Indian Institute of Management Calcutta

Working Paper Series

WPS No. 901/July 2023

Does an exclusive relationship with government banks matter during climate shocks?

Harish Kamal*
Doctoral Candidate
Finance and Control Group
Indian Institute of Management Calcutta
harishk19@iimcal.ac.in

Samit Paul
Assistant Professor
Finance and Control Group
Indian Institute of Management Calcutta
samit@iimcal.ac.in

Avijit Bansal
Assistant Professor
Finance and Control Group
Indian Institute of Management Calcutta
avijit@iimcal.ac.in

* Corresponding author

Indian Institute of Management Calcutta, Joka, D.H. Road, Kolkata 700104
URL: https://www.iimcal.ac.in/faculty/publications/working-papers/

Does an exclusive relationship with government banks matter during climate shocks?*

Harish Kamal† Samit Paul‡ Avijit Bansal§

First Draft: July 18, 2023

This Draft: July 18, 2023

Abstract

Climate shocks adversely affect firms' operations and performance. Is maintaining an exclusive relationship with government banks (GOBs), a potential solution for firms (GOB firms) to emerge out of distress caused by climate shocks when government aids are unavailable? Using abnormal rainfall conditions as a proxy of climate shock and firms' banking relationship, our study finds that GOB firms, compared to other firms, secure 7.2% higher funds and invest 2.2% more, which enables them to earn 6.7% higher profit during abnormal rainfall periods vis-á-vis normal rainfall periods. While exploring the channels, we find support for the "flight-to-safety" hypothesis, i.e., GOB firms, due to implicit government guarantees associated with GOB relationship, secure loans from banks other than GOBs. Our evidence is inconsistent with the view which suggests there is an implicit commitment of welfare-maximizing GOBs to help the firms, especially GOB firms, during times when firms are adversely affected by climate shocks.

Key words: Government banks, Bank financing, Relationship lending, climate-related shock, corporate investment and performance

JEL classifications: G21, G31

*Author Correspondence: Harish Kamal, Finance Doctoral Candidate at Indian Institute of Management Calcutta; H4-311, Ramanujan Hostel, Indian Institute of Management Calcutta D.H. Road, Joka, Kolkata 700104, Email: harishk19@iimcal.ac.in. We take full responsibility for any errors.

†Finance & Control area, Indian Institute of Management Calcutta, India. harishk19@iimcal.ac.in

‡Finance & Control area, Indian Institute of Management Calcutta, India. samit@iimcal.ac.in

§Finance & Control area, Indian Institute of Management Calcutta, India. avijit@iimcal.ac.in

1. Introduction

Climate shocks adversely affect firms' operations and performance (Pankratz et al., 2023), shareholders wealth (Rao et al., 2022; Dessaint and Matray, 2017), and cost of financing (Javadi and Masum, 2021; Huang et al., 2021). Since credit plays a crucial role in firms' recovery, higher financial frictions during climate shocks prevent them from overcoming financial difficulties (Collier et al., 2020). At the same time, banks being concerned about the uncertainty of firms' loan repayment, resort to the credit rationing (Noth and Schüwer, 2018; Noy, 2009). However, prior studies document that banks increase the supply of credit when the government provides financial aid to firms during climate shock[1,2] (Koetter et al., 2020; Duqi et al., 2021; Rehbein and Ongena, 2022). Yet, we don't know how banks would respond in the absence of any explicit government funding support. Since the estimated cost of financial distress is considerably high on firm value (Almeida and Philippon, 2007; Andrade and Kaplan, 1998), naturally, firms have incentives to find a mechanism to avoid such costs. Is maintaining an exclusive banking relationship, particularly with government banks, an effective mechanism for firms to emerge out of distress caused by climate shocks?

The theoretical literature on relationship lending suggests that banks collect firms' proprietary information over the course of their relationship, thereby mitigating informational frictions (Rajan, 1992). As a result, banks are likely to offer favorable contracting terms and reduce firms' financial constraints, therefore, they should continue lending during times of distress— *"insurance hypothesis"* (Boot and Thakor, 1994; Diamond, 1991; Petersen and Rajan, 1994; Hoshi et al., 1990; Chemmanur and Fulghieri, 1994). Alternatively, the information monopoly enjoyed by relationship banks compared to other banks could allow them to extract informational rent from the firms due to switching costs and information hold-up, particularly more at the times of distress[3]— *"bank hold-up hypothesis"* (Rajan, 1992; Sharpe, 1990; Ioannidou and Ongena, 2010). Recent studies suggest that relationship banks do not help during times of distress (Li et al., 2019). Even if they provide financial support during such times, they tend to extract rents in the periods following the distress (Schäfer, 2019). Given these conflicting views from existing theories and empirical evidence, whether relationship banks enable firms to emerge out of dis-

[1]Recent flooding in Germany— German Cabinet approves some $472 million in first flood aid.
[2]Federal Support for Hurricane Ian Tops $3.3 Billion
[3]Specifically, at the time of distress, relationship banks enjoy greater information advantage and may hold-up firms by charging higher interest rates. This, in turn, increases firms' insolvency risk.

tress caused by climate-related shocks is an empirical question. More importantly, we do not know whether firms having an exclusive relationship with welfare-maximizing government bank enables them to weather out the adverse effects of climate-related shocks, especially in the case when government aids are not available to either firms or banks.

The existing literature on the role of government banks in the credit market suggests that government banks have welfare-maximizing objectives, and their lending is less procyclical (Stiglitz, 1993; Behr et al., 2013; Brei and Schclarek, 2013; Coleman and Feler, 2015). Therefore, during climate shocks, these banks are likely to support the firms with increased supply of credit. Another strand of literature shows that politicians with the motive of winning electoral support often use government banks to provide preferential loans to firms (Sapienza, 2004; Shleifer, 1998; Shleifer and Vishny, 1994; Kumar, 2020). Therefore, in the aftermath of a climate shock, politicians may induce these banks to increase the supply of credit in the affected regions. On the other hand, constraints faced by government banks perhaps limit their ability to increase credit supply. There are two such constraints. First, since the loan officers face considerably high penalties in case of loan defaults, they become highly risk-averse, especially at the time of distress (Banerjee et al., 2006). Second, government banks' capital impairments are financed by the Government, which has a negative association with the fiscal deficit (Acharya, 2020). Therefore, capital impairments caused by climate shocks perhaps induce government banks to opt for a policy that delays recapitalization, such as loan forbearance, instead of increasing supply of fresh loans. In sum, it is not apparent whether government banks would be able to mitigate the adverse effects on the firms caused by climate-related shocks.

Investigating the role of firms' exclusive relationship with government banks in recovery from climate-related shock is quite challenging as it requires four essential components for appropriate identification. First, it requires local climate-related exogenous events that have large effects on firms' operations. Second, bank loans should be the main source of the external finance for firms so that banking relationships are crucial. This is important because most of the existing studies explore the role of banks during climate-related shocks in developed economies, where firms have access to a large number of alternative financing[4] (Duqi et al., 2021; Cortés and Strahan, 2017). Third, firms should be operating in an economy where government banks play a prominent role

[4]For instance, Duqi et al. (2021) study natural disasters in US context, and find that disaster-affected firms use US government subsidised loans instead of bank loans; owing to such explicit government guarantees reduces firms credit risk and encourage unaffected region banks to increase the supply in the affected regions (Cortés and Strahan, 2017). Therefore, such government aids pose a serious threat to identifying the role of banks or banking relationship in attenuating the adverse effects on firms' operations caused by any climate-related shocks.

in credit market. Fourth, granular data on firms' banking relationships needs to be available on yearly basis. In developed economies, prominence of bank loans is little and government banks do not play a major role in credit market. More importantly, firms of developed nations, such as US firms, are less dependent on the climate condition of the area of operation. Hence, we need to conduct our study in the context of an emerging economy. However, in the case of emerging economies, meeting all four essential components are also difficult. Especially, there is a dearth of relevant banking relationship data in most of the emerging economies. Further, a large effect on firms' operations due to unexpected abnormal rainfall is not so common for all emerging economies.

Hence, we conduct our study in an unique setting where all necessary conditions are satisfied for identification. Fortunately, the Indian context meets all such conditions. First, India is a tropical region that experience unpredictable rainfall variations every year, especially during the monsoon season. This variation of rain has considerable large effects on firms' operations and market valuations (Rao et al., 2022). Therefore, we consider the large rainfall departure as an exogenous climate shock. Second, bank loans are the main source of external finance for Indian firms. Third, government banks dominate the Indian credit market, as shown in the Figure 1. Therefore objectives, incentive structure, and constraints faced by these banks must have significant effects on financing of firms (Srinivasan and Thampy, 2017). Fourth, the Indian companies are required to disclose the list of bankers in their financial statements, which allows us to identify firms that have an exclusive relationship with GOBs and firms that do not. Thus, the Indian context provides us with an ideal laboratory setting to investigate the role of firms' exclusive relationship with GOBs in overcoming their financial difficulties when their area of operations are affected by unanticipated abnormal rainfall.

Using abnormal rainfall as an exogenous climate shock and exploiting firms' banking relationships at the time of climate shock, we conduct our study. We find that firms having an exclusive relationship with GOBs attenuate their financial constraints. As a result, they secure a higher level of debt than that of non-GOB firms during abnormal rainfall periods compared to normal rainfall periods. Particularly, during abnormal rainfall periods, GOB firms are able to attract higher levels of bank debt, secured borrowing, and long-term debt in comparison to non-GOB firms. Further, we investigate whether this benefit is derived by all GOB firms uniformly. Our analysis of heterogeneous treatment effect on treated suggests that GOB firms with higher tangible assets, lower liquid assets, and lower profitability receive significantly higher levels of funding during unanticipated abnormal rainfall conditions.

While exploring potential channels of this funding, we find that implicit government guarantee associated with GOB firms is mainly driving the results— consistent with the view of *"flight-to-safety"* (Caballero and Krishnamurthy, 2008). Interestingly, we do not find support for the most obvious channels. First, there is no evidence of welfare-maximizing GOBs increasing the supply of credit to affected firms. Second, firms maintaining multiple banking relationships are experiencing higher financial constraints. This indicates that firms' liquidity risk diversification appears to be not beneficial during abnormal rainfall periods. To be more specific, we find no significant change in the level of debt for firms maintaining existing banking associations (GOBs remain GOB after abnormal rainfall or non-GOB firms remain non-GOB after the abnormal rainfall year) following abnormal rainfall conditions. These findings can be explained in the following way. The constraints faced by the GOBs: stringent incentive structure[5] and capital constraints[6] as highlighted above, perhaps prevent them from increasing the credit supply during abnormal rainfall conditions when government aids are unavailable. As a result, they may resort to the forbearance policy, as they did in the aftermath of global financial crisis (Chari et al., 2021), thereby, perhaps, declining profitable lending opportunities - such as loan demand from healthy GOB firms (Banerjee et al., 2006). In such a scenario, the profit-maximizing banks may encash these profitable lending opportunities denied by GOBs, by granting loans to GOB firms, specifically to healthy GOB firms. The implicit government guarantee associated with GOB firms makes them a safer lending option, compared to existing borrowers, and an opportunity to reduce the riskiness of banks' loan portfolios during climate shocks. This is exactly what we have found in our study. Specifically, during the time of abnormal rainfall, banks other than GOBs increase the amount of lending to healthy GOB firms compared to other firms.

Next, we move our attention towards firms' investments following the abnormal rainfall periods. Since GOB firms are able to secure more funds than that of non-GOB firms during the time of abnormal rainfall periods, they either use these funds to increase capital expenditure (Aretz et al., 2019) or accumulate cash buffers to avoid liquidity shortfalls (Dessaint and Matray,

[5]GOBs' loan officers incentives are structured in such a way that they face considerably large bad loan penalties but little reward for better loan performance, making them highly risk-averse, particularly during times of distress when adverse selection costs significantly increase

[6]The impairment of capital, which increase during times of distress, in the GOBs needs to be recapitalized by the government, thereby increasing the government fiscal burden and inducing the government to opt for forebears policy

2017). Consistent with our hypothesis, we find that GOB firms significantly increase the level of investment instead of keeping a cash buffer during abnormal rainfall periods vis-á-vis normal rainfall periods. This is consistent with risk-shifting hypothesis of (Jensen and Meckling, 1976; Black and Scholes, 1973), which suggest that managers shift their investment strategy from taking safe investments to risky investment projects during the time of distress. By doing this, they act in the best interest of the shareholders.

Finally, we explore the firms' performance following the abnormal rainfall. We find that GOB firms' profitability is higher than that of non-GOB firms following abnormal rainfall condition periods. It indicates that GOB firms being able to access finance to immediately invest in risky but profitable projects to regain the lost capacity, outperform non-GOB counterparts during episodes of abnormal rainfall vis-á-vis normal rainfall. This is consistent with the notion that maintaining an exclusive banking relationship is positively associated with the firms' profitability (Degryse and Ongena, 2001). This, in turn, enables firms to emerge out of distress (Rosenfeld, 2014). Our results are in contrast with Weinstein and Yafeh (1998). It argues that firms having close ties with banks face lower financial constraints, but this does not lead to higher profitability due to higher cost of capital for these firms than other comparable firms. Moreover, banks discourage these firms to invest in risky but profitable investment projects.

Our study contributes to the four strands of the literature. First, we contribute to the burgeoning literature that studies the effects of climate-related shocks on credit supply and the role of banks. Researchers have primarily explored banks' response to climate-related shock or natural disaster when explicit government aids are available to the affected firms and banks (Noth and Schüwer, 2018; Noy, 2009; Schüwer et al., 2019; Koetter et al., 2020; Duqi et al., 2021; Cortés and Strahan, 2017). However, there is very little work on how do banks respond to climate-related shocks when no government support is available to the firms and banks. Our unique laboratory setting, the Indian context, enables us to present the first comprehensive evidence of banks' willingness to supply credit during times of distress caused by climate-related shocks and its implications on the firms' investment and performance.

Second, our study is related to the extant literature on relationship lending. Some researches suggest that banks provide financial insurance during times of distress by providing necessary financial support to their clients to overcome financial difficulties (Petersen and Rajan, 1994; Diamond, 1991; Berger et al., 2017; Bolton et al., 2016; Beck et al., 2018; Chemmanur and

Fulghieri, 1994). Others, however, show that banks often hold-up by charging higher interest rates or collateral requirements during the times of distress (Santos and Winton, 2008; Rajan, 1992; Sharpe, 1990; Schäfer, 2019). This is more so when banks face lower competition and borrowers bear high transportation cost (Degryse and Ongena, 2005) or there are issues of high switching costs and information lock-in (Ioannidou and Ongena, 2010). However, from the extant literature, we do not really know how beneficial is the firms' exclusive relationship with GOBs when they are adversely impacted by the climate-related shock. We fill this gap by showing that GOB firms reap the benefits of having a lending relationship with GOBs when they are adversely affected by abnormal rainfall.

Third, our study examines the channels of access to finance for GOB firms during climate shocks. Our result supports the *"flight-to-safety"* hypothesis, wherein GOB firms, being considered safe due to their implicit government guarantee, are able to secure a higher amount of credit compared to non-GOB firms during the climate shock. Surprisingly, the primary source of this credit is non-GOBs (i.e., banks other than GOBs) rather than GOBs. This is inconsistent with the view that there is an implicit commitment of welfare-maximizing GOBs to help the firms, especially GOB firms, during the period of difficulties (Stiglitz, 1993; Chen et al., 2016; Brei and Schclarek, 2013, 2015; Ogura, 2018). Hence, our finding is surprising and counterintuitive. Moreover, we also contribute to the literature that studies the impact of various constraints on GOB policies (Acharya, 2020; Banerjee et al., 2005, 2004, 2006). We show that GOB firms do not receive funds from GOBs during the climate shock when no government aids are available. It implies that, during the times of distress, GOBs' capital constraints and stringent incentive structure prevent their loan officers from providing recovery lending. However, these firms are able to secure finance from banks other than GOBs. Thus, our study shares a crucial insight, i.e., firms' exclusive association with GOBs benefits them in raising funds during climate shock, no matter whether the benefit is coming from GOBs. Hence, such an association could be a potential solution for firms to emerge out of disruptions caused by such shocks. This evidence is consistent with the view that non-relationship lenders opportunistically lend to safe borrowers when adverse selection risk increases due to climate shocks (Ioannidou and Ongena, 2010). From firms' point of view, this could be one of the incentives for firms to build an exclusive relationship with GOB, despite the cost associated with a GOB relationship.

Finally, the extant literature on relationship lending primarily focuses on access to finance, rent extraction by banks, and the hold-up problem of firms. However, there is limited attention on the implication of the cost and benefits of relationship lending on firms' performance, especially during times of distress caused by climate shock. The closest papers to our study argue that lending relationships could have positive effects on firms' profitability due to ease of access to finance (Degryse and Ongena, 2001). Others, however, suggest that banks expropriate informational rents (Ioannidou and Ongena, 2010). As a result, the ease of access to finance does not convert into higher investments and profitability (Weinstein and Yafeh, 1998). Moreover, some recent studies suggest that borrowers in distress don't derive benefits from their banking relationships (Li et al., 2019). On the other hand, Schäfer (2019) show that relationship banks absorb delinquency risk, and offer financing when firms are in distress. However, banks extract rents following the emergence of firms from distress. Apparently, these studies do not focus on the firms' performance following the episodes of borrowers' distress, particularly the distress caused by climate shock. Therefore, our study contributes to this pool of literature by showing the positive impact of banking relationships with GOBs on GOB firms' performance resulted from profitable investments using credit obtained during periods of abnormal rainfall.

The present study is structured as follows: section 2 describes the institutional background of the study; section 3 develops relevant hypotheses; section 4 presents the data and methodology adopted; section 5 discusses the findings; section 6 checks the robustness of findings; and finally, section 7 concludes the study.

2. Institutional Background

2.1. Rainfall conditions in India

Since India is a tropical region, the amount of rainfall significantly affects the real activities and economic growth[7]. Rao et al. (2022) show that extreme rainfall adversely affects the rain-sensitive firms market valuations, thereby having considerable effects on the firm's investment policy. Moreover, the majority of the Indian regions receive the most of the annual rainfall, ranging from 70% to 90%, during the monsoon season— starting from June till September month in a given year. The studies have found that there are considerable unanticipated variations in the annual rainfall, over the years, in India during the monsoon season (e.g., Gadgil,

[7] https://mintgenie.livemint.com/news/markets/why-is-the-current-monsoon-so-crucial-for-the-indian-economy-and-the-rbi-151658984552948

2003). The researchers have been studying these variations to understand the main drivers of Indian monsoon (Kumar et al., 1999; Ashok et al., 2001; Kucharski et al., 2007; Gadgil et al., 2003). They suggest that monsoon rainfall in India is determined by the complex equilibrium of tropical teleconnections, which mainly includes El Nino Southern Oscillation (ENSO) cycle, the tropical Atlantic variability (ATL), the Indian Ocean Dipole (IOD), the Equatorial Indian Ocean Oscillation (EQUINOO), and preceding winter ENSO.

