0.000***	
	(3.21)	(1.29)	(1.17)	(3.89)	
Time	-0.032	-0.000	-0.003***	-0.012***	0.016
	(-1.47)	(-1.18)	(-5.60)	(-8.45)	(0.17)
R^2(within)	0.0001	0.094	0.019	0.009	0.045
Firm FE	Yes	Yes	Yes	Yes	Yes
No. of Firms	3,145	3,092	3,163	3,092	3,163
No. of Obs.	14817	14635	14904	14672	14905

Table A7: GDP contribution by the Agriculture sector in high rainfall countries

This table provides information on the GDP contribution from the Agriculture sector. It should be noted that there is a slight deviation in the totals of Panels A and B as provided by the database. Source: World Bank database.

Panel A: Total GDP contribution by the Agriculture sector for countries grouped by income

Income Category	Mean Rainfall in mm	GDP	%GDP	Agri income
High income	1,026.06	54,205.70	1	542.06
Upper middle income	1,303.75	24,446.10	6	1,466.77
Lower middle income	1,236.46	6,702.10	15	1,005.32
Low income	1,028.55	588.2	26	152.93
Total GDP Contribution 2018 USD billions		**85,942.10**		**3,167.07**

Panel B: Total GDP contribution by the Agriculture sector for countries grouped by geography

Geographic Divisions	Mean Rainfall in mm	GDP	%GDP	Agri income
East Asia & Pacific	1,896.48	25,942.40	5	1,297.12
Europe & Central Asia	774.50	23,068.40	2	461.37
North America	626.00	22,264.30	1	222.64
Latin America & Caribbean	1,817.50	5,800.60	5	290.03
Middle East & North Africa	216.24	3,610.50	4	144.42
Sub-Saharan Africa	1,108.17	1,709.90	16	273.58
South Asia	1,494.25	3,452.40	15	517.86
Total GDP Contribution 2018 USD billions		**85,848.50**		**3,207.03**

Panel C: For this panel we identify the countries falling in the top quintile of annual average rainfall. In this subsample of countries, we present the total GDP contribution by the Agriculture sector for the top five countries based on GDP in each income group as per World Bank data.

Country Name	Mean Rainfall in mm	GDP	%GDP	Agri income
High income countries				
Japan	1,668	4,971.3	1	49.71
Switzerland	1,537	705.1	1	7.05
Singapore	2,497	364.2	0	0.00
New Zealand	1,732	204.9	7	14.34
Puerto Rico	2,054	101.1	1	1.01
Total USD billions		**6,346.6**		**72.118**
Upper middle-income countries				
Malaysia	2,875	358.6	8	28.69
Colombia	3,240	331	6	19.86
Ecuador	2,274	108.4	9	9.76
Costa Rica	2,926	60.1	5	3.01
Equatorial Guinea	2,156	13.4	2	0.27
Total USD billions		**871.5**		**61.577**
Lower middle-income countries				
Indonesia	2,702	1,042.2	13	135.49
Philippines	2,348	330.9	9	29.78
Bangladesh	2,666	274	13	35.62
Papua New Guinea	3,142	23.5	18	4.23
Nicaragua	2,280	13.1	15	1.97
Total USD billions		**1,683.7**		**207.082**
Low income countries				
Congo, Dem. Rep.	1,543	47.2	19	8.97
Madagascar	1,513	13.9	24	3.34
Guinea	1,651	10.9	24	2.62
Sierra Leone	2,526	4.1	59	2.42
Liberia	2,391	3.3	37	1.22
Total USD billions		**79.4**		**18.56**

Online Appendix

References for the Appendix Table A2

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