The ENSO mainly affect the Indian monsoon rainfall, in a cycle of El Nino (La Nina), the Indian sub-continent generally experiences deficit (excess) rainfall in a given year. However, the ENSO effect can be moderated by the positive ATL (cooler Atlantic ocean), IOD (cooler Indian ocean) and EQUINOO (increased cloud formation) cycle, which is associated with high pressure in the southeastern part of the Indian ocean, leading to heavy rainfall in a particular year[8]. It is worth noting that there could be number of possible combination of tropical teleconnections that might be working in a given year. In other words, it is hard to ex-ante quantify which mechanism is going to dominate the others in a given year. Therefore, it is impossible to predict the amount of rainfall during the monsoon season, suggesting that by no means the Indian firms could have ex-ante adjusted their operations, capital structure, and banking relationships to limit the effects of abnormal rainfall conditions in a particular year. Hence, the unanticipated Indian monsoon rainfall provides us with a unique exogenous shock, just like a laboratory experimental set-up, to study the impact of such abnormal rainfall on the firms' debt structure, investments, and profitability. Therefore, we use abnormal rainfall in a given year as an exogenous shock in our study.

2.2. Indian Banking system

The Indian banking system is regulated by the central bank of India, the Reserve Bank of India (RBI). The banks are required to have an RBI charter to conduct business in India, this is unlike the US where banks can have federal or state charters. Mainly, there three banks that provide financial services in Indian market[9], which includes government-owned banks (GOBs), privately

[8] https://india.mongabay.com/2022/04/explainer-what-factors-affect-the-indian-summer-monsoon/

[9] There are other banks such as regional rural banks (RRBs), small finance banks (SFB), and payment banks (PBs). These banks have small market share and operate in rural and agriculture sector. The RRBs and SFBs take deposits and provide small-ticket loans for agricultural activities, small businesses, and human development activities. These banks typically operate in rural areas to prevent market failure. The PBs can take small ticket deposits (up to ₹200,000 or $2,400) but are not allowed to give loans, primarily providing transaction and deposit services to the household sector.

owned banks (POBs), and foreign-owned banks (FOBs). Out of all the banks, GOBs dominate the credit market and deposit market, having on average more than 70% of the market share in both markets, as shown in Figure 1. Importantly, India does not have an active public bond market therefore bank loans are the main source of external finance for corporate sector when the need arises, particularly loans from GOBs. As a consequence, it is reasonable to expect that objective of the GOBs and the incentive structure of the GOB officials will have a considerable impact on the firms' decision-making and real activities.

From the prior studies, we know that political and bureaucratic involvement in the GOBs' considerably impacts their day-to-day functioning and bank policies (see, Kumar, 2020; Bery, 1994; Ghosh, 2000). In addition to this, RBI requires banks, GOBs in particular, to achieve a required level of loan growth and to give subsidised loans— such as 40% of total lending should be given to the priority sector, which mainly includes agriculture, Micro, Small and Medium Enterprises (MSMEs), export credit, housing, education, social infrastructure, and renewable energy sectors[10]. More importantly, the incentive structure of the GOBs rewards little for the improvement in loan performance but penalises heavily in case of bad loans; corruption charges can be probed against the loan officers for giving bad loans. As a consequence, such incentives make GOB officials risk-averse[11]: they are reluctant to give fresh loans (under-lending) and decline profitable lending opportunities such as not lending to the existing profitable corporate borrowers (Banerjee et al., 2006, 2004, 2005). In addition, GOBs' loan officers tend to evergreen the bad loans during their tenure at a particular branch to avoid the cost of defaulting loans (Tantri, 2021). Thus, it is apparent that GOBs' incentive structure induce loan officers to hide bad loans to the extent possible.

Moreover, it is worth noting that the capital shortfalls in GOBs arising due to an increase in bad loans increase the fiscal burden of the government therefore, it is optimal for the government to opt for a forbearance policy instead of recapitalization, particularly during the crisis times, because latter will further increase the government's fiscal pressure (Acharya, 2020). During the time of the global financial crisis of 2008-09, the RBI introduced the forbearance policy that lowered the provision rate on the loans that were affected by the crisis. Chari et al. (2021)

[10] https://www.rbi.org.in/Scripts/BS_ViewMasDirections.aspx?id=11959

[11] The risk-aversion or reluctance to give credit by the GOBs can be observed in the Figure 1, where it is apparent that even though GOBs have most of the deposits/funding available in Indian market, still the credit market share is declining in the recent years. Given that India is one of the fastest growing economy in the recent years, it implies that GOBs perhaps declining profitable lending opportunities, consistent with the findings of (Banerjee et al., 2004).

studied this policy, and find that the policy gave license to the banks to hide sub-standard loans, the loans were given to the firms facing serious solvency issues and also increased the reallocation of credit towards the weakest firms from the healthy firms. The policy essentially allowed banks to hide their true asset quality and exploited the regulatory arbitrage, particularly in the case of GOBs. This further lends support to the above view that GOBs' loan officers have a tendency to avoid serious penalties arising from bad loans. To do so, they either forebear the bad loans using a forbearance policy or evergreen the bad loans to avoid such costs. Therefore, it is reasonable to expect that during the time of distress, GOBs are likely to forebear the loans or evergreen their bad loans, and certainly, they are less likely to give fresh loans or provide more loans to their profitable or distressed borrowers due to serious default penalties associated with defaulting loans.

Overall, government banks' objectives and incentive structure of loan officers undermine their operational flexibility and weaken the incentives to improve loan performance, thereby leading to lower productivity of GOB employees compared to private banks counterparts[12]. Hence, it makes the Indian context an ideal institutional setting to study the role of firms' exclusive banking relationship with GOBs in mitigating the adverse effects occurring from non-crisis-related shock. That is when firms' operations are disrupted by unanticipated abnormal rainfall conditions in their local area of operation, in the context of our study.

3. Hypothesis Development

As highlighted above, we attempt to study the role of firms' exclusive relationship with GOBs in mitigating their location-specific climate-related shock, i.e. abnormal rainfall conditions in the firms' area of operations. Recent studies suggest that firms prone to climate-related shocks are exposed to higher default risk, thereby, inducing banks to charge higher interest rates (e.g., Huang et al., 2021; Javadi and Masum, 2021). The reason is that sudden changes in the climate conditions in firms' locations adversely affect their operations and financial performance (Pankratz et al., 2023). Therefore, during periods of abnormal rainfall, firms' demand for loans would normally increase. However, they may not obtain adequate credit due to their higher perceived riskiness that lowers banks' willingness to supply the credit (e.g., Berg and Schrader, 2012). In such scenario, government banks with social welfare objectives may provide financial

[12] *"India's Banks Are Seen as Antiquated and Unproductive"– The New York Times, 2007* –https://www.nytimes.com/2007/03/23/business/worldbusiness/23india.html

support to the affected firms. Thus, firms having an exclusive relationship with the government banks, i.e. GOB firms, may face lower financial constraints than non-GOB firms during the period of shocks. This is mainly due to three reasons. First, the relationship bankers, GOBs, are likely to provide the required support in terms of restructuring the existing loans, forbearing the loans, or providing fresh loans in adverse situation (e.g., Hoshi et al., 1990). Second, GOBs with social welfare objectives are likely to provide additional funds to GOB firms affected by abnormal rainfall, thereby internalise the increased adverse selection cost. In addition to this, banks having market power, GOBs in Indian context, are usually highly profitable which allow them generate higher reserves during the normal periods (in our case, normal rainfall conditions). Therefore, these banks use the reserves to absorb the increased adverse selection cost without increasing interest rates during the times of distress (Crawford et al., 2018), and thus, prevent the credit rationing. Third, although the average riskiness of the borrowers increases (disruptions in firms operations increase information asymmetry between firms and lenders, leading to increased adverse selection cost) during the period of abnormal rainfall, an exclusive relationship with GOBs is likely to signal the safety associated with GOB firms compared to other firms[13] (e.g., Khwaja and Mian, 2005). Particularly, the implicit government guarantee to GOB firms makes them less risky than other comparable firms, and accordingly, funds are likely to flow towards the GOBs firms in time of distress. Hence, we conjecture that GOB firms are more likely to secure the required funds than non-GOB firms during the abnormal rainfall year vis-á-vis normal rainfall year. Thus, we have our first hypothesis:

Hypothesis 1

H1: GOB firms due to their exclusive relationship with GOBs secure higher level of funding than non-GOB firms during the abnormal rainfall period compared to normal period

If GOB firms actually secure higher level of funding than non-GOB firms during abnormal rainfall, it should be reflected in the level of investment by GOB firms in post-abnormal rainfall period. From the prior literature, we know that firms' operations, on an average, are adversely affected by extreme climate changes in their area of operations (e.g., Rao et al., 2022; Pankratz et al., 2023). Given this premise, firms in the abnormal rainfall-affected regions are more likely to increase investment in order to regain their prior level of operations at a particular year.

[13] This is due to the government and politicians typically provide financial support to GOB associated firms through government banks during times of distress (i.e., implicit government guarantee to GOB firms, which makes these firms less risky at the time of distress than other comparable firms). As a consequence, the funds typically flow towards relatively safe assets/less-risky firms (in our case, GOB firms) from riskier assets/firms (non-GOB firms) during times of distress.

Hence, we conjecture that the increase in the investments of the GOB firms is likely to be greater than non-GOB firms during the abnormal rainfall year vis-á-vis normal rainfall year. This materialized into our second hypothesis:

Hypothesis 2

H2: The level of investment is higher for the GOB firms vis-á-vis non-GOB firms during the abnormal rainfall period compared to that of normal period.

Further, the risk-shifting theory suggests that managers typically change their investment policy from safe to risky profitable investment projects during times of distress, thereby acting in the best interest of the shareholders (Jensen and Meckling, 1976; Black and Scholes, 1973). Besides, we know that extreme climate changes adversely affect firms' performance (Pankratz et al., 2023) and their market valuations (Rao et al., 2022). Therefore, it is optimal for managers to shift their investments in such a way so that it leads to regaining the lost market valuations (or, firm profitability) and acting in the best interest of the shareholders. Investing in risky but profitable projects make firms able to perform better than other comparable firms. Based on this, we argue that in an abnormal rainfall year, GOB firms compared to non-GOB firms are more likely to secure funds and immediately invest in risky but profitable projects to regain production capacity. It indicates that firms having exclusive relationships with GOBs mitigate the adverse effects of abnormal rainfall on their operations and outperform the other comparable firms during such trying times. Hence, we conjecture that GOB firms perform better than non-GOB firms during abnormal rainfall period compared to normal period. Thus, we have our third hypothesis:

Hypothesis 3

H3: GOB firms perform better than non-GOB firms during the abnormal rainfall period compared to that of the normal period

4. Data and Methodology

4.1. Data and sample

We obtain rainfall data from the Indian Meteorological Department (IMD), Ministry of Earth Sciences website. The dataset contains the monthly normal and actual rainfall data for 36 meteorological subdivisions belonging to several districts of the different Indian states. These subdivisions essentially have homogeneous rainfall conditions. The IMD estimates the monthly normal and actual rainfall for 36 meteorological subdivisions using the daily rainfall data obtained from 3500 rain-gauge stations spread across India. For each subdivision, the IMD computes normal rainfall using the historical records of the last 50 years, from 1951 to 2000, which is known as Long-Period Average. Since most regions receive the majority of annual rainfall during monsoon season in India[14]. Therefore, large departures from normal, long-period average rainfall during the monsoon season would have significant economy-wide effects, from farmers to industries[15]. We, therefore, use meteorological subdivision level monsoon season (months of June-July-August-September) rainfall data for our study.

Using the subdivisions' normal and actual rainfall statistics, IMD computes the rainfall departure, i.e., the difference between actual and normal rainfall for each subdivision. If the rainfall departure is between $\pm 19\%$, it is considered normal rainfall conditions and otherwise abnormal (excess or deficit) rainfall conditions. We, instead of using an arbitrary value of $\pm 19\%$ to categorize normal and abnormal rainfall, use a slightly different and more conservative approach. Specifically, using the subdivision-year panel data, we first sort the rainfall departure data into quintiles (highest to lowest). We then categorize the quintiles into two groups; both the extreme quintiles (i.e., 5^{th} and 1^{st} quintiles) are categorized as abnormal rainfall condition, and mid-quintiles (3^{rd}) is categorized as normal rainfall conditions. We do not consider the 4^{th} and 2^{nd} quintiles to eliminate the potential noise. Therefore, each year, some subdivisions encounter unexpected abnormal rainfall, and others receive the normal or expected levels of rainfall.

Further, we draw companies level data from the Prowess database maintained by the Centre for Monitoring Indian Economy (CMIE). The database has the most comprehensive data on Indian firms, and covers the financial statement information of listed and unlisted firms. It is widely used by researchers (e.g., Vig, 2013; Gopalan et al., 2007; Srinivasan and Thampy, 2017) to conduct studies on Indian firms. The database not only contains the financial information, i.e., balance sheet, income statement, and cash flow statements data, but also have useful firm identifiers such as data on firms' location, their year of incorporation, industry, affiliation to business groups, and ownership structure.

Moreover, Prowess contains data on the list of all the banks with whom the firm has a rela-

[14] https://www.cpc.ncep.noaa.gov/products/assessments/assess_96/india.html

[15] *"Do monsoon rains really matter to economy and market"– The Economic Times, 2018* – https://economictimes.indiatimes.com/markets/stocks/news/do-monsoon-rains-really-matter-to-economy-and-market/articleshow/63728449.cms?from=mdr

tionship in a particular financial year. We use this list to define the firm's banking relationship on a yearly basis. Specifically, we first categorize all the banks according to their ownership: government-owned banks (GOBs), privately-owned banks (POBs), and foreign-owned banks (FOBs). Thereafter, using the firms' bankers list, we categorize the firms into two groups. If the firm's banker list consists of all the GOBs, then we categorize that firm as a GOB firm for that particular year, indicating that the firm has an exclusive relationship with GOBs in a given year. In case the firm's banker list consists of all the private banks, foreign banks, or a mix of all the banks, it implies the firm does not have an exclusive relationship with GOBs., hence we classify such firms as non-GOB firms in that particular year. Srinivasan and Thampy (2017) adopt a similar approach to classify a firm based on its bankers.

We use all the non-financial, non-government public, and private companies available in the database during the period from 2000 to 2020. We consider the firms in our sample that have no missing data on total assets, total debt, tangibility, and liquidity. In addition, a firm is required to have at least |10 million of total assets, positive leverage, positive book value of equity capital, and at least three years of financial data. We also require a firm to have data on banking relationships. Finally, we combine our subdivision-level rainfall data from IMD with firm-level data using the location of the firm. Our final sample consists of 31,899 firm-year observations of non-financial firms. In some of the analyses, the observations may vary owing to missing data on some of the variables. The detailed definition of all the variables is provided in Table A1. We report the distribution of the sample by industry, meteorological subdivision-wise distribution of firms, and distribution of GOB firms and non-GOB firms that are exposed to unexpected abnormal and normal rainfall over the sample years in Table A2, Table A3, and Table A4, respectively.

Table 1 reports the descriptive statistics of the key variables by firm-year observation for the sample period of 2000 to 2020. The rainfall departure with a considerably large standard deviation of 26.48 indicates that Indian firms are exposed to extreme rainfall conditions. Crucially, this evident that Indian weather conditions provide us with an ideal experimental laboratory setting to explore the impact of abnormal rainfall on the firms.

Table 2 reports the descriptive statistics for firm-year grouped by the firms' bank relationship– firms that have an exclusive relationship with GOBs (GOB firms) in a particular year and non-GOB firms that do not maintain an exclusive relationship with the GOBs. We find that relative to non-GOB firms, the firms' having an exclusive relationship with GOBs are, on average smaller in size, higher leverage, greater bank debt, lower interest expense, lower cash holding, higher liquidity, lower return on assets, more tangible assets, and are younger firms. Therefore, it indicates that GOB firms are more financially constrained than that of non-GOB firms. Since GOBs have welfare and developmental goals, therefore, it is natural to find that financially constrained firms have exclusive relationships with GOBs. These characteristics of the GOB firms are consistent with findings of (Srinivasan and Thampy, 2017; Sapienza, 2004).

4.2. Identification and Empirical approach

The main objective of this paper is to identify the impact of the firms-specific exogenous shock on the debt structure/borrowing of the firms that have an exclusive relationship with the GOBs than those firms that do not have such a relationship. To do so, we exploit the role of GOBs' banking relationship for the firms in absorbing unanticipated climate-related shocks, particularly when unexpected abnormal rainfall seasons occur in the firms' area of operation. Studying the firms' banking relationship with GOBs when firms experience rainfall shocks also allows us to understand how GOBs respond to such climate-related shocks when government support is not available. During macroeconomic shocks, such as the financial crisis, the government intervenes in the market from multiple channels to support the economy, which poses serious challenges in teasing out the benefits of the GOB banking relationship to the firms, suggesting that the relationship is endogenous.

Given this premise, the identification requires four essential components. First, it requires a local exogenous shock which significantly impacts the firms' operations. For this, we choose climate-related exogenous events, that is, variations in the rainfall in the location of the firms' operation. To satisfy the exogeneity, the variation in the rainfall should have large and economically meaningful effects on the firms' operations and real activities, and by no means can the firms predict the variations in the rainfall in a given year. Second, bank loans should be the main source of external finance so that banking relationships play an important role in the economy. Third, firms should be operating in an economy where government banks play a prominent role in reducing firms' financial constraints. Fourth, the availability of granular data on firms' banking relationships on a yearly basis.

Fortunately, the Indian context meets all the components needed to conduct the study. First, India is a tropical region and has large unpredictable rainfall variations each year during the monsoon season[16], which, in turn, adversely affects firms' operations and market valuations (Rao et al., 2022). Therefore, we exploit the disruption caused by large rainfall departure in firms' areas of operation as an exogenous shock. Second, the inactivity in the Indian bond market makes bank loans a main source of external finance for firms. Third, government banks dominate the Indian credit market, as shown in the Figure 1, implying that the objectives, incentives, and constraints faced by GOBs will have considerable effects on the firms (Srinivasan and Thampy, 2017). Fourth, the Indian firms are required to disclose their banking relationships in their financial statements which allows us to identify the firms that have an exclusive relationship with GOBs and firms that do not. Therefore, the Indian context provides us with an ideal laboratory setting to investigate the role of GOBs' banking relationships on the firms when they are exposed to unanticipated rainfall conditions in their local areas.

In order to formally test this, first, we use unanticipated rainfall in the local area of the firms as an exogenous shock in a given year. To be specific, every year, we have two sets of firms, one set of firms located in the regions experiencing abnormal rainfall and another set of firms located in the regions experiencing normal rainfall. Second, we rely on firms' banking relationship lists to identify a firm as a GOB firm and a non-GOB firm in a given year. That is, a firm is considered a GOB firm if that firm has banking relationships only with GOBs, and otherwise, we consider that firm as a non-GOB firm. In other words, in a particular year, we consider the GOB firms as treated firms and non-GOBs as control firms.

In our setting, our exogenous shock follows "on-off" scenario or is staggered in nature, where each year, some regions experience abnormal rainfall and other regions experience normal rainfall conditions. According to this scenario, for a particular firm, the "on" period includes those years when their region of operation experiences abnormal rainfall, whereas "off" periods are those years when their region of operation experiences normal rainfall conditions. Therefore, each year we would have some firms that receive abnormal rainfall and other firms experiencing normal rainfall. Next, to study whether firms' having exclusive GOBs relationship benefits when firms are exposed to abnormal rainfall conditions compared to other non-GOB firms that do not have such banking relationships. To do so, we employ the following regression specification:

$$Y_{i,t} = \gamma_i + \delta_{s\times j\times t} + \beta_1 \, Abnormal\ Rain_{s,t} \times GOB_{i,t-1} + \beta X_{i,t-1} + \epsilon_{it} \tag{1}$$

[16][17]

where, $Y_{i,t}$ is the dependent variable in the regression equation. $Abnormal\ Rain_{s,t}$ is an indicator variable that takes a value of 1 if firm i by the virtue of its location in subdivision s experiences abnormal rains in year t. The rainfall data is collected at a subdivision-year level, and the subdivisions are classified by the Indian Meteorological Department (IMD). A subdivision consists of multiple pincodes, and we map the location of a firm to a particular subdivision based on the pincode of the firm. Hence, any subdivision may contain multiple firms at any time. If a subdivision experiences abnormal rainfall in year t, then $Abnormal\ Rain_{s,t}$ takes a value of 1 for all firms in that particular subdivision in year t. $GOB_{i,t-1}$ is a dummy variable that takes the value 1 for the firms that exclusively borrow from government-owned banks (GOB firms) at the beginning of the year and 0 otherwise. The interaction variable $Abnormal\ Rain_{s,t} \times GOB_{i,t-1}$ is the main variable of interest. The β_1 captures the causal effect of abnormal rainfall on the GOB firms' outcome variables of interest, such as credit, investments, and profitability. γ_i and $\delta_{s \times j \times t}$ is firm and subdivision $\times$ industry $\times$ year fixed effects, respectively. $X_{i,t-1}$ is a set of control variables size, liquidity, profitability, tangibility, and age. The selection of control variables follows (e.g., Bae and Goyal, 2009; Vig, 2013; Thapa et al., 2020; Bose et al., 2021). We lagged time-varying control variables by one period to eliminate possible simultaneity problems. This estimation approach is similar to triple difference-in-difference due to both the staggered nature of abnormal rainfall across subdivisions and the difference in banking relationships across the firms in a given year.

We add two kinds of fixed effects in the estimations to account for the impact of time-invariant and time-variant unobservable heterogeneities. First, we add firm-level fixed effects (γ_i) to account for the influence of any time-invariant firm-level characteristics, such as its location. Second, we account for the unobservable characteristics that can vary with time (t) at the subdivision (s), industry (j), and subdivision-industry levels by including ($\delta_{s \times j \times t}$). For example, the sentiment concerning a particular industry might be high in some years, like pharmaceuticals during the global pandemic. Furthermore, a specific development in a particular year in a subdivision, such as the local elections, can impact the policies of all the firms in that geographic location. Lastly, any time-varying unobservable factor at a subdivision-industry level that impacts the output and policies of firms will also be accounted for by $\delta_{s \times j \times t}$. This also allows the identification to come from comparing firms varying in terms of their banking relationships belonging to the same industry and subdivision. Since the rainfall data from IMD is at a subdivision-year level, the coefficient of $Abnormal\ Rain_{s,t}$ will get absorbed by $\delta_{s \times j \times t}$. In all the estimations, we compute robust standard errors clustered at the subdivision level, the level at which exogenous shock occurs.

5. Findings and discussion

5.1. Impact on firm borrowing

In this section, we explore the impact of unexpected abnormal rainfall on GOB firms' debt structure than that of non-GOB firms, compared to when these firms experience normal rainfall conditions. We mainly measure firms' level of debt as total debt scaled by the beginning of the year total assets and also consider total debt net of cash holding scaled by the beginning of the year total assets, as in (Vig, 2013). We use these debt measures as dependent variables in our baseline regression specification, Equation 1. To control the influence of firm-level heterogeneity on their debt structure, we include firm-fixed effects in all our regressions. We also include subdivision-year fixed effects to control time-varying economic changes at the subdivision level. We report the result of the impact of unexpected abnormal rainfall on firms that have an exclusive relationship with GOBs than those who do not have, in Table 3. In columns (1) to (4), we report the impact of firms' debt structure using our main measure (i.e., total debt scaled by the beginning of the year total assets) as the dependent variable in Equation 1. In all the estimated specifications, we find that firms having an exclusive relationship with GOBs has significantly higher leverage than firms that do not have an exclusive relationship with GOBs when firms are exposed to unexpected abnormal rainfall conditions compared to normal or expected rainfall. In column 1, we report the basic results with no control variables. It essentially observes that the GOB firms' on average increase 5.5% of total debt to asset ratio than non-GOB firms during abnormal rainfall years compared to normal or expected rainfall years. These effects are greater when we control for firm-level control variable that influences the firm's debt structure in column 3. To be specific, following the prior literature, we control for size, liquidity, profitability, tangibility, and age (e.g., Bae and Goyal, 2009; Vig, 2013), and find that relative to non-GOB firms, GOB firm significantly increase 6.7% borrowing when exposed to abnormal rainfall.

We further test the robustness of our results by introducing subdivision-industry-year fixed effects, which essentially control for the changes in the firm's debt structure arising from time-varying industry shocks at the subdivision level. We find higher and stronger results compared to the baseline regression in column 2, the average effect without any control variables. In column 4, it can be observed that the estimated coefficient is significantly higher and stronger when we run our baseline regression with control variables. In particular, we find that compared to non-GOB firms, the GOB firms significantly increase their leverage ratio by 7.2% during the abnormal rain year compared to the non-GOB firm in a normal rainfall year. These effects are statistically significant at a 1% significance level. Moreover, we find similar results when we use the second measure, that is, debt net of cash holding normalized by total assets, in our baseline regression specification, Equation 1, as reported in columns 5 to 8 in Table 3.

Overall, our results confirm Hypothesis H1, that having an exclusive relationship with GOBs increases the access to finance than those firms that do not have such a relationship during the abnormal rainfall periods *vis-á-vis* normal rainfall periods. This evidence lends support to the view that maintaining a banking relationship with GOB is a potential solution for firms to emerge out of distress caused by climate shocks.

5.1.1. Exploring the impact on different components of debt structure

Following the impact of abnormal rainfall on the firms' overall debt structure, we further investigate the impact on different components of firms' debt structure when exposed to abnormal rainfall compared to normal rainfall conditions. To be specific, we explore the impact on firms' bank debt, secured borrowings, and long-term borrowings. We rerun our baseline regression specification using these different components of the debt structure as the dependent variables. Table 4 reports the impact on GOB firms' bank debt in columns 1 and 2, secured borrowings in columns 3 and 4, and long-term debt in columns 5 and 6 during the abnormal rainfall periods than expected normal rainfall periods. We find that during unexpected abnormal rainfall, GOB firms take significantly higher bank debt, secured debt, and long-term debt compared to non-GOB firms. These results remain qualitatively similar when we include subdivision-industry-year fixed effects in our baseline regression model. These results are statistically significant at a 5% level of significance. Finally, in columns 7 and 8 of Table 4, we explore the impact on the firm's interest expense during the abnormal rainfall year compared to the normal rainfall year. Interestingly, we do not find an increase in the interest expenses of GOB firms than non-GOB firms during the abnormal rainfall year compared to normal rainfall years. The result implies that GOB firms attract more credit supply at competitive rates. In other words, since having a relationship with GOBs signals signs of safety, therefore, banks are more willing to provide loans at a competitive rate to GOB firms than to non-GOB firms counterparts.

5.1.2. Exploring cross-sectional heterogeneity

Given our identification strategy above, we compared the GOB firms' quantity of debt with that of non-GOB firms during unexpected rainfall conditions vis-a-vis normal rainfall conditions. In this section, we explore the heterogeneous treatment effects on GOB firms.

There is a growing body of literature that explore the firms' determinants of capital structure decisions and provide several stylized facts[18]. The firms' tangible assets are positively correlated with the total amount of debt owing to greater debt capacity, whereas the profitability of the firm is negatively associated with total debt. Similarly, highly liquid firms are likely to borrow less than those with less liquid firms. Finally, small-size firms are more dependent on external finance, particularly bank loans, whereas large-size firms are less dependent on external finance owing to their internal funding capacity. Therefore, we anticipate that during the unexpected rainfall conditions, firms with high tangible assets will borrow more, whereas firms with greater profitability, high liquidity, older, and larger in size are likely to borrow less owing to greater internal capacity.

We formally test these anticipated cross-sectional effects using the following regression specification. We specifically interact the treatment indicator variables with the above-mentioned characteristics, using the pre-treatment (i.e., a year prior to the unexpected abnormal rainfall) values.

$$Y_{i,t} = \gamma_i + \delta_{s\times j\times t} + \tau \; Abnormal\ Rain_{s,t} \times GOB_{i,t-1} \times \eta_{i,t-1} + \beta X_{i,t-1} + \epsilon_{it} \tag{2}$$

Following the Equation 1, i denotes firm, t denotes the year, s denotes subdivision, and j denotes industry. $Y_{i,t}$ is dependent variable of interest, $Abnormal\ Rain_{s,t}$ is indicator variables which takes a value of 1 if subdivision experiences unanticipated abnormal rainfall in year t, and otherwise zero. $GOB_{i,t-1}$ is a dummy variable that takes the value 1 for the firms that exclusively borrow from government-owned banks (GOB firms) at the beginning of the year and 0 otherwise. $X_{i,t-1}$ is a set of control variables such as tangibility, liquidity, size, profitability, and age. ϵ_{it} is error term. $\eta_{i,t-1}$ is a set of continuous cross-sectional firms' characteristics, that is, tangibility,

[18](e.g., Titman and Wessels, 1988; Rajan and Zingales, 1995; Booth et al., 2001)

size, liquidity, ROA, and age. The interaction variable $Abnormal\ Rain_{s,t} \times GOB_{i,t-1} \times \eta_{i,t-1}$ is the main variable of interest. The coefficient τ estimates firms' cross-sectional heterogeneity during abnormal rainfall conditions.

Table 5 reports the results from different specifications using Equation 2. In column 1, we find that, within our defined treatment and control groups, the firms with high tangible assets have significantly more debt than that of low tangible asset firms during abnormal rainfall years (coefficient of 0.299). The results are consistent with the notion that high tangible assets firms have greater debt capacity (Gan, 2007; Shleifer and Vishny, 1992). Therefore, profit-maximizing banks' would be willing to give more loans to such firms during times of distress. In other words, banks tend to take more collateral on riskier loans (Berger and Udell, 1990). Therefore, when the riskiness of an average borrower increases during unexpected abnormal rainfall due to disruption in firms' cash flows and value of their collateral assets, naturally, banks are more likely to give loans to firms having high collateral than firms with low collateral assets. In column 2, we explore the impact on the total debt of small versus large firms during abnormal rainfall periods. We find no significant impact of firm size on the debt ratio.

In column 3, we investigate the impact on the high versus low profitable firms and find that less profitable firms significantly increase the level of leverage during abnormal rainfall than that of highly profitable firms. This is consistent with the notion that profitable firms use internal funds, whereas financially constrained, less profitable would rely on external finance during times of distress. The results are consistent with the finding of Vig (2013), that is, profitability is negatively associated with leverage (Rajan and Zingales, 1995; Booth et al., 2001).

We further explore the impact on firms that has high versus low liquidity and find that compared to high-liquid firm, firms with lower liquidity significantly borrow more debt during abnormal rainfall year. This is consistent with the argument that firms having high liquid assets are typically better-performing firms, thereby, are less financially constrained (Fang et al., 2009). Therefore, at the time of distress, highly liquid firms are less likely to rely on external finance compared to firms with lower liquidity. In column 5, we explore the impact on the younger versus older firms and find that compared to older firms, younger firms are likely to increase borrowing during abnormal rainfall, although the effect is not statistically significant. The result is consistent with the argument that young firms are financially constrained, thereby excessively relying on external finance (particularly bank debt), and have high leverage (Klapper et al., 2002).

Finally, we run a horse race model using all the firm-level characteristics in column 6 and find similar results as documented in columns 1 to 5. All the cross-sectional characteristics are statistically significant, except for size. Overall, our findings suggest that firms with high tangible assets, less profitability, and less liquid assets borrow more when they experience abnormal rainfall conditions.

5.2. Channel of lending

Our baseline results document that having banking relationships exclusively with GOB help in mitigating the financial constraints during an abnormal rainfall year. In this section, we explore the potential channels of funding that GOB firms secure during an abnormal rainfall year.

There is a growing body of literature that suggest that climate shocks adversely affect firms' cash flows, the value of their collateralized assets, and their market value (Pankratz et al., 2023; Rao et al., 2022; Dessaint and Matray, 2017). As a result, firms experience a lower supply of credit and higher cost of financing (Javadi and Masum, 2021; Noy, 2009; Noth and Schüwer, 2018), leading to their dampening investment and exaggerating distress. Importantly, findings of Berg and Schrader (2012) suggest that climate-related shocks increase the demand for loans, but the supply of credit becomes restricted. So far, our evidence suggests that GOB firms benefit from their GOB relationship to secure recovery finance during abnormal rainfall periods. Yet, it is not apparent whether this access to finance came from GOBs or from other profit-maximizing banks.

The most obvious channel would be that welfare-maximizing GOBs increase the supply of credit to prevent financial instability and promote economic growth— *Government bank insurance* hypothesis (Brei and Schclarek, 2013, 2015). Specifically, GOBs perhaps provide new subsidized loans to GOB firms when these firms are exposed to unexpected abnormal rainfall conditions. On the contrary, the GOBs may not be able to do so due to constraints faced by them. The two salient constraints are high bad loan penalties on their loan officers, and their recapitalization enlarges the fiscal burden (Acharya, 2020; Banerjee et al., 2004, 2006). Both of them would prevent GOBs from increasing the credit supply. Therefore, they may resort to the forbearance policy, as they did in the aftermath of the global financial crisis (Chari et al., 2021), thereby perhaps declining profitable lending opportunities such as loan demand from healthy GOB firms.

In such a scenario, the profit-maximizing banks may encash these profitable lending opportunities denied by GOBs by granting loans to healthy GOB firms. This is due to, compared to lending to existing borrowers, the implicit government guarantee associated with GOB firms can be considered a safer lending option during climate shocks and an opportunity to reduce the riskiness of banks' loan portfolios. Therefore, our second channel is *flight-to-safety* hypothesis, wherein banks other than GOBs lend to relatively safer GOB firms in the episode of climate shocks than those non-GOB firms.

If the first channel, *government bank insurance* hypothesis, is driving our results. Then, GOBs should increase the credit supply to all kinds of firms, especially grant loans to those who have lower debt capacity (i.e., lower tangible assets). In contrast, our evidence in the previous section suggests that GOB firms with higher tangible assets are able to borrow more than other firms during abnormal rainfall periods. This is surprising because, given that GOBs have welfare goals, unlike profit-maximizing banks, it is less likely that GOBs will lend only to those risky borrowers that have greater collateral assets, especially during the time of distress (Hoshi et al., 1990; Harhoff and Körting, 1998). Our evidence is inconsistent with the first channel and the theories that argue banking relationships substitute collateral requirements in mitigating credit market frictions (Holmstrom and Tirole, 1997; Boot, 2000). Therefore, we expect that the second channel, *flight-to-safety* hypothesis, is more likely to be driving our results due to the following reasons. The unanticipated abnormal rainfall is likely to increase the financial fragility of the banks, especially GOBs that dominate the market, owing to the increase in liquidity risk and borrowers' credit risk (Klomp, 2014). As a result, it would impair the GOBs' capital buffer. Therefore, the two salient constraints, as discussed above, faced by GOBs when government aids are unavailable perhaps induce them to forebear or evergreen the loans in the aftermath of climate shock (Acharya, 2020). On the other hand, the profit-maximizing banks face two types of borrowers— existing borrowers and GOB firms— when the riskiness of their loan portfolio has significantly increased following unexpected abnormal rainfall due to higher default risk. The economic logic suggests that it would be optimal for profit-maximizing banks to lend to relatively safe GOB firms than other firms during the episodes of distress caused by climate shock. To further reduce their loan portfolio riskiness, they may grant loans to healthy GOB firms than unhealthy GOB firms and, correspondingly, reduce their exposure to existing borrowers.

First, we investigate whether profit-maximizing banks are opportunistically lending to GOB firms following unexpected abnormal rainfall. We empirically capture this channel using the following regression specification. Specifically, we interact the treatment indicator variables with indicator variables that capture the switch of GOB firms to non-GOB firms in the year of abnormal rainfall. If this interaction term turns out to be positive, it suggests that profit-maximizing banks are opportunistically lending to GOB firms during abnormal rainfall conditions.

$$Y_{i,t} = \gamma_i + \delta_{s \times j \times t} + \theta \; Abnormal\ Rain_{s,t} \times GOB_{i,t-1} \times NoNGOB_{i,t} + \beta X_{i,t-1} + \epsilon_{it} \tag{3}$$

Following the Equation 1, i denotes firm, t denotes year, s denotes subdivision, and j denotes industry. $Y_{i,t}$ is dependent variable, that is, total debt, $Abnormal\ Rain_{s,t}$ is indicator variables which takes a value of 1 if subdivision experiences unanticipated abnormal rainfall in year t, and otherwise zero. $GOB_{i,t-1}$ is a dummy variable that takes the value 1 for the firms that exclusively borrow from government-owned banks (GOB firms) at the beginning of the year and 0 otherwise. $NoNGOB_{i,t}$ is an indicator variable that takes the value 1 for the firms that do not exclusively borrow from GOBs at the year t, and 0 otherwise. $X_{i,t-1}$ is a set of control variables such as tangibility, liquidity, size, profitability, and age. ϵ_{it} is error term. The main variable of interest is interaction term, $Abnormal\ Rain_{s,t} \times GOB_{i,t-1} \times NoNGOB_{i,t}$, which directly estimates the total debt given by financial institute other than GOBs when abnormal rainfall strikes in year t.

Table 6 reports the results from Equation 3. We find that the higher leverage of GOB firms during abnormal rainfall periods mainly comes from loans provided by banks other than GOBs. In other words, profit-maximizing banks are opportunistically lending capital to GOB firms. Consistent with our second channel, when it comes to initiating new lending to a firm located in an area with abnormal rainfall, the profit-maximizing banks may see the exclusive relationship with GOBs as a sign of safety— owing to the implicit government guarantee. GOBs' tendency to forebear or evergreen the loans during times of distress makes GOB firms safer and more attractive options for profit-maximizing banks during such times. Moreover, the results are also consistent with the theory that it is optimal for the firms to borrow from nonrelationship banks and engage in multiple banking relationships to reduce their liquidity risk, particularly when credit risk significantly increases, and the probability of relationship termination is greater (Detragiache et al., 2000).

Furthermore, the coefficient of the interaction term between abnormal rain and GOB_{t-1} is positive but insignificant, indicating that firms that continue to borrow exclusively from GOB in year t do not witness a significant increase in the leverage ratio. This is consistent with our argument that GOBs are likely to opt for a forbearance policy instead of initiating new loans. Lastly, the interaction term between abnormal rain and $NoNGOB_t$ indicates that if the firm continues to remain non-GOB, it negatively affects the leverage, although the effect is not statistically significant. This indicates that given a choice between the GOB firms and existing relationship firms, the profit-maximizing banks tend to choose GOBs firm over existing borrowers and are likely to reduce their exposure to existing borrowers when the credit risk of the average firm increase due to abnormal rainfall. This provides further support to our second channel. Hence, additional debt comes from banks other than GOBs in the year with abnormal rainfall. The question of interest here is, do the profit-maximizing banks give out loans to all kinds of firms as long as they exclusively borrow from GOB? Or do they lend only to financially healthy GOB firms?

From the above findings, we know that banks other than GOBs are the main source of finance during a climate shock. Therefore, we expect that profit-maximizing banks are less likely to lend to a risky and financially distressed borrower because it not only adversely impacts banks' health but also has negative wealth effects on their shareholder (Dahiya et al., 2003). Therefore, we test this conjecture and investigate whether banks hesitate to provide extra capital to a distressed firm during an abnormal rain year using the following regression specification. Specifically, we interact the treatment indicator variables with the indicator variable of distressed firms. We use the regulatory accounting-based definition of the distressed firm as employed by Bose et al. (2021). That is, firms are called financially distressed if, in a given year, accumulated losses are greater than or equal to 50% average net worth of the preceding four years.

$$Y_{i,t} = \gamma_i + \delta_{s\times j\times t} + \alpha\ Abnormal\ Rain_{s,t} \times GOB_{i,t-1} \times Distress_{i,t} + \beta X_{i,t-1} + \epsilon_{it} \quad (4)$$

Following the Equation 1, i denotes firm, t denotes the year, s denotes subdivision, and j denotes industry. $Y_{i,t}$ is the dependent variable of interest, that is, total debt, debt net of cash, bank debt, and secured debt, $Abnormal\ Rain_{s,t}$ is indicator variables which takes a value of 1 if subdivision experiences unanticipated abnormal rainfall in year t, and otherwise zero. $GOB_{i,t-1}$ is a dummy variable that takes the value 1 for the firms that exclusively borrow from government-owned banks (GOB firms) at the beginning of the year and 0 otherwise. $Distress_{i,t}$ is an indicator variable that takes the value 1 for the firms that are financially distressed at the year t, and 0 otherwise. $X_{i,t-1}$ is a set of control variables such as tangibility, liquidity, size, profitability, and age. ϵ_{it} is error term. The main variable of interest is interaction term, $Abnormal\ Rain_{s,t} \times GOB_{i,t-1} \times Distress_{i,t}$, which directly captures the debt of distressed firms that are GOB firms when unanticipated abnormal rainfall strikes.

Table 7 reports the results from Equation 4 using different specifications. We report the results for total debt, debt net of cash, bank debt, and secured debt in columns 1, 2, 3, and 4, respectively. The main variable of interest in the interaction term, $AbnormalRain_{s,t} \times GOB_{i,t-1} \times Distress_{i,t}$, which captures the impact of abnormal rainfall on the GOB firms that are distressed. For all the variables of debt structure, we find a significant reduction in the leverage of distressed firms when they are exposed to unexpected abnormal rainfall. This is consistent with the view of *"flight-to-safety"*, according to which banks tend to reduce their exposure to distressed firms during times of financial distress since it negatively affects banks' capital base and financial health. The results are in line with the findings of (e.g., Deyoung et al., 2015; De Marco, 2019; Balduzzi et al., 2018). The main idea of these papers is during times of crisis, financial friction becomes more binding, leading to credit rationing (banks becoming more risk-averse), that in turn, adversely affects economic activities. Consistent with our baseline results, the estimated coefficient on interaction term, $AbnormalRain_{s,t} \times GOB_{i,t-1}$, suggests GOB firms indeed significantly raise debt when firms are exposed to abnormal rainfall. Taking these results together suggests that profit-maximizing banks cherry-pick GOB firms and lend to financially healthy GOB firms when borrowers are exposed to abnormal rainfall. The banks' strategy of not lending or rolling over the debt of financially distressed firms is optimal since lending to such firms will negatively affect banks' health and the wealth of their shareholders; in the case of GOBs, it will increase the government's fiscal burden and increase the loan officers' probability of getting default penalties on the bad loans (i.e., loans given to distressed firms). We find further support to this argument as the coefficient on interaction term, $AbnormalRain_{s,t} \times Distress_{i,t}$, shows an increase in debt other than bank debt of distressed when abnormal rainfall strikes. Specifically, we find that significant increase in secured debt and a weakly significant increase in the debt and net debt, but an insignificant increase in bank debt of financially distressed firms during the abnormal rainfall conditions. These findings suggest that distressed firms raise capital from financial institutes other than banks. The results are consistent with the notion that distressed firms face greater financial frictions owing to higher credit risk at the time of adverse economic shocks. This evidence further lends support to our second channel of *flight-to-safety* hypothesis.

5.3. Impact on Investment

So far, we have established that GOB firms are able to secure more finance during an abnormal rainfall year, and the funding mainly comes from banks other than GOBs. Of all the GOB firms, the banks lend to financially healthy firms. In this section, we explore the impact on the firms' investments when they are exposed to unexpected rainfall.

Authors have shown that climate-related shocks adversely affect firms' operations (or economic capital) and the shareholders' wealth (Rao et al., 2022; Dessaint and Matray, 2017; Berg and Schrader, 2012). In response to that, firms typically experience a trade-off between accumulating cash (Dessaint and Matray, 2017) and investing in risky projects (Aretz et al., 2019). The accumulation of cash creates a buffer against liquidity shortfall but requires delaying investment projects– consistent with real options theory (McDonald and Siegel, 1986). On the other hand, raising funds and immediately investing in risky projects would allow them to regain production capacity quickly, thereby improving shareholders' value– consistent with theories of Jensen and Meckling (1976); Black and Scholes (1973).

In our setting, given that GOB firms are able to secure finance when unanticipated rainfall strikes, compared to non-GOB firms. Therefore, GOB firms may use these funds either to accumulate cash or to invest in risky projects. The cash accumulation strategy is usually followed by high credit risk firms (Acharya et al., 2012), and we know that financially healthy firms largely secure the finance from the above evidence. Taken together, economic logic dictates that GOB firms are likely to choose to invest in risky projects, enabling them to regain their full capacity. That, in turn, would allow GOB firms to perform better compared to non-GOB firms following the unexpected rainfall. Therefore, we are going to evaluate the impact on the firms' performance in the next section.

To test this conjecture, we run our baseline regression specification, Equation 1, with different specifications in Table 8. We report the results with four different measures of investments (i) percentage increase in fixed assets in columns 1 and 2, (ii) percentage increase in tangible assets in columns 3 and 4, (iii) change in PPE as a percentage of total assets in columns 5 and 6, and (iv) CAPEX as a percentage of total assets in columns 7 and 8. The main variable of interest is the interaction term, $AbnormalRain_{s,t} \times GOB_{i,t-1}$, which captures the impact of abnormal rainfall on the GOB firms' investment compared to non-GOB firms. In all the columns of Table 8, the estimated coefficient suggests, with different measures of firms' investment, GOB firms' quantity of investment is significantly greater than non-GOB firms when firms experience abnormal rainfall conditions. The results indicate that GOB firms choose to do greater capital expenditure to improve the performance of the firm. Moreover, we do not find support for the view that firms may accumulate cash to create a liquidity buffer when abnormal rainfall strikes in Table A5. Hence, these results confirm our Hypothesis H2.

Our evidence is consistent with the risk-shifting theory that managers often change their investment strategy from investing in safe to risky projects during the time of distress, which is in line with shareholders' interest (Jensen and Meckling, 1976). In the following section, we compare the performance of GOB firms with non-GOB firms in an abnormal rain year.

5.4. Impact on firms performance

We explore the impact of abnormal rainfall on the profitability indicators such as earnings before interest, tax, depreciation, and amortization (EBITDA). Similar indicators were employed by Gopalan et al. (2007). We report the results in Table 9 with different specifications. In columns 1 and 2, we report the results with a natural logarithm of EBITDA, followed by EBITDA scaled by beginning the year total assets in columns 3 and 4. The main variable of interest is the interaction term, $AbnormalRain_{s,t} \times GOB_{i,t-1}$, which directly estimates the impact on the GOB firms' performance than that of non-GOB firms when abnormal rainfall strikes. Our findings corroborate our conjecture that GOB firms are likely to perform better than non-GOB firms during abnormal rainfall years. All the columns of Table 9 clearly indicate that GOB firms are performing better than non-GOB firms following the abnormal rainfall. Specifically, we find a significant increase in the GOB firms' overall profitability (log of EBITDA) than that of non-GOB firms in abnormal rain years (coefficients of 0.052 in column 1). Moreover, when we scale EBITDA by total assets, we get similar results. It indicates GOB firms are efficiently utilizing their assets to improve their performance. This is in line with the view that borrowing from profit-maximizing banks is likely to discipline the firms. These results are greater and even stronger compared to our baseline results when we use subdivision×industry×year fixed effects in our regression model. Hence, these findings confirm our Hypothesis H3.

The results are in line with the view that firms that are able to secure finance and take risky investments during times of distress are likely to perform better than the firms that are not (e.g., Hoshi et al., 1990). Moreover, our results are inconsistent with the findings of Weinstein and Yafeh (1998). According to them, firms having close ties with the banks face lower financial constraints, but this does not lead to higher profitability due to the higher cost of capital for these firms than other comparable firms, and banks discourage these firms to invest in risky but profitable investment projects.

6. Robustness Section

6.1. Placebo test

A potential concern with our results is that these results may not be driven by the unanticipated abnormal rainfall in the subdivision in a given year. In this section, we provide evidence that the results from our regressions are indeed driven by the abnormal rainfall and not by any other event or seasonality across years. In our settings, we essentially assume that in the absence of abnormal rainfall, we would have found no significant difference between the GOB firms and non-GOB firms. However, to test this assumption, we need the counterfactual that never occurs. Therefore, we perform placebo tests to provide enough confidence for our identification strategy. Specifically, we perform two placebo tests, one to ensure that abnormal rainfall drives our results and the second to ensure that treatment firms and control firms have differential effects when abnormal rainfall strikes. To do so, we randomly assign the subdivision the treatment of abnormal or normal rainfall in a given year (i.e., fake treatment) instead of using actual rainfall data from IMD[19]. Next, we run our baseline regression specification, Equation 1, using this artificially generated sample and extract the main coefficient of interest β_1. We repeat this process 1000 times to obtain a non-parametric distribution of estimated coefficients. Figure 2, we plot the non-parametric distribution and compare the coefficients for the key variables of interest. In all four panels, it can be seen that, for all the primary variables, the main estimated coefficients lie on the extreme right tail, and lend support to our identification strategy that our main results are indeed driven by the abnormal rainfall in the subdivision, thereby ensuring that our regressions are not picking up some spurious relationship.

We follow a similar procedure for the falsification of treatment and control firms (i.e., fake

[19] Bharadwaj et al. (2014) conduct similar placebo test in DID setting, although in a different context, and call this approach as exact randomization.

treatment and control firms). To be specific, we assign randomly assign firms to GOB firms and non-GOB firms, and use this artificially generated sample to estimate our baseline regression model. We repeat this process 1000 times to get a non-parametric distribution of estimated coefficients. In Figure 3, we compare the plots of the non-parametric distribution with the main estimated coefficient obtained from the original sample for key variables of interest. It can be observed, in all four panels, that the main estimated coefficients lie in the extreme tail. The results provide support to our identification that abnormal rainfall conditions deferentially impact GOB firms and non-GOB firms.

6.2. Standalone firms

The prior literature suggests that standalone firms are financially constrained (Thapa et al., 2020), owing to the fact that they do not have access to internal capital markets as firms that are affiliated to business groups (Khanna and Palepu, 2000). In this section, we explore whether standalone firms that have an exclusive relationship with the GOBs secure the finance during abnormal rainfall, compared to standalone firms that do not have a relationship exclusive relationship with GOBs. To do so, we run our baseline specification with the sample that only contains the standalone firms in Table 10. The regression analysis suggests that standalone firms that have a relationship with the GOBs have significantly increased the quantity of debt than those firms that do not have an exclusive relationship with GOBs when abnormal rainfall strikes compared to normal rainfall years. These results are robust to a variety of specifications: with or without control variables, subdivision-year fixed effects, and subdivision-industry-year fixed effects. The result is consistent with the view that relative to business group firms, standalone firms' activities are less opaque (means lower credit risk) therefore, banks would be more comfortable in giving loans to those firms, for which they incur lower informational frictions during the time of distress. As Gopalan et al. (2007) document that business group firms support the weaker firms during the time of distress, thereby having negative spillovers on other group firms, consequently increasing the probability of bankruptcy. Therefore, when abnormal rainfall strikes lending to business-affiliated firms becomes risky, as a result, banks prefer giving loans to standalone firms, which is what we have found– consistent with Lin et al. (2011). Moreover, results are also consistent with the view of *"Flight-to-safety"*; according to the view, at the time of distress funds flow from risky to safer firms, that is, less opaque or low-credit risk firms (Baele et al., 2020).

6.3. *Publicly listed firms*

A potential concern with our results is that a small number of unlisted firms might be driving our results and may not be generalizable to all the firms. In this section, we investigate whether the phenomenon exists for the listed firms or not. To do so, we rerun our baseline regression model, Equation 1, using a sample that consists of only publicly listed firms (i.e., we drop the unlisted firms from the main sample). We report the results for the main variable of interest, i.e., the quantity of debt in Table 11. The estimated coefficients are consistent with our baseline results. Furthermore, the estimated coefficients are greater than our main baseline results, suggesting that the publicly listed firms are largely driving our results. These results are robust to a variety of specifications and significant at a 1% level of significance. The results further support the view that during the time of distress, credit flows to safer firms, i.e., lower credit risk firms or firms with less information fiction, than riskier firms. The results are also consistent with survey findings of Allen et al. (2012), who documented that unlisted firms largely rely on alternative finance instead of bank finance. Furthermore, they find that these firms fund their investment and growth using credit from business partners, trade credit, friends, and family due to the fact that securing bank finance is a costly and time-consuming process. In undocumented results, we also find that during abnormal rainfall years, the unlisted firms do not significantly increase debt, implying that they are more likely to use alternative finance instead of bank debt.

6.4. *Asset Quality Review*

In our baseline analysis, we primarily argue that profit-maximizing banks are likely to lend to GOB firms not only because having an exclusive relationship with GOBs signals safety but also because GOBs are likely to opt for a forbearance policy as the government finances capital shortfalls. If this channel is driving our results, then the bank clean-up policy, which limits the possibility of forbearance or evergreening of loans, is likely to disrupt this channel. During our sample period, the central bank of India introduced a bank clean-up policy in 2015, Asset Quality Review (AQR), which essentially reviews the classification of loans, loan evergreening, and assumptions related to loan recovery (see, Chopra et al., 2021, for more details). Following the policy, the bad loans of banks increased from 4.3% to 11.2% of total advances; GOBs largely drove this as their NPAs increased to 14.6% from 5%. What followed was a reduction in the credit supply and ended the forbearance policy of the GOBs. Sice GOBs are unlikely to forebear the loans, and correspondingly, profit-maximizing banks' willingness to lend would be lower in the post-AQR regime, it is reasonable to expect that firms' ability to raise funds may decrease during the abnormal rainfall year in the period following the AQR policy. It is consistent with the findings of Chopra et al. (2021) as they find that the AQR policy significantly reduced the credit supply, thereby adversely affecting economic activities.

To test this conjecture, we carry out a sub-sample analysis based on the introduction of AQR policy, that is, pre-AQR from 2000 to 2014 and post-AQR from 2015 to 2020. Using these sub-samples, we run our baseline regression specification, Equation 1, and present the results in Table 12. The findings corroborate conjecture. In the pre-AQR period, the estimated coefficients in columns 1 and 4 are in line with our baseline results. However, in the post-AQR period, estimated coefficients are positive but statistically insignificant, implying that supply-side shock adversely affects GOB firms' ability to raise funds when abnormal rainfall strikes. The results not only lend support for our second channel but also adds to the findings of (Chopra et al., 2021), that bank-clean-up policy in normal times can have negative consequences on the economy.

6.5. Alternative measure of total debt

In our baseline analysis, we measure the debt structure of the firms using total debt. Here, we use two alternative measures of debt– (i) the sum of firms' long-term bank debt and short-term bank debt scaled by the beginning of the year total assets (Rodano et al., 2016; Lin et al., 2011), and (ii) the sum of firms' secured (secured by tangible assets) and unsecured borrowing (not secured by tangible assets) scaled by the beginning of the year total assets (Thapa et al., 2020). Using these alternative measures of leverage, we run our baseline regression specification and report the results in Table 13. It can be seen that the estimated coefficients are consistent with our baseline results. Columns 1 and 2 show that GOB firms' quantity of bank debt (long-term plus short-term debt) is significantly higher than those of non-GOB firms when abnormal rainfall strikes (coefficient of 0.024). The coefficient remains unchanged when we use subdivision-industry-year fixed effects and is significant at a 1% significance level. The results further lend support to the view that during the time of abnormal rainfall, the bank credit flows to GOB firms. Columns 3 and 4 document similar results that GOB firms' total quantity of secured and unsecured debt is significantly higher than non-GOB firms when abnormal rainfall strikes (coefficient of 0.043). The estimated coefficient is greater (0.048) when we use subdivision-industry-year fixed effects and remain statistically significant at a 1% level of significance. The higher coefficient on sum secured and unsecured debt than total bank debt indicates that GOB firms perhaps get finance from other financial institutes as well during the time of abnormal rainfall. The results are consistent with the survey findings of Allen et al. (2012) that Indian firms rely on alternative sources of finance.

6.6. Alternative measure of investment

In the main analysis, we measure the level of firms' investment with four different measures that are widely used in the corporate finance literature. We replicate our baseline analysis with two alternative measures to showcase that our results are not specific to the way we define our variables. To be specific, we measure investment– (i) natural logarithm of the total asset at year t over total asset at year t-1 (Gopalan et al., 2007), and (ii) change in the fixed asset from t-1 to t scaled by the beginning of year total assets (Srinivasan and Thampy, 2017). The results are reported in Table 14. It can be observed that the results are in line with our baseline results. That is, GOB firms' quantity of investment is significantly higher than non-GOB firms following abnormal rainfall. Overall, our results are robust to the alternative definitions of the firms' investments.

6.7. Alternative measure of firms performance

In the main regression analysis, we measure firms' profitability using operating profits– EBITDA. Here, we measure firms' profitability as earnings before interest and taxes (EBIT) scaled by the beginning of the year total asset (e.g., Vig, 2013). We run our baseline regression specification using the $EBIT/TotalAssets$ as the dependent variable and report the results in Table 15 with different specifications. The analysis with alternative measures of performance shows qualitatively similar results to our main analysis. Specifically, GOB firms' profitability is significantly greater than non-GOB firms during the abnormal rainfall years (coefficient of 0.01). The estimated interaction term of interest is greater and remains statistically significant when we use subdivision-industry-year fixed effects (coefficient of 0.012). These effects are statistically significant at a 1% significance level.

6.8. *Using IMD definition of abnormal rainfall*

In the baseline analysis, we decided the level of abnormal rainfall conditions based on the quantiles– each year, extreme quantiles are considered abnormal rainfall, and the middle quantile is considered normal rainfall. As a robustness check, we re-estimate our baseline results using the definition of abnormal rainfall as per IMD (beyond ±19% of rainfall deviation). We adopt a similar approach as employed in the baseline analysis but classify a subdivision in the abnormal rainfall category if rainfall deviation is more ±19% in that division and year combination. Specifically, each year, we divide the subdivisions into two five quantiles and remove the third and fourth quantiles to eliminate the potential noise. Then, we consider a subdivision experiencing normal rainfall if the rainfall departure is within ±19%, and otherwise, subdivisions that are experiencing abnormal rainfall– excess of ±19% rainfall deviation. Finally, we integrate our firm-level sample with subdivision rainfall-year data based on the firms' location.

Table 16 report the results for firms' quantity of debt from our baseline regression model, Equation 1, using this new sample based on IMD abnormal rainfall definition. Columns 1 and 2 report the results for total debt scaled by the beginning of the year total assets, followed by the results for debt net of cash holding scaled by the beginning of the year total assets in columns 3 and 4. Our results are qualitatively similar to the baseline results. Therefore, our results are robust to the alternative definition of abnormal rainfall.

7. Conclusion

Challenges posed by climate change are increasingly becoming an integral part of risk assessment by stakeholders as it is impacting the investing and financing choices of firms. We explore whether maintaining an exclusive relationship with government banks helps firms emerge out of distress triggered by climate shocks when government aids are unavailable. We do so by considering abnormal rainfall as an exogenous climate shock and firms' banking relationships while using a unique setting, the Indian context. Using firm-level data from CMIE prowess and subdivision-wise rainfall data from IMD, our study documents the benefit of maintaining an exclusive relationship with government banks and finds the support of the "flight-to-safety" hypothesis.

Our main findings indicate that exclusive borrowing relationships with Government Banks have significant advantages. GOB firms are able to borrow more compared to non-GOB firms during abnormal rainfall periods vis-á-vis normal periods. In addition, we document heterogeneous effects on treated firms, that is, funds flow towards that GOB firms, which have low profitability, low liquidity, and high tangible assets. Furthermore, the additional capital raised by GOB firms is primarily diverted toward meeting capital expenditure needs caused by disruptions from abnormal rainfall, leading to higher levels of investments by GOB firms. Surprisingly, we find that the additional debt to GOB firms during the abnormal rainfall periods comes from profit-maximizing banks, suggesting that GOB firms having implicit government guarantees from GOBs may be perceived as relatively less risky by the banks. Finally, we find evidence that GOB firms have higher profitability than other firms during abnormal rainfall periods vis-á-vis normal periods. We argue that GOB firms are able to do so primarily due to the ease of accessing finance to invest in profitable investment projects for regaining the lost production capacity caused by climate shock.

Our results add to the extant literature of relationship banking and the growing field of climate finance. Particularly, it explores the role of banking relationships with GOBs for firms emerging out of distress caused by climate shocks. Our results highlight the advantages associated with borrowing exclusively from GOBs. Our findings imply that GOB firms are able to raise capital with a higher degree of ease than non-GOB firms, particularly in the face of a looming climate crisis. In spite of the exclusive relationship with GOBs, the capital flows primarily to firms that are financially healthy but may have some temporary liquidity issues due to climate shock. It implies that profit-maximizing banks are cautious and exercise a high degree of scrutiny while lending during such shocks. Future researchers can explore the role of other financial institutes, such as institutional investors, and promoters, in enabling firms to emerge out of distress caused by climate shocks, and its implication on the firms' investment policy, payout policy, and financing policy in the periods following climate shocks.

References

Acharya, V. (2020). *Quest for restoring financial stability in India.* Sage Publications Pvt. Limited.

Acharya, V., Davydenko, S. A., and Strebulaev, I. A. (2012). Cash holdings and credit risk. *The Review of Financial Studies*, 25(12):3572–3609.

Allen, F., Chakrabarti, R., De, S., Qian, M., et al. (2012). Financing firms in india. *Journal of financial intermediation*, 21(3):409–445.

Almeida, H. and Philippon, T. (2007). The risk-adjusted cost of financial distress. *The Journal of Finance*, 62(6):2557–2586.

Andrade, G. and Kaplan, S. N. (1998). How costly is financial (not economic) distress? evidence from highly leveraged transactions that became distressed. *The journal of finance*, 53(5):1443–1493.

Aretz, K., Banerjee, S., and Pryshchepa, O. (2019). In the path of the storm: does distress risk cause industrial firms to risk-shift? *Review of Finance*, 23(6):1115–1154.

Ashok, K., Guan, Z., and Yamagata, T. (2001). Impact of the indian ocean dipole on the relationship between the indian monsoon rainfall and enso. *Geophysical research letters*, 28(23):4499–4502.

Bae, K.-H. and Goyal, V. K. (2009). Creditor rights, enforcement, and bank loans. *The Journal of Finance*, 64(2):823–860.

Baele, L., Bekaert, G., Inghelbrecht, K., and Wei, M. (2020). Flights to safety. *The Review of Financial Studies*, 33(2):689–746.

Balduzzi, P., Brancati, E., and Schiantarelli, F. (2018). Financial markets, banks' cost of funding, and firms' decisions: Lessons from two crises. *Journal of Financial Intermediation*, 36:1–15.

Banerjee, A., Cole, S., and Duflo, E. (2005). Bank financing in india. *India's and China's recent experience with reform and growth*, pages 138–157.

Banerjee, A., Cole, S., and Duflo, E. (2006). Are the monitors over-monitored? evidence from corruption and lending in indian banks. Technical report, MIMEO: MIT.

Banerjee, A., Cole, S., Duflo, E., et al. (2004). Banking reform in india. In *India policy forum*, volume 1, pages 277–332. National Council of Applied Economic Research; Brookings Institution.

Beck, T., Degryse, H., De Haas, R., and Van Horen, N. (2018). When arm's length is too far: Relationship banking over the credit cycle. *Journal of Financial Economics*, 127(1):174–196.

Behr, P., Norden, L., and Noth, F. (2013). Financial constraints of private firms and bank lending behavior. *Journal of banking & finance*, 37(9):3472–3485.

Berg, G. and Schrader, J. (2012). Access to credit, natural disasters, and relationship lending. *Journal of financial intermediation*, 21(4):549–568.

Berger, A. N., Bouwman, C. H., and Kim, D. (2017). Small bank comparative advantages in alleviating financial constraints and providing liquidity insurance over time. *The Review of Financial Studies*, 30(10):3416–3454.

Berger, A. N. and Udell, G. F. (1990). Collateral, loan quality and bank risk. *Journal of Monetary Economics*, 25(1):21–42.

Bery, S. K. (1994). Financial rehabilitation of public sector banks: Conceptual and policy aspects. *Economic and Political Weekly*, pages 251–255.

Bharadwaj, P., Johnsen, J. V., and Løken, K. V. (2014). Smoking bans, maternal smoking and birth outcomes. *Journal of Public economics*, 115:72–93.

Black, F. and Scholes, M. (1973). The pricing of options and corporate liabilities. *Journal of political economy*, 81(3):637–654.

Bolton, P., Freixas, X., Gambacorta, L., and Mistrulli, P. E. (2016). Relationship and transaction lending in a crisis. *The Review of Financial Studies*, 29(10):2643–2676.

Boot, A. W. (2000). Relationship banking: What do we know? *Journal of Financial Intermediation*, 9(1):7–25.

Boot, A. W. and Thakor, A. V. (1994). Moral hazard and secured lending in an infinitely repeated credit market game. *International economic review*, pages 899–920.

Booth, L., Aivazian, V., Demirguc-Kunt, A., and Maksimovic, V. (2001). Capital structures in developing countries. *The journal of finance*, 56(1):87–130.

Bose, U., Filomeni, S., and Mallick, S. (2021). Does bankruptcy law improve the fate of distressed firms? the role of credit channels. *Journal of Corporate Finance*, 68:101836.

Brei, M. and Schclarek, A. (2013). Public bank lending in times of crisis. *Journal of financial stability*, 9(4):820–830.

Brei, M. and Schclarek, A. (2015). A theoretical model of bank lending: Does ownership matter in times of crisis? *Journal of Banking & Finance*, 50:298–307.

Caballero, R. J. and Krishnamurthy, A. (2008). Collective risk management in a flight to quality episode. *The Journal of Finance*, 63(5):2195–2230.

Chari, A., Jain, L., and Kulkarni, N. (2021). The unholy trinity: Regulatory forbearance, stressed banks and zombie firms. Technical report, National Bureau of Economic Research.

Chemmanur, T. J. and Fulghieri, P. (1994). Reputation, renegotiation, and the choice between bank loans and publicly traded debt. *Review of financial Studies*, 7(3):475–506.

Chen, Y.-S., Chen, Y., Lin, C.-Y., and Sharma, Z. (2016). Is there a bright side to government banks? evidence from the global financial crisis. *Journal of Financial Stability*, 26:128–143.

Chopra, Y., Subramanian, K., and Tantri, P. L. (2021). Bank cleanups, capitalization, and lending: Evidence from india. *The Review of Financial Studies*, 34(9):4132–4176.

Coleman, N. and Feler, L. (2015). Bank ownership, lending, and local economic performance during the 2008–2009 financial crisis. *Journal of Monetary Economics*, 71:50–66.

Collier, B. L., Haughwout, A. F., Kunreuther, H. C., and Michel-Kerjan, E. O. (2020). Firms' management of infrequent shocks. *Journal of Money, Credit and Banking*, 52(6):1329–1359.

Cortés, K. R. and Strahan, P. E. (2017). Tracing out capital flows: How financially integrated banks respond to natural disasters. *Journal of Financial Economics*, 125(1):182–199.

Crawford, G. S., Pavanini, N., and Schivardi, F. (2018). Asymmetric information and imperfect competition in lending markets. *American Economic Review*, 108(7):1659–1701.

Dahiya, S., Saunders, A., and Srinivasan, A. (2003). Financial distress and bank lending relationships. *The Journal of Finance*, 58(1):375–399.

De Marco, F. (2019). Bank lending and the european sovereign debt crisis. *Journal of Financial and Quantitative Analysis*, 54(1):155–182.

Degryse, H. and Ongena, S. (2001). Bank relationships and firm profitability. *Financial management*, pages 9–34.

Degryse, H. and Ongena, S. (2005). Distance, lending relationships, and competition. *The Journal of Finance*, 60(1):231–266.

Dessaint, O. and Matray, A. (2017). Do managers overreact to salient risks? evidence from hurricane strikes. *Journal of Financial Economics*, 126(1):97–121.

Detragiache, E., Garella, P., and Guiso, L. (2000). Multiple versus single banking relationships: Theory and evidence. *The Journal of finance*, 55(3):1133–1161.

Deyoung, R., Gron, A., Torna, G., and Winton, A. (2015). Risk overhang and loan portfolio decisions: Small business loan supply before and during the financial crisis. *The Journal of Finance*, 70(6):2451–2488.

Diamond, D. W. (1991). Monitoring and reputation: The choice between bank loans and directly placed debt. *Journal of political Economy*, 99(4):689–721.

Duqi, A., McGowan, D., Onali, E., and Torluccio, G. (2021). Natural disasters and economic growth: The role of banking market structure. *Journal of Corporate Finance*, 71:102101.

Fang, V. W., Noe, T. H., and Tice, S. (2009). Stock market liquidity and firm value. *Journal of financial Economics*, 94(1):150–169.

Gadgil, S. (2003). The indian monsoon and its variability. *Annual Review of Earth and Planetary Sciences*, 31(1):429–467.

Gadgil, S., Vinayachandran, P., and Francis, P. (2003). Droughts of the indian summer monsoon: Role of clouds over the indian ocean. *Current Science*, pages 1713–1719.

Gan, J. (2007). Collateral, debt capacity, and corporate investment: Evidence from a natural experiment. *Journal of Financial Economics*, 85(3):709–734.

Ghosh, D. (2000). Budget proposals on public sector banks. *Economic and Political Weekly*, pages 1055–1056.

Gopalan, R., Nanda, V., and Seru, A. (2007). Affiliated firms and financial support: Evidence from Indian business groups. *Journal of Financial Economics*, 86(3):759–795.

Harhoff, D. and Körting, T. (1998). Lending relationships in germany–empirical evidence from survey data. *Journal of Banking & Finance*, 22(10-11):1317–1353.

Holmstrom, B. and Tirole, J. (1997). Financial intermediation, loanable funds, and the real sector. *the Quarterly Journal of economics*, 112(3):663–691.

Hoshi, T., Kashyap, A., and Scharfstein, D. (1990). The role of banks in reducing the costs of financial distress in japan. *Journal of financial economics*, 27(1):67–88.

Huang, B., Punzi, M. T., and Wu, Y. (2021). Do banks price environmental transition risks? evidence from a quasi-natural experiment in china. *Journal of Corporate Finance*, 69:101983.

Ioannidou, V. and Ongena, S. (2010). "time for a change": loan conditions and bank behavior when firms switch banks. *The Journal of Finance*, 65(5):1847–1877.

Javadi, S. and Masum, A.-A. (2021). The impact of climate change on the cost of bank loans. *Journal of Corporate Finance*, 69:102019.

Jensen, M. C. and Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of financial economics*, 3(4):305–360.

Khanna, T. and Palepu, K. (2000). Is group affiliation profitable in emerging markets? an analysis of diversified indian business groups. *The journal of finance*, 55(2):867–891.

Khwaja, A. I. and Mian, A. (2005). Do lenders favor politically connected firms? rent provision in an emerging financial market. *The quarterly journal of economics*, 120(4):1371–1411.

Klapper, L., Sarria-Allende, V., and Sulla, V. (2002). *Small-and medium-size enterprise financing in Eastern Europe*, volume 2933. World Bank Publications.

Klomp, J. (2014). Financial fragility and natural disasters: An empirical analysis. *Journal of Financial Stability*, 13:180–192.

Koetter, M., Noth, F., and Rehbein, O. (2020). Borrowers under water! rare disasters, regional banks, and recovery lending. *Journal of Financial Intermediation*, 43:100811.

Kucharski, F., Bracco, A., Yoo, J., and Molteni, F. (2007). Low-frequency variability of the indian monsoon–enso relationship and the tropical atlantic: The "weakening" of the 1980s and 1990s. *Journal of Climate*, 20(16):4255–4266.

Kumar, K. K., Rajagopalan, B., and Cane, M. A. (1999). On the weakening relationship between the indian monsoon and enso. *Science*, 284(5423):2156–2159.

Kumar, N. (2020). Political interference and crowding out in bank lending. *Journal of Financial Intermediation*, 43:100815.

Li, Y., Lu, R., and Srinivasan, A. (2019). Relationship bank behavior during borrower distress. *Journal of Financial and Quantitative Analysis*, 54(3):1231–1262.

Lin, C., Ma, Y., Malatesta, P., and Xuan, Y. (2011). Ownership structure and the cost of corporate borrowing. *Journal of Financial Economics*, 100(1):1–23.

McDonald, R. and Siegel, D. (1986). The value of waiting to invest. *The quarterly journal of economics*, 101(4):707–727.

Noth, F. and Schüwer, U. (2018). Natural disaster and bank stability: Evidence from the us financial system.

Noy, I. (2009). The macroeconomic consequences of disasters. *Journal of Development economics*, 88(2):221–231.

Ogura, Y. (2018). The objective function of government-controlled banks in a financial crisis. *Journal of Banking & Finance*, 89:78–93.

Pankratz, N., Bauer, R., and Derwall, J. (2023). Climate change, firm performance, and investor surprises. *Management Science*.

Petersen, M. A. and Rajan, R. G. (1994). The benefits of lending relationships: Evidence from small business data. *The journal of finance*, 49(1):3–37.

Rajan, R. G. (1992). Insiders and outsiders: The choice between informed and arm's-length debt. *The Journal of finance*, 47(4):1367–1400.

Rajan, R. G. and Zingales, L. (1995). What do we know about capital structure? some evidence from international data. *The journal of Finance*, 50(5):1421–1460.

Rao, S., Koirala, S., Thapa, C., and Neupane, S. (2022). When rain matters! investments and value relevance. *Journal of Corporate Finance*, 73:101827.

Rehbein, O. and Ongena, S. (2022). Flooded through the back door: The role of bank capital in local shock spillovers. *Journal of Financial and Quantitative Analysis*, 57(7):2627–2658.

Rodano, G., Serrano-Velarde, N., and Tarantino, E. (2016). Bankruptcy law and bank financing. *Journal of Financial Economics*, 120(2):363–382.

Rosenfeld, C. M. (2014). The effect of banking relationships on the future of financially distressed firms. *Journal of Corporate Finance*, 25:403–418.

Santos, J. A. and Winton, A. (2008). Bank loans, bonds, and information monopolies across the business cycle. *The Journal of Finance*, 63(3):1315–1359.

Sapienza, P. (2004). The effects of government ownership on bank lending. *Journal of Financial Economics*, 72(2):357–384.

Schäfer, L. (2019). "forgive but not forget": the behavior of relationship banks when firms are in distress. *Review of Finance*, 23(6):1079–1114.

Schüwer, U., Lambert, C., and Noth, F. (2019). How do banks react to catastrophic events? evidence from hurricane katrina. *Review of Finance*, 23(1):75–116.

Sharpe, S. A. (1990). Asymmetric information, bank lending, and implicit contracts: A stylized model of customer relationships. *The journal of finance*, 45(4):1069–1087.

Shleifer, A. (1998). State versus private ownership. *Journal of economic perspectives*, 12(4):133–150.

Shleifer, A. and Vishny, R. W. (1992). Liquidation values and debt capacity: A market equilibrium approach. *The journal of finance*, 47(4):1343–1366.

Shleifer, A. and Vishny, R. W. (1994). Politicians and firms. *The quarterly journal of economics*, 109(4):995–1025.

Srinivasan, A. and Thampy, A. (2017). The effect of relationships with government-owned banks on cash flow constraints: Evidence from india. *Journal of Corporate Finance*, 46:361–373.

Stiglitz, J. E. (1993). The role of the state in financial markets. *The world bank economic review*, 7(suppl_1):19–52.

Tantri, P. (2021). Identifying ever-greening: Evidence using loan-level data. *Journal of Banking & Finance*, 122:105997.

Thapa, C., Rao, S., Farag, H., and Koirala, S. (2020). Access to internal capital, creditor rights and corporate borrowing: does group affiliation matter? *Journal of Corporate Finance*, 62:101585.

Titman, S. and Wessels, R. (1988). The determinants of capital structure choice. *The Journal of finance*, 43(1):1–19.

Vig, V. (2013). Access to Collateral and Corporate Debt Structure: Evidence from a Natural Experiment. *Journal of Finance*, 68(3):881–928.

Weinstein, D. E. and Yafeh, Y. (1998). On the costs of a bank-centered financial system: Evidence from the changing main bank relations in japan. *The journal of Finance*, 53(2):635–672.

Table 1: Descriptive statistics

Variable	N	Mean	P_{25}	P_{50}	P_{75}	SD
Rainfall-Departure	31899	4.78	-9.809	-0.703	25.716	26.482
Size	31899	6.509	5.123	6.385	7.866	1.813
Debt	31899	0.721	0.251	0.547	0.85	1.74
(Debt-Cash Holding)	31899	0.667	0.197	0.506	0.814	1.739
Bank Debt	27769	0.274	0.094	0.215	0.343	0.414
Secured Debt	28838	0.388	0.117	0.27	0.418	1.537
Long-term Debt	19625	0.462	0.058	0.168	0.315	5.933
Interest Expense	28856	0.136	0.045	0.064	0.09	1.575
Cash	31242	0.054	0.009	0.024	0.055	0.139
Liquidity	31899	0.111	-0.011	0.14	0.324	1.201
ROA	31695	0.024	-0.006	0.022	0.058	0.215
Tangibility	31899	0.663	0.331	0.582	0.857	0.814
Age	31893	3.084	2.708	3.135	3.466	0.648

The table present the descriptive statistics of the key variables for the full sample period from 2000 to 2020. The variables are defined in Table A1.

Table 2: Descriptive statistics: GOB firms and non-GOB firms

Firm-Bank	GOB firms				non-GOB firms			
Variable	N	Mean	P_{50}	SD	N	Mean	P_{50}	SD
Size	12011	5.934	5.867	1.505	19888	6.857	6.877	1.893
Debt	12011	0.774	0.601	1.28	19888	0.689	0.514	1.966
(Debt-Cash Holding)	12011	0.726	0.566	1.284	19888	0.632	0.47	1.963
Bank Debt	10757	0.293	0.226	0.407	17012	0.261	0.208	0.417
Secured Debt	11050	0.403	0.288	0.963	17788	0.378	0.259	1.803
Long-term Debt	7211	0.496	0.141	8.58	12414	0.443	0.183	3.59
Interest Expense	10872	0.102	0.064	0.565	17984	0.156	0.064	1.946
Cash	11637	0.05	0.021	0.147	19605	0.057	0.026	0.135
Liquidity	12011	0.145	0.169	0.594	19888	0.09	0.124	1.448
ROA	11903	0.018	0.016	0.218	19792	0.028	0.026	0.213
Tangibility	12011	0.729	0.657	0.609	19888	0.623	0.541	0.913
Age	12009	3.057	3.091	0.625	19884	3.101	3.135	0.662

The table present the descriptive statistics of the key variables for GOB firms and non-GOB firms. The sample period is from 2000 to 2020. The variables are defined in Table A1.

Table 3: Impact of abnormal rainfall on GOB firms borrowings

Dependent Variables:	$\frac{Debt}{Total\ Assets}$				$\frac{(Debt\ -\ Cash\ Holdings)}{Total\ Assets}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Abnormal\ Rain_t \times GOB_{t-1}$	0.055***	0.061***	0.067***	0.072***	0.052**	0.059***	0.064***	0.070***
	(0.019)	(0.016)	(0.020)	(0.013)	(0.020)	(0.017)	(0.020)	(0.013)
GOB_{t-1}	0.047***	0.037*	-0.026	-0.031	0.047***	0.035*	-0.019	-0.025
	(0.015)	(0.019)	(0.019)	(0.021)	(0.015)	(0.018)	(0.019)	(0.020)
$Size_{t-1}$			-0.357***	-0.362***			-0.315***	-0.317***
			(0.044)	(0.038)			(0.042)	(0.036)
$Cash_{t-1}$			0.140	0.144			0.116	0.130
			(0.280)	(0.290)			(0.312)	(0.325)
ROA_{t-1}			-0.441	-0.414			-0.446	-0.416
			(0.333)	(0.340)			(0.326)	(0.333)
$Tangibility_{t-1}$			-0.063	-0.080			-0.058	-0.075
			(0.072)	(0.085)			(0.070)	(0.083)
Age_{t-1}			0.034	0.031			0.069	0.059
			(0.075)	(0.101)			(0.072)	(0.098)
Fixed-effects								
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Subdivision × Year	Yes		Yes		Yes		Yes	
Subdivision × Industry × Year		Yes		Yes		Yes		Yes
Observations	31,899	31,899	30,382	30,382	31,899	31,899	30,382	30,382
Adjusted R^2	0.61913	0.58131	0.65963	0.62544	0.62233	0.58517	0.65919	0.62543

The table present the results from baseline regression model, Equation 1. The dependent variable is total debt in columns 1 to 4, and total debt net of cash holding in columns 5 to 8. The main variable of interest is $Abnormal\ Rain_t \times GOB_{t-1}$, which estimate the impact of unexpected abnormal rainfall on GOB firms debt than that of non-GOB firms, compared to normal rainfall periods. The key explanatory variables are defined in Table A1. Robust standard errors clustered at the subdivision level are reported in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Table 4: Impact of abnormal rainfall on GOB firms borrowings

Dependent Variables:	$\frac{Bank\ Debt}{Total\ Assets}$		$\frac{Secured\ Borrowings}{Total\ Assets}$		$\frac{Long\ Term\ Debt}{Debt}$		$\frac{Interest\ Expense}{Total\ Assets}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Abnormal\ Rain_t \times GOB_{t-1}$	0.022**	0.020**	0.032**	0.035***	0.146***	0.164***	0.002	0.002
	(0.008)	(0.007)	(0.015)	(0.013)	(0.034)	(0.041)	(0.001)	(0.001)
GOB_{t-1}	-0.014	-0.016	-0.001	-0.009	-0.073	-0.128*	-0.000	-0.001
	(0.009)	(0.010)	(0.017)	(0.016)	(0.062)	(0.074)	(0.002)	(0.002)
$Size_{t-1}$	-0.134***	-0.144***	-0.225***	-0.222***	-0.346***	-0.414***	-0.009**	-0.008***
	(0.014)	(0.014)	(0.045)	(0.036)	(0.061)	(0.080)	(0.004)	(0.002)
$Cash_{t-1}$	0.045	0.043	0.159	0.166	0.594	0.761	0.025	0.026
	(0.050)	(0.056)	(0.263)	(0.246)	(0.448)	(0.561)	(0.025)	(0.027)
ROA_{t-1}	-0.111	-0.110	-0.309	-0.271	0.080	0.017	-0.083*	-0.086*
	(0.069)	(0.071)	(0.353)	(0.349)	(0.131)	(0.152)	(0.046)	(0.047)
$Tangibility_{t-1}$	-0.033	-0.040	-0.045	-0.059	-0.006	-0.004	-0.000	-0.000
	(0.029)	(0.034)	(0.043)	(0.049)	(0.013)	(0.017)	(0.003)	(0.003)
Age_{t-1}	0.038	0.066	-0.025	-0.076	-0.579***	-0.674***	0.003	0.001
	(0.041)	(0.046)	(0.040)	(0.064)	(0.153)	(0.204)	(0.003)	(0.007)
Fixed-effects								
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Subdivision × Year	Yes		Yes		Yes		Yes	
Subdivision × Industry × Year		Yes		Yes		Yes		Yes
Observations	26,710	26,710	27,705	27,705	18,896	18,896	27,941	27,941
Adjusted R^2	0.37224	0.30660	0.72775	0.69457	0.25799	0.12453	0.50477	0.45293

The table present the results from baseline regression model, Equation 1. The dependent variable is bank debt in columns 1 and 2, secured borrowings in columns 3 and 4, long-term debt in columns 5 and 6, and interest expense in columns 7 and 8. The main variable of interest is $Abnormal\ Rain_t \times GOB_{t-1}$, which measure the effect on dependent variable of GOB firms than that of non-GOB firms during unexpected abnormal rainfall periods vis-á-vis normal rainfall periods. The key explanatory variables are defined in Table A1. Robust standard errors clustered at the subdivision level are reported in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Table 5: Impact of abnormal rainfall on GOB firms borrowings: Heterogeneity

Dependent Variable:	$\frac{Debt}{Total\ Assets}$					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
$AbnormalRain_t \times GOB_{t-1} \times Tangibility_{t-1}$	0.299***					0.171**
	(0.084)					(0.079)
$AbnormalRain_t \times GOB_{t-1} \times Size_{t-1}$		-0.045				-0.016
		(0.027)				(0.023)
$AbnormalRain_t \times GOB_{t-1} \times ROA_{t-1}$			-0.973***			-0.963**
			(0.345)			(0.421)
$AbnormalRain_t \times GOB_{t-1} \times Liquidity_{t-1}$				-0.478***		-0.411***
				(0.141)		(0.130)
$AbnormalRain_t \times GOB_{t-1} \times Age_{t-1}$					-0.018	-0.050**
					(0.027)	(0.023)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
SubDiv × Industry × Year	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	30,382	30,382	30,382	30,928	30,382	30,928
Adjusted R^2	0.62779	0.62554	0.62611	0.62182	0.62539	0.62478

The table present the results from regression model, Equation 2, that is heterogeneous treatment effect on treated analysis. The dependent variable is total debt of the firms. The key explanatory variables are defined in Table A1. Robust standard errors clustered at the subdivision level are reported in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Table 6: Which type of banks are giving loans to GOB firms during abnormal rainfall

Dependent Variables:	$\frac{Debt}{Total\ Assets}$		$\frac{(Debt - CashHolding)}{Total\ Assets}$	
Model:	(1)	(2)	(3)	(4)
Variables				
$AbnormalRain_t \times GOB_{t-1} \times NoNGOB_t$	0.127**	0.102**	0.135**	0.114***
	(0.055)	(0.040)	(0.056)	(0.041)
$AbnormalRain_t \times NoNGOB_t$	-0.033	-0.008	-0.040	-0.020
	(0.030)	(0.043)	(0.031)	(0.036)
$NoNGOB_t$	0.033	0.004	0.034	0.004
	(0.027)	(0.032)	(0.028)	(0.028)
$GOB_{t-1} \times NoNGOB_t$	-0.069	-0.039	-0.085	-0.053
	(0.063)	(0.042)	(0.067)	(0.046)
$AbnormalRain_t \times GOB_{t-1}$	0.025	0.054	0.015	0.041
	(0.045)	(0.044)	(0.047)	(0.039)
GOB_{t-1}	0.004	-0.028	0.017	-0.016
	(0.042)	(0.039)	(0.042)	(0.037)
Controls	Yes	Yes	Yes	Yes
Fixed-effects				
Firm	Yes	Yes	Yes	Yes
SubDiv × Year	Yes		Yes	
SubDiv × Industry × Year		Yes		Yes
Fit statistics				
Observations	30,382	30,382	30,382	30,382
Adjusted R^2	0.65960	0.62540	0.65916	0.62538

The table present the results from regression model, Equation 3. The dependent variable is total debt of the firms in columns 1 and 2, and debt net of cash holding in columns 3 and 4. The key explanatory variables are defined in Table A1. Robust standard errors clustered at the subdivision level are reported in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Table 7: Impact of abnormal rainfall on GOB firms Credit that are distressed

Dependent Variables:	$\frac{Debt}{Total\ Assets}$	$\frac{(Debt - CashHolding)}{Total\ Assets}$	$\frac{BankDebt}{Total\ Assets}$	$\frac{SecuredDebt}{Total\ Assets}$
Model:	(1)	(2)	(3)	(4)
$AbnormalRain_t \times GOB_{t-1} \times$ Distress	-0.156***	-0.154***	-0.034**	-0.093***
	(0.049)	(0.052)	(0.014)	(0.024)
$AbnormalRain_t \times$ distress	0.077*	0.072*	0.027	0.062**
	(0.039)	(0.038)	(0.016)	(0.029)
Distress	-0.076	-0.093**	-0.006	-0.078***
	(0.045)	(0.045)	(0.021)	(0.026)
Distress $\times GOB_{t-1}$	0.087*	0.083	0.009	0.055
	(0.050)	(0.049)	(0.022)	(0.044)
$AbnormalRain_t \times GOB_{t-1}$	0.153***	0.149***	0.039***	0.084***
	(0.035)	(0.036)	(0.014)	(0.025)
GOB_{t-1}	-0.083*	-0.071*	-0.023	-0.037
	(0.043)	(0.041)	(0.020)	(0.039)
Controls	Yes	Yes	Yes	Yes
Fixed-effects				
Firm	Yes	Yes	Yes	Yes
SubDiv × Industry × Year	Yes	Yes	Yes	Yes
Observations	27,651	27,651	24,398	25,303
Adjusted R^2	0.62832	0.62843	0.29017	0.69682

The table present the results from regression model, Equation 4. The dependent variable is total debt of the firms in column 1, debt net of cash holding in column 2, bank debt in column 3, and secured debt in column 4. The key explanatory variables are defined in Table A1. Robust standard errors clustered at the subdivision level are reported in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Table 8: Impact of abnormal rainfall on GOB firm investments

Dependent Variables:	$log\left(\frac{FixedAssets}{FixedAssets_{t-1}}\right)$		$log\left(\frac{TangibleAssets}{TangibleAssets_{t-1}}\right)$		$Investment$		$CAPEX$	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$AbnormalRain_t \times GOB_{t-1}$	0.020***	0.025**	0.017***	0.022***	0.012***	0.011***	0.013***	0.012***
	(0.007)	(0.010)	(0.005)	(0.006)	(0.004)	(0.003)	(0.005)	(0.003)
GOB_{t-1}	-0.030***	-0.037***	-0.029***	-0.035***	-0.007	-0.010	-0.007	-0.011
	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.010)	(0.008)	(0.011)
$Size_{t-1}$	0.001	-0.000	0.002	0.001	-0.016**	-0.019**	-0.018**	-0.020**
	(0.004)	(0.005)	(0.004)	(0.004)	(0.007)	(0.008)	(0.008)	(0.009)
$Cash_{t-1}$	0.074	0.058	0.107**	0.093*	-0.001	-0.005	-0.001	-0.006
	(0.048)	(0.056)	(0.044)	(0.054)	(0.017)	(0.020)	(0.018)	(0.022)
ROA_{t-1}	0.138*	0.151**	0.127*	0.141**	0.068**	0.074**	0.075**	0.080***
	(0.073)	(0.071)	(0.064)	(0.064)	(0.027)	(0.027)	(0.029)	(0.029)
Age_{t-1}	-0.118***	-0.104***	-0.107***	-0.094***	-0.060***	-0.051***	-0.064***	-0.054***
	(0.027)	(0.029)	(0.032)	(0.034)	(0.019)	(0.018)	(0.020)	(0.019)
Fixed-effects								
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SubDiv × Year	Yes		Yes		Yes		Yes	
SubDiv × Industry × Year		Yes		Yes		Yes		Yes
Fit statistics								
Observations	29,041	29,041	28,994	28,994	28,994	28,994	28,994	28,994
Adjusted R^2	0.12182	0.05875	0.13166	0.07752	0.11188	0.04623	0.10237	0.03685

The table present the results from baseline regression model, Equation 1. The dependent variable is different measures of investments, that is, logarithmic of fixed asset over previous year fixed assets in columns 1 and 2, logarithmic of tangible asset over previous year tangible assets in columns 3 and 4, investments in columns 5 and 6, and capex in columns 7 and 8. The main variable of interest is $Abnormal\ Rain_t \times GOB_{t-1}$, which measure the effect on GOB firms' level of investments compared to non-GOB firms during unexpected abnormal rainfall periods vis-á-vis normal rainfall periods. Investment is defined as change in property, plant, and equipment scaled by beginning of the year total assets. CAPEX is defined as sum of change in property, plant, and equipment (PPE) and change in depreciation scaled by total assets. The key explanatory variables are defined in Table A1. Robust standard errors clustered at the subdivision level are reported in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Table 9: Impact of abnormal rainfall on GOB firms performance

Dependent Variables:	$log(EBITDA)$		$\frac{EBITDA}{Total\ Assets}$	
Model:	(1)	(2)	(3)	(4)
Variables				
$AbnormalRain_t \times GOB_{t-1}$	0.052**	0.067***	0.012***	0.013***
	(0.020)	(0.019)	(0.004)	(0.004)
GOB_{t-1}	-0.069**	-0.080**	-0.002	-0.005
	(0.033)	(0.037)	(0.006)	(0.006)
$Size_{t-1}$	0.698***	0.671***	-0.064***	-0.070***
	(0.011)	(0.015)	(0.009)	(0.011)
$Cash_{t-1}$	0.227***	0.214***	0.001	-0.000
	(0.066)	(0.065)	(0.022)	(0.020)
$Tangibility_{t-1}$	-0.001	-0.003	-0.019	-0.024
	(0.009)	(0.010)	(0.019)	(0.022)
Age_{t-1}	-0.112**	0.034	-0.032**	-0.021
	(0.053)	(0.043)	(0.014)	(0.018)
Fixed-effects				
Firm	Yes	Yes	Yes	Yes
SubDiv-Year	Yes		Yes	
SubDiv-Industry-Year		Yes		Yes
Fit statistics				
Observations	26,886	26,886	30,411	30,411
Adjusted R^2	0.87815	0.87561	0.19546	0.14887

The table present the results from the baseline regression model, Equation 1. The dependent variable is the logarithm of EBITDA in columns 1 and 2, and EBITDA scaled by total assets in columns 3 and 4. The main variable of interest is $Abnormal\ Rain_t \times GOB_{t-1}$, which measures the effect on the GOB firms' profitability compared to non-GOB firms during unexpected abnormal rainfall periods vis-á-vis normal rainfall periods. The key explanatory variables are defined in Table A1. Robust standard errors clustered at the subdivision level are reported in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Table 10: Impact of abnormal rainfall on GOB firms borrowings: Standalone firms only

Dependent Variables:	$\frac{Debt}{Total\ Assets}$				$\frac{Debt - CashHolding}{Total\ Assets}$			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
$GOB_{t-1} \times AbnormalRain_t$	0.073***	0.074***	0.085***	0.077***	0.072***	0.074***	0.084***	0.078***
	(0.025)	(0.023)	(0.024)	(0.020)	(0.026)	(0.025)	(0.024)	(0.021)
GOB_{t-1}	0.038	0.016	-0.038	-0.046	0.038	0.015	-0.030	-0.041
	(0.028)	(0.046)	(0.027)	(0.041)	(0.028)	(0.045)	(0.024)	(0.039)
$Size_{t-1}$			-0.417***	-0.428***			-0.375***	-0.381***
			(0.056)	(0.050)			(0.055)	(0.050)
$Cash_{t-1}$			0.142	0.137			0.049	0.044
			(0.289)	(0.286)			(0.296)	(0.294)
ROA_{t-1}			-0.706	-0.788			-0.717	-0.792
			(0.518)	(0.613)			(0.518)	(0.612)
$Tangibility_{t-1}$			-0.145	-0.163			-0.137	-0.155
			(0.104)	(0.112)			(0.100)	(0.108)
Age_{t-1}			-0.062	-0.148			-0.032	-0.129
			(0.145)	(0.205)			(0.148)	(0.207)
Fixed-effects								
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SubDiv × Year	Yes		Yes		Yes		Yes	
SubDiv × Industry × Year		Yes		Yes		Yes		Yes
Fit statistics								
Observations	22,799	22,799	21,576	21,576	22,799	22,799	21,576	21,576
Adjusted R^2	0.63069	0.58120	0.66084	0.61388	0.63416	0.58585	0.66174	0.61536

The table presents the results from the baseline regression model, Equation 1. The sample consists of only standalone firms, that is, we remove all the firms that are associated with business groups. The dependent variable is total debt in columns 1 to 4, and total debt net of cash holding in columns 5 to 8. The main variable of interest is $Abnormal\ Rain_t \times GOB_{t-1}$, which measures the impact of unexpected abnormal rainfall on GOB firms debt than that of non-GOB firms, compared to normal rainfall periods. The key explanatory variables are defined in Table A1. Robust standard errors clustered at the subdivision level are reported in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Table 11: Impact of abnormal rainfall on GOB firms borrowings: Publicly listed firms only

Dependent Variables:	$\frac{Debt}{Total\ Assets}$				$\frac{Debt - CashHolding}{Total\ Assets}$			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
$GOB_{t-1} \times AbnormalRain_t$	0.062**	0.072***	0.069***	0.080***	0.057**	0.068***	0.064***	0.077***
	(0.025)	(0.020)	(0.022)	(0.014)	(0.025)	(0.020)	(0.022)	(0.014)
GOB_{t-1}	0.048***	0.031	-0.027	-0.039	0.050***	0.032*	-0.018	-0.029
	(0.017)	(0.018)	(0.021)	(0.024)	(0.018)	(0.018)	(0.022)	(0.023)
$Size_{t-1}$			-0.359***	-0.364***			-0.317***	-0.319***
			(0.046)	(0.040)			(0.044)	(0.038)
$Cash_{t-1}$			0.160	0.174			0.134	0.158
			(0.307)	(0.315)			(0.346)	(0.355)
ROA_{t-1}			-0.441	-0.414			-0.443	-0.415
			(0.345)	(0.356)			(0.338)	(0.349)
$Tangibility_{t-1}$			-0.069	-0.089			-0.064	-0.083
			(0.073)	(0.086)			(0.072)	(0.084)
Age_{t-1}			0.050	0.050			0.085	0.080
			(0.085)	(0.117)			(0.082)	(0.113)
Fixed-effects								
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SubDiv × Year	Yes		Yes		Yes		Yes	
SubDiv × Industry × Year		Yes		Yes		Yes		Yes
Fit statistics								
Observations	27,485	27,485	26,411	26,411	27,485	27,485	26,411	26,411
Adjusted R^2	0.64131	0.60297	0.67642	0.64189	0.64420	0.60651	0.67592	0.64179

The table presents the results from the baseline regression model, Equation 1. The sample consists of only publicly listed firms. The dependent variable is total debt in columns 1 to 4, and total debt net of cash holding in columns 5 to 8. The main variable of interest is $Abnormal\ Rain_t \times GOB_{t-1}$, which estimates the impact of unexpected abnormal rainfall on GOB firms' debt than that of non-GOB firms, compared to normal rainfall periods. The key explanatory variables are defined in Table A1. Robust standard errors clustered at the subdivision level are reported in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Table 12: Impact of abnormal rainfall on GOB firms' debt due to Asset Quality Review (AQR) policy

Sample	Pre-AQR (2001 to 2014)				Post-AQR (2015 to 2020)			
Dependent Variable:				$\frac{Debt}{Total\ Assets}$				
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
$GOB_{t-1} \times AbnormalRain_t$	0.062***	0.068***	0.069***	0.069***	0.035	0.006	0.040	0.020
	(0.018)	(0.014)	(0.021)	(0.016)	(0.044)	(0.047)	(0.069)	(0.068)
GOB_{t-1}	0.066***	0.066**	-0.002	0.005	-0.042	-0.022	-0.049	-0.025
	(0.020)	(0.026)	(0.025)	(0.031)	(0.046)	(0.057)	(0.063)	(0.067)
$Size_{t-1}$			-0.291***	-0.285***			-0.862***	-0.910***
			(0.071)	(0.070)			(0.273)	(0.303)
$Cash_{t-1}$			-0.123	-0.093*			-0.028	-0.018
			(0.085)	(0.050)			(0.118)	(0.120)
ROA_{t-1}			-0.361*	-0.342			0.868***	0.850***
			(0.194)	(0.217)			(0.304)	(0.308)
$Tangibility_{t-1}$			0.013	0.016			-0.354***	-0.360***
			(0.014)	(0.012)			(0.073)	(0.066)
Age_{t-1}			-0.038	-0.041			0.147	0.137
			(0.060)	(0.075)			(0.110)	(0.139)
Fixed-effects								
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SubDiv-Year	Yes		Yes		Yes		Yes	
SubDiv-Industry-Year		Yes		Yes		Yes		Yes
Fit statistics								
Observations	19,545	19,545	18,454	18,454	11,712	11,712	11,316	11,316
Adjusted R^2	0.62809	0.58899	0.66725	0.63230	0.73881	0.69071	0.80945	0.77373

The table presents the results from the baseline regression model, Equation 1. The dependent variable is total debt. Here, we take two sub-samples; the results for the sub-sample consist of the period before Asset Quality Review (AQR), i.e., from 2001 to 2014, is reported in columns 1 to 4; and the results for the sub-sample consist of the period after Asset Quality Review (AQR), i.e., from 2015 to 2020, is reported in columns 1 to 4. The main variable of interest is $Abnormal\ Rain_t \times GOB_{t-1}$, which estimates the impact of unexpected abnormal rainfall on GOB firms' debt than that of non-GOB firms, compared to normal rainfall periods. The key explanatory variables are defined in Table A1. Robust standard errors clustered at the subdivision level are reported in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Table 13: Impact of abnormal rainfall on GOB firms borrowings: Alternative measures

Dependent Variables:	$\frac{(Long + Short\ BankDebt)}{Total\ Assets}$		$\frac{(Secured + UnSecuredDebt)}{Total\ Assets}$	
Model:	(1)	(2)	(3)	(4)
Variables				
$AbnormalRain_t \times GOB_{t-1}$	0.024***	0.024***	0.043***	0.048***
	(0.007)	(0.006)	(0.015)	(0.009)
GOB_{t-1}	-0.008	-0.008	-0.018	-0.023
	(0.008)	(0.009)	(0.012)	(0.015)
$Size_{t-1}$	-0.072***	-0.080***	-0.285***	-0.282***
	(0.011)	(0.011)	(0.037)	(0.030)
$Cash_{t-1}$	0.029	0.025	0.111	0.119
	(0.043)	(0.052)	(0.237)	(0.238)
ROA_{t-1}	-0.111*	-0.108*	-0.330	-0.306
	(0.059)	(0.059)	(0.296)	(0.308)
$Tangibility_{t-1}$	-0.030	-0.037	-0.032	-0.042
	(0.027)	(0.032)	(0.045)	(0.053)
Age_{t-1}	0.010	0.039	0.024	-0.008
	(0.032)	(0.038)	(0.049)	(0.074)
Fixed-effects				
Firm	Yes	Yes	Yes	Yes
SubDiv × Year	Yes		Yes	
SubDiv × Industry × Year		Yes		Yes
Fit statistics				
Observations	30,382	30,382	30,382	30,382
Adjusted R^2	0.34667	0.28543	0.70231	0.67085

The table present the results from the baseline regression model, Equation 1, using alternatives measure of the total debt of the firm. The dependent variable in columns 1 to 2 is the sum of long-term and short-term bank debt scaled by the beginning of the year total assets, and the sum of secured and unsecured debt scaled by the beginning of the year total assets in columns 3 and 4. The main variable of interest is $Abnormal\ Rain_t \times GOB_{t-1}$, which estimate the impact of unexpected abnormal rainfall on GOB firms debt than that of non-GOB firms, compared to normal rainfall periods. The key explanatory variables are defined in Table A1. Robust standard errors clustered at the subdivision level are reported in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Table 14: Impact of abnormal rainfall on GOB firm investments: Alternative measures

Dependent Variables:	$log\left(\frac{TotalAssets}{TotalAssets_{t-1}}\right)$		$Investment$	
Model:	(1)	(2)	(3)	(4)
Variables				
$AbnormalRain_t \times GOB_{t-1}$	0.015**	0.016**	0.015***	0.014**
	(0.007)	(0.007)	(0.006)	(0.005)
GOB_{t-1}	-0.011	-0.013**	-0.009	-0.013
	(0.007)	(0.006)	(0.007)	(0.010)
$Size_{t-1}$	-0.021***	-0.023***	-0.018**	-0.020**
	(0.003)	(0.003)	(0.008)	(0.008)
$Cash_{t-1}$	-0.035	-0.045	-0.030	-0.037*
	(0.032)	(0.032)	(0.020)	(0.021)
ROA_{t-1}	0.151***	0.147***	0.081**	0.088**
	(0.039)	(0.039)	(0.034)	(0.035)
Age_{t-1}	-0.142***	-0.134***	-0.068***	-0.058***
	(0.021)	(0.021)	(0.021)	(0.020)
Fixed-effects				
Firm	Yes	Yes	Yes	Yes
SubDiv × Year	Yes		Yes	
SubDiv × Industry × Year		Yes		Yes
Fit statistics				
Observations	29,406	29,406	29,041	29,041
Adjusted R^2	0.15487	0.10425	0.10179	0.02911

The table presents the results from the baseline regression model, Equation 1, using alternatives measure of the investments of the firm. The dependent variable in columns 1 to 2 is the logarithm of total assets over beginning of the total assets, and the change in fixed assets scaled by the beginning of the year total assets in columns 3 and 4. The main variable of interest is $Abnormal\ Rain_t \times GOB_{t-1}$, which estimate the impact of unexpected abnormal rainfall on GOB firms' level of investments than that of non-GOB firms, compared to normal rainfall periods. The key explanatory variables are defined in Table A1. Robust standard errors clustered at the subdivision level are reported in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Table 15: Impact of abnormal rainfall on GOB firms performance: Alternative measure

Dependent Variable:	$\frac{EBIT}{Total\ Assets}$	
Model:	(1)	(2)
Variables		
$AbnormalRain_t \times GOB_{t-1}$	0.010***	0.012***
	(0.003)	(0.003)
GOB_{t-1}	-0.001	-0.004
	(0.005)	(0.005)
$Size_{t-1}$	-0.050***	-0.055***
	(0.006)	(0.007)
$Cash_{t-1}$	0.013	0.011
	(0.025)	(0.026)
$Tangibility_{t-1}$	-0.010	-0.012
	(0.010)	(0.012)
Age_{t-1}	-0.025*	-0.017
	(0.015)	(0.019)
Fixed-effects		
Firm	Yes	Yes
SubDiv × Year	Yes	
SubDiv × Industry × Year		Yes
Fit statistics		
Observations	30,411	30,411
Adjusted R^2	0.18221	0.14871

The table presents the results from the baseline regression model, Equation 1, using an alternative measure of the firms' profitability. The dependent variable is earnings before interest and tax scaled by the beginning of the year total assets. The main variable of interest is $Abnormal\ Rain_t \times GOB_{t-1}$, which estimates the impact of unexpected abnormal rainfall on GOB firms' profitability than that of non-GOB firms, compared to normal rainfall periods. The key explanatory variables are defined in Table A1. Robust standard errors clustered at the subdivision level are reported in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

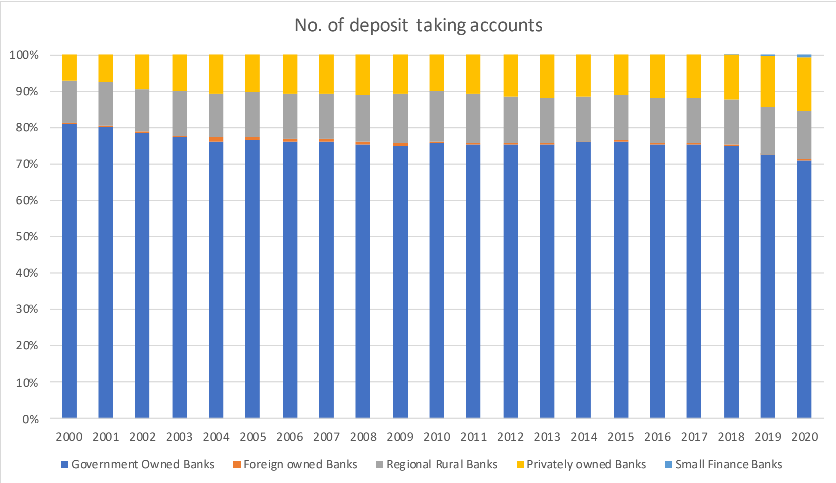
Table 16: Impact of abnormal rainfall on GOB firms borrowings: defining the abnormal rainfall according to India Meteorological Department (± 19% of deviation from normal rainfall in a sub-division.)

Dependent Variables:	$\frac{Debt}{Total\ Assets}$		$\frac{Debt - CashHolding}{Total\ Assets}$	
Model:	(1)	(2)	(3)	(4)
Variables				
$AbnormalRain_t \times GOB_{t-1}$	0.054***	0.048***	0.056**	0.052***
	(0.019)	(0.014)	(0.021)	(0.015)
GOB_{t-1}	-0.012	-0.010	-0.008	-0.007
	(0.017)	(0.020)	(0.018)	(0.018)
$Size_{t-1}$	-0.357***	-0.362***	-0.315***	-0.317***
	(0.044)	(0.038)	(0.042)	(0.036)
$Cash_{t-1}$	0.140	0.144	0.116	0.130
	(0.280)	(0.290)	(0.312)	(0.325)
ROA_{t-1}	-0.442	-0.414	-0.446	-0.416
	(0.333)	(0.340)	(0.326)	(0.333)
$Tangibility_{t-1}$	-0.063	-0.080	-0.058	-0.075
	(0.072)	(0.085)	(0.070)	(0.083)
Age_{t-1}	0.034	0.032	0.069	0.059
	(0.075)	(0.101)	(0.072)	(0.098)
Fixed-effects				
Firm	Yes	Yes	Yes	Yes
SubDiv × Year	Yes		Yes	
SubDiv × Industry × Year		Yes		Yes
Fit statistics				
Observations	30,382	30,382	30,382	30,382
Adjusted R^2	0.65961	0.62540	0.65918	0.62540

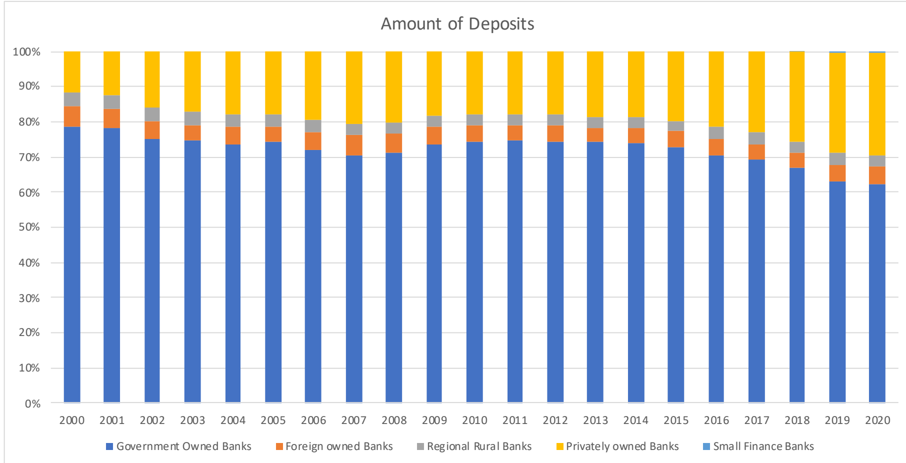
The table presents the results from the baseline regression model, Equation 1, using an alternative measure of the abnormal rainfall year. Specifically, we defined the abnormal rainfall according to India Meteorological Department, that is, ± 19% of deviation from normal rainfall in a subdivision. This is different from the definition used in the main analysis, wherein let the data decide the level of abnormal rainfall conditions based on the quantiles– each year, extreme quantiles are considered abnormal rainfall, and the middle quantile is considered normal rainfall. The dependent variable is total debt in columns 1 and 2, and debt net of cash holding in columns 3 and 4. The main variable of interest is $Abnormal\ Rain_t \times GOB_{t-1}$, which estimates the impact of unexpected abnormal rainfall on GOB firms' profitability than that of non-GOB firms, compared to normal rainfall periods. The key explanatory variables are defined in Table A1. Robust standard errors clustered at the subdivision level are reported in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Figure 1: Indian Banking Industry

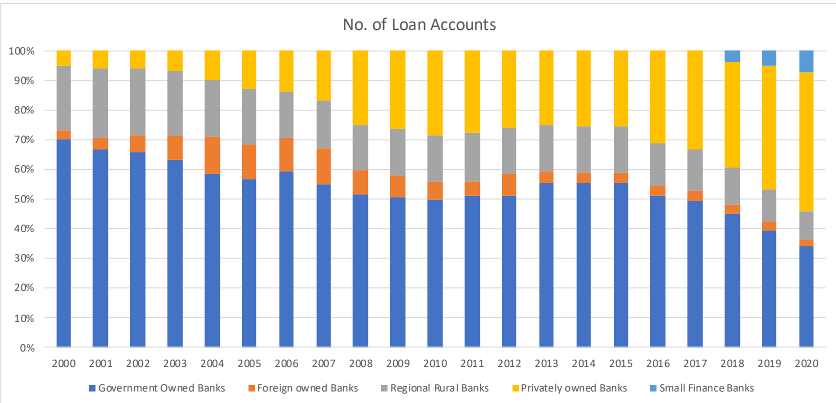
In this figure, we plot the yearly market share of all the banks in credit market and deposits market.



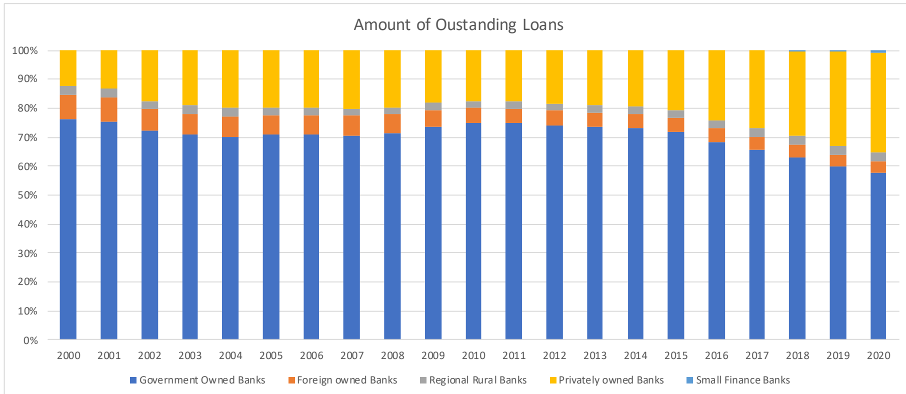
(a) Banks' market Share of no. of deposit accounts



(b) Banks' market Share of total deposits



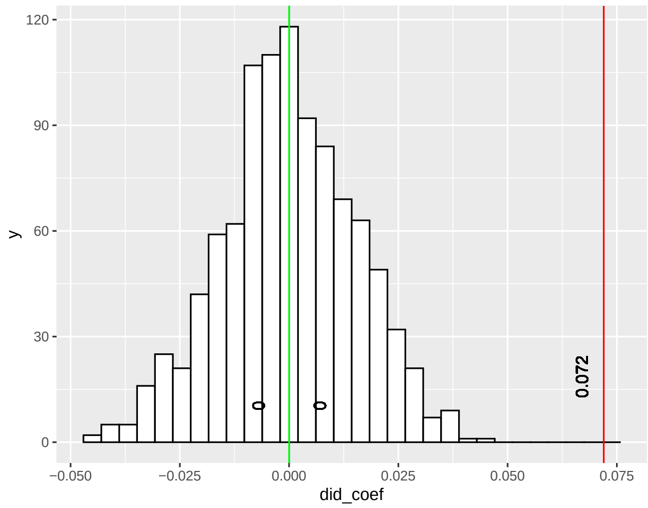
(c) Banks' market Share of no. of loan accounts



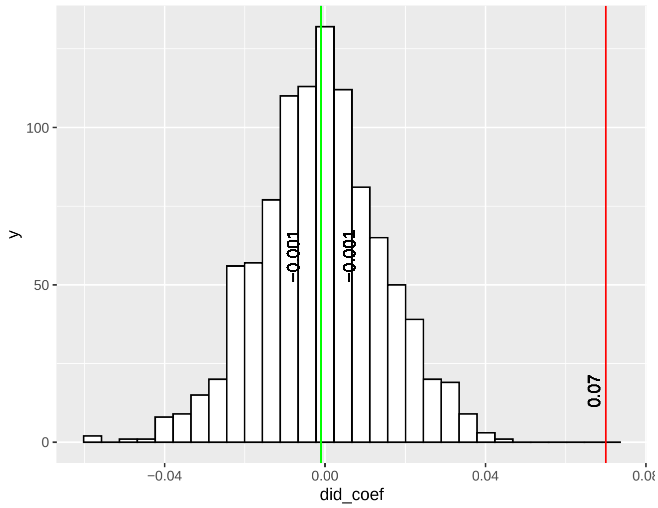
(d) Banks' market Share of total credit

Figure 2: Abnormal and normal rainfall - Falsification test

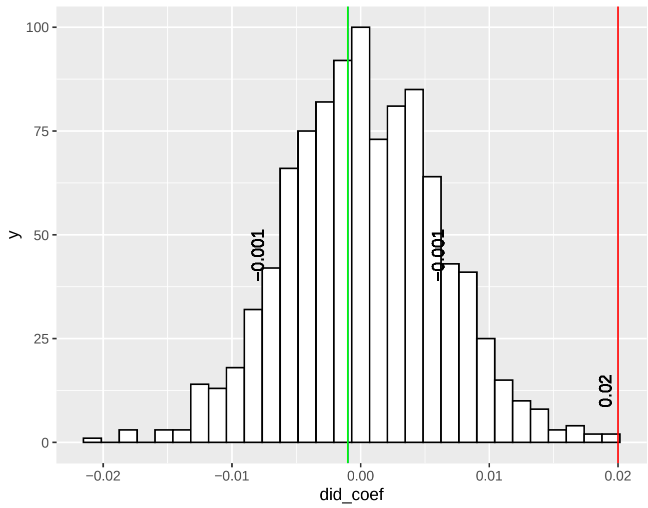
In this figure, we plot the coefficients from a regression using DID specification for each of the artificially generated sample of abnormal and normal rainfall sub-divisions. We compare the distribution of the coefficients from randomly assigned abnormal and normal rainfall sub-division on GOB versus non-GOB firms outcome variables, and compare it with our main regression estimates. We find that in all the plots the estimated coefficient of our main regression lies on extreme right of each of the distribution.



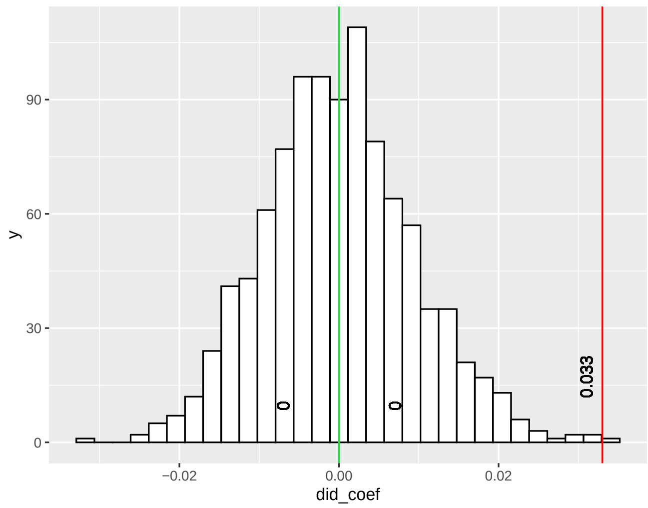
(a) Total debt scaled by total assets



(b) Debt minus cash scaled by total assets



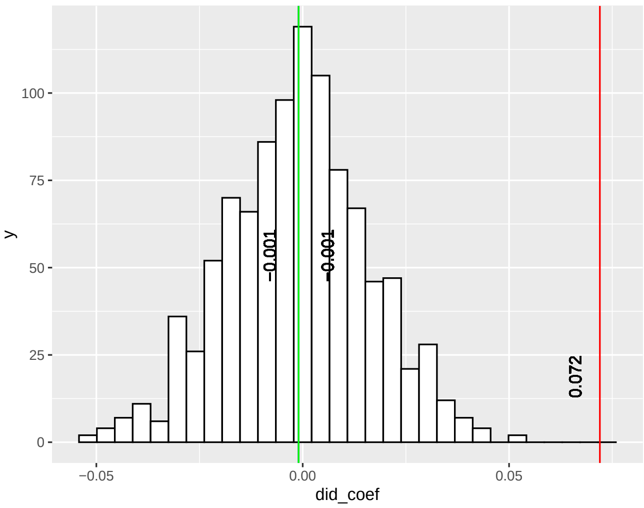
(c) Bank borrowing scaled by total assets



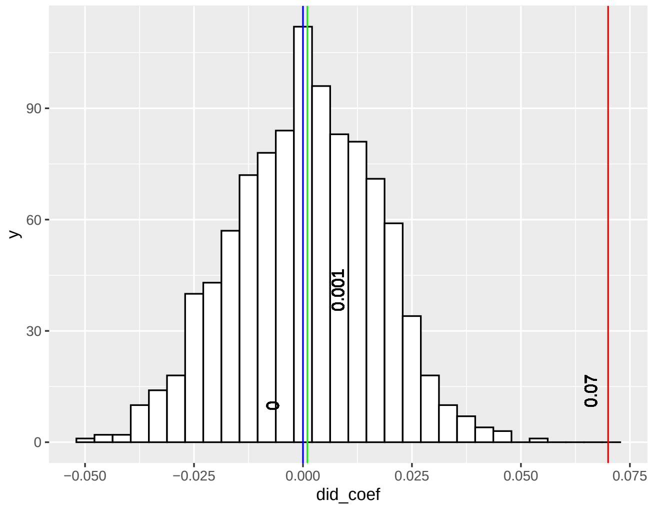
(d) Secured debt scaled by total assets

Figure 3: Treatment and control group - Falsification test

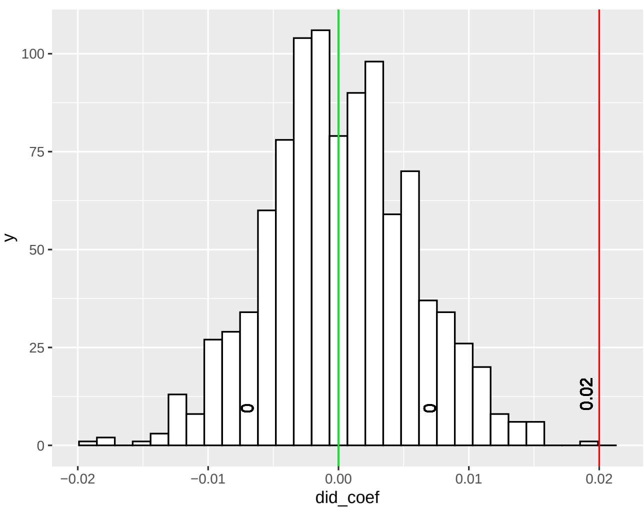
In this figure, we plot the coefficients from a regression using DID specification for each of the artificially generated sample of treatment and control groups. We compare the distribution of the coefficients from randomly assigned treatment and control group and compare it with our main regression estimates. We find that in all the plots the estimated coefficient of our main regression lies on extreme right of each of the distribution.



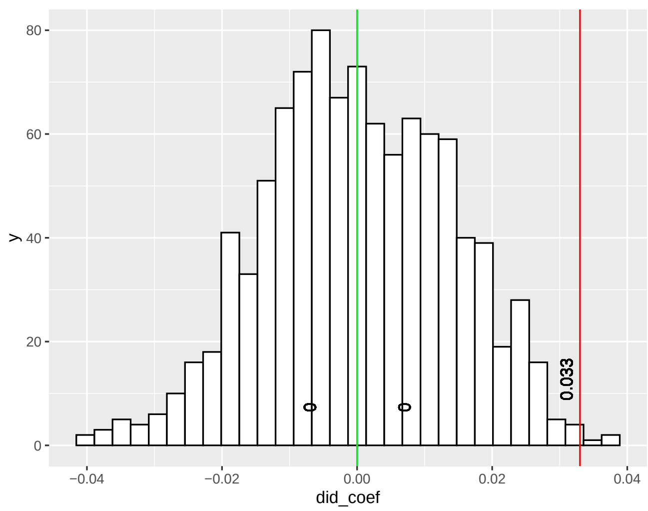
(a) Total debt scaled by total assets



(b) Debt minus cash scaled by total assets



(c) Bank borrowing scaled by total assets



(d) Secured debt scaled by total assets

8. Appendix

Table A1: Variable definitions

Variable Name	Description
$GOB_{i,t}$	1 if firm i borrows exclusively from Government Owned Banks in year t, else 0
$NGOB_{i,t}$	1 if firm i does not borrow exclusively from Government Owned Banks in year t, else 0
$Abnormal\ Rain_{s,t}$	1 if subdivision s experiences abnormal rainfall in year t, else 0
$Size_{i,t}$	Size of firm i measured by log of total assets in year t
$Cash_{i,t}$	Cash holding of the firm i is defined as cash holding scaled by beginning of the year total asset.
$ROA_{i,t}$	Return on assets (ROA) of the firm i is defined as profit after tax scaled by beginning of the year total asset.
$Tangibility_{i,t}$	Tangibility of the firm i is defined as sum of fixed asset and capital work in progress scaled by beginning of the year total asset.
$Age_{i,t}$	Age of the firm i is log age of the firm from the year of incorporation.
$Debt_{i,t}$	Debt of firm i is measured as firm's total debt scaled by beginning of the year total assets.
$Bank\ Debt_{i,t}$	Bank debt of firm i is measured as amount of bank loans of the firm normalized by beginning of the year total assets.
$Secured\ Borrowings_{i,t}$	Secured borrowing of firm i is measured as the firm's total secured loans normalized by the beginning of the year total assets.
$Long\ Term\ Debt_{i,t}$	Long-term debt of the firm i is proportion of firm's total debt is long-term debt, that is, maturity of the debt is over 12 months.
$Interest\ Expense_{i,t}$	Interest expense of firm i is defined as firm's total interest expense scaled by the beginning of the year total assets.
$Liquidity_{i,t}$	Liquidity of firm i is measured as firm's current asset minus current liability scaled by the beginning of the year total assets.
$Investment_{i,t}$	Investment of the firm i is measured as change in property, plant, and equipment scaled by the beginning of the year total assets asset.
$CAPEX_{i,t}$	Capital expenditure of the firm i is measured as sum of change in property, plant, and equipment and change in depreciation scaled by the beginning of the year total assets asset.
$EBITDA_{i,t}$	EBITDA i is measured as firm's profit before interest tax depreciation and amortization scaled by the beginning of the year total assets.

This table contains a description of the variables employed in the analysis.

Table A2: Industry Distribution

Industry	Firm-Year	Firm_year_%	Firms	Firms_%
Agriculture	510	1.599%	123	1.778%
Automobile	993	3.113%	187	2.703%
Chemical	3821	11.978%	658	9.513%
Communication	135	0.423%	30	0.434%
Construction	2874	9.010%	666	9.628%
Consumer Good	1136	3.561%	225	3.253%
Diversified	1274	3.994%	265	3.831%
Electronics and Equipment's	1073	3.364%	228	3.296%
Entertainment	324	1.016%	62	0.896%
Food Products	1666	5.223%	341	4.930%
Hotel and Restaurants	547	1.715%	122	1.764%
Machinery	1287	4.035%	273	3.947%
Metal	2643	8.286%	526	7.604%
Minerals Products	577	1.809%	97	1.402%
Misc Items	295	0.925%	75	1.084%
Paper and Business Supplies	728	2.282%	152	2.197%
Power Generation	375	1.176%	126	1.822%
Retail	330	1.035%	95	1.373%
Rubber and Plastic Products	1115	3.495%	207	2.993%
Services	3288	10.308%	848	12.260%
Textile	2506	7.856%	437	6.318%
Transportation	672	2.107%	186	2.689%
Utility	55	0.172%	12	0.173%
Wholesale	3563	11.170%	949	13.720%
Wood Products	112	0.351%	27	0.390%

Table A3: Sub-Division wise firms Distribution

Sub-Division	Firm-Year	Firm_year_%	Firms	Firms_%
ARUNACHAL PRADESH	1	0.003%	1	0.014%
ASSAM & MEGHALAYA	292	0.915%	44	0.636%
BIHAR	39	0.122%	14	0.202%
CHHATTISGARH	107	0.335%	43	0.622%
COASTAL AP AND YANAM	654	2.050%	145	2.096%
COASTAL KARNATAKA	62	0.194%	17	0.246%
EAST MADHYA PRADESH	77	0.241%	13	0.188%
EAST RAJASTHAN	937	2.937%	201	2.906%
EAST UTTAR PRADESH	302	0.947%	92	1.330%
GANGETIC WEST BENGAL	86	0.270%	26	0.376%
GUJARAT REGION	6359	19.935%	1173	16.958%
HAR. CHD & DELHI	1329	4.166%	276	3.990%
HIMACHAL PRADESH	170	0.533%	41	0.593%
JAMMU & KASHMIR AND LADAKH	10	0.031%	5	0.072%
JHARKHAND	38	0.119%	19	0.275%
KERALA & MAHE	803	2.517%	157	2.270%
KONKAN & GOA	10690	33.512%	2100	30.360%
MADHYA MAHARASHTRA	1959	6.141%	628	9.079%
MARATHWADA	62	0.194%	19	0.275%
N. I. KARNATAKA	156	0.489%	37	0.535%
ODISHA	391	1.226%	68	0.983%
PUNJAB	687	2.154%	146	2.111%
RAYALASEEMA	127	0.398%	24	0.347%
S. I. KARNATAKA	1128	3.536%	336	4.858%
SHWB & SIKKIM	33	0.103%	9	0.130%
TELANGANA	3516	11.022%	804	11.624%
UTTARAKHAND	57	0.179%	20	0.289%
VIDARBHA	418	1.310%	129	1.865%
WEST MADHYA PRADESH	625	1.959%	189	2.732%
WEST RAJASTHAN	91	0.285%	22	0.318%
WEST UTTAR PRADESH	693	2.172%	119	1.720%

Table A4: Distribution of GOB and NoN GOB exposed to abnormal and normal rainfall over sample period.

Rainfall:	Abnormal		Normal	
Year	GOB	NoN-GOB	GOB	NoN-GOB
2000	349	242	45	19
2001	185	197	416	414
2002	527	362	351	418
2003	369	306	134	61
2004	335	277	138	124
2005	364	498	143	119
2006	683	794	13	15
2007	615	841	127	169
2008	416	476	176	209
2009	354	409	405	823
2010	459	493	55	54
2011	546	937	56	137
2012	264	429	386	791
2013	576	1047	63	134
2014	125	202	258	653
2015	468	1087	31	49
2016	108	152	136	321
2017	299	633	251	546
2018	381	1085	335	848
2019	594	1960	190	456
2020	404	1297	53	96

Table A5: Impact of abnormal rainfall on GOB firms' Cash Holdings

Dependent Variable:	Cash Holding		
Model:	(1)	(2)	(3)
Variables			
$AbnormalRain_t \times GOB_{t-1}$	0.003	0.002	0.001
	(0.003)	(0.003)	(0.002)
GOB_{t-1}	0.001	-0.007**	-0.006
	(0.003)	(0.003)	(0.004)
$Size_{t-1}$		-0.040***	-0.043***
		(0.003)	(0.004)
$Tangibility_{t-1}$		-0.004**	-0.004**
		(0.002)	(0.002)
Age_{t-1}		-0.036***	-0.028***
		(0.004)	(0.006)
ROA_{t-1}		0.011	0.007
		(0.009)	(0.010)
$Debt/TotalAssets$		0.006	0.006
		(0.005)	(0.005)
Fixed-effects			
Firm	Yes	Yes	Yes
SubDiv-Year	Yes	Yes	
SubDiv-Industry-Year			Yes
Fit statistics			
Observations	31,242	30,328	30,328
R^2	0.38552	0.40882	0.48381
Adjusted R^2	0.20219	0.23195	0.19844

Notes: The key explanatory variables are defined in Table A1. Robust standard errors clustered at the subdivision level are reported in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Table A6: Parallel Trend

Dependent Variables:	$\frac{Debt}{Total\ Assets}$		$\frac{(Debt - CashHolding)}{Total\ Assets}$		$\frac{BankDebt}{Total\ Assets}$		$\frac{SecuredDebt}{Total\ Assets}$	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Year	0.019		0.017		0.004		0.025*	
	(0.014)		(0.014)		(0.003)		(0.013)	
GOB_{t-1}	18.080	12.288	19.973	13.432	-0.375	2.540	19.107	13.124
	(12.764)	(8.617)	(12.576)	(8.796)	(5.588)	(5.408)	(12.610)	(9.943)
$Size_{t-1}$	-0.265***	-0.259***	-0.244***	-0.238***	-0.101***	-0.101***	-0.185***	-0.172***
	(0.038)	(0.040)	(0.038)	(0.039)	(0.026)	(0.031)	(0.032)	(0.025)
$Cash_{t-1}$	0.021	-0.015	-0.037	-0.072	-0.019	-0.036	0.046	0.022
	(0.158)	(0.132)	(0.190)	(0.166)	(0.036)	(0.033)	(0.117)	(0.081)
$Tangibility_{t-1}$	0.027*	0.017	0.027*	0.018	0.067**	0.066**	0.074**	0.057
	(0.015)	(0.019)	(0.014)	(0.018)	(0.027)	(0.029)	(0.031)	(0.035)
ROA_{t-1}	-0.357	-0.393	-0.369	-0.395	-0.497***	-0.578***	-0.475	-0.474
	(0.480)	(0.508)	(0.482)	(0.505)	(0.087)	(0.096)	(0.777)	(0.760)
Age_{t-1}	0.163	0.089	0.185	0.108	0.183***	0.141**	-0.004	-0.106
	(0.199)	(0.243)	(0.200)	(0.245)	(0.044)	(0.059)	(0.132)	(0.175)
Year × GOB_{t-1}	-0.009	-0.006	-0.010	-0.007	0.000	-0.001	-0.010	-0.007
	(0.006)	(0.004)	(0.006)	(0.004)	(0.003)	(0.003)	(0.006)	(0.005)
Fixed-effects								
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year		Yes		Yes		Yes		Yes
Fit statistics								
Observations	9,588	9,588	9,588	9,588	5,940	5,940	8,721	8,721
R^2	0.84161	0.84910	0.84056	0.84809	0.75088	0.78116	0.82234	0.83010
Adjusted R^2	0.70663	0.69343	0.70469	0.69139	0.47254	0.45183	0.66647	0.64658

The key explanatory variables are defined in Table A1. Robust standard errors clustered at the subdivision level are reported in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Figure 4: Parallel Trends