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Assessing the fiscal implications of flood disasters in India: insights for general and special category states

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Abstract

This study provides a comprehensive analysis of the fiscal consequences arising from flood disasters in India, with a specific focus on the challenges encountered by General Category States (GCS) and Special Category States (SCS). Recognizing India's vulnerability to floods due to its diverse geographical and climatic landscape, the research emphasizes the need for a coordinated disaster response framework involving both central and state governments. Utilizing a panel vector autoregression (VAR) methodology alongside impulse response functions (IRFs), the study finds that flood disasters significantly impact fiscal variables over a medium-term horizon of 3–5 years. Our findings indicate that fiscal deficits widen for up to three years post-disaster, while expenditures on flood control surge in the following years. Notably, SCS face a disproportionate fiscal strain, exacerbated by their geographical disadvantages and heightened susceptibility to disasters, leading to a decline in non-tax revenue after flood shocks. The study advocates for tailored fiscal policies that enhance the resilience and recovery capacity of both GCS and SCS in addressing flood-induced fiscal challenges.

1. Introduction

Natural disasters pose significant threats to economic stability and growth, leaving devastating consequences that resonate across multiple facets of society. The fiscal implications of these calamities can be profound, as they often exacerbate existing vulnerabilities and hinder recovery efforts. Over the past two decades, India has faced economic losses totaling a staggering $79.5 billion due to natural disasters, as reported by the United Nations Office of Disaster Risk Reduction (UNDRR). This alarming statistic highlights the urgent need for a comprehensive understanding of the economic and fiscal impacts of such events, which extend far beyond immediate damages to infrastructure and property.

The financial repercussions of natural disasters can manifest in various ways, creating long-lasting effects on a nation's economic well-being. The literature indicates that these impacts are not only immediate but also cumulative, affecting fiscal policy and economic growth over extended periods. Studies conducted by Loayza *et al* (2012), Bergholt and Lujala (2012), Miao *et al* (2023), Melecky and Raddatz (2011), and Skidmore and Toya (2013) have highlighted the significant fiscal repercussions that natural disasters can inflict on nations, emphasizing the urgency for proactive measures to mitigate their adverse effects on economies.

Governments, often at the forefront of disaster response, are tasked with managing the substantial costs associated with these events. Such expenses inevitably strain public finances, challenging fiscal management practices and compelling policymakers to navigate complex economic landscapes. According to the Organization for Economic Co-operation and Development (OECD/The World Bank 2019), the fiscal impact of disasters depends on the intricate interplay between changes in government expenditures and revenues following the event. Typically, natural disasters exert downward pressure on the tax base, as they reduce personal and corporate incomes, property values, economic growth, and employment opportunities. This phenomenon is supported by the findings of Strobl (2011) and Davlasheridze *et al* (2017). Davlasheridze *et al* (2017) demonstrate that hurricanes result in significant property losses, while Strobl (2011) analyzes the economic growth implications of hurricanes using a dataset from U.S. coastal counties.

The fiscal pressure on governments following natural disasters is compounded by increased expenditures for reconstruction efforts, alongside a decline in tax revenue resulting from the downturn in economic activity caused by such events. This has been well documented in the work of Rasmussen (2006), Benson and Clay (2004), and Noy and Nualsri (2011). For instance, flood damages in India have been shown to lead to a decline of 0.6 percent in male employment and 3 percent in female employment within the agricultural sector (Chowdhury *et al* 2022). Furthermore, policy-driven tax reductions aimed at facilitating recovery efforts can exacerbate the decline in revenues in the short term. However, the OECD (2015) argues that these measures are designed to stimulate economic recovery and reignite the tax base as growth resumes.

The existing literature has employed a variety of economic methods and datasets to estimate the impacts of natural disasters on economic growth, employment opportunities, and the fiscal pressures faced by governments. Siyi *et al* (2017) confirm that typhoon damage significantly reduces local companies' tax avoidance levels in China. The adverse effects of natural disasters extend beyond government tax and expenditure dynamics; they can also adversely impact personal income, as noted by Benson and Clay (2004). Recent evidence shows that hurricanes have led to a 0.5 percent decline in employment in Puerto Rico (2023). Similarly, in India's agricultural sector, flood damages have resulted in reductions of 0.6 percent and 3 percent in male and female employment, respectively (Chowdhury *et al* 2022).

The overall economic landscape can be dramatically affected by natural disasters, which can lead to reduced growth in per capita gross state domestic product. For example, Parida and Prasad Dash (2020) found that a 10 percent increase in flood damages correlated with a 0.03 percent decline in per capita gross state domestic product in India. In the context of U.S. coastal counties, Strobl (2011) reports that hurricane strikes have resulted in significant reductions in local economic growth, estimating a decline of 0.8 percent. Furthermore, Raddatz (2007) finds that climatic disasters can lead to a 2 percent reduction in gross domestic product (GDP). Davlasheridze *et al* (2017) illustrate that a one percent increase in annual spending on ex-ante risk and ex-post recovery associated with hurricanes leads to a decline in per capita property loss by 0.21 percent and 0.12 percent, respectively, in the U.S. Notably, in developing countries like India, higher per capita income has been associated with a 1.4 percent decline in total flood damage, including both private and public properties (Parida 2020).

Conversely, in certain instances, disasters can paradoxically expand the tax base, primarily due to increased international aid or robust economic recovery driven by reconstruction efforts, as noted by the OECD/The World Bank (2019). Nevertheless, the immediate fiscal challenge following a disaster is the transformation of contingent liabilities into actual government expenditures. This process is complex, particularly after significant disasters, as highlighted by the OECD (2012), OECD/The World Bank (2019). The scale of these expenses can lead to fiscal imbalances, resulting in increased public debt. A prominent example of this is the aftermath of the 2011 Great East Japan Earthquake, where government funding accounted for 4% of Japan's GDP in 2010, according to the OECD/The World Bank (2019).

The indiscriminate nature of disasters leads to economic and fiscal repercussions that can vary widely across different regions. Factors such as geographical location, economic structure, governance quality, and the strength of fiscal management systems play crucial roles in determining the degree of fiscal vulnerability and resilience to natural disasters. Hallegatte (2017) and Atreya *et al* (2017) highlight these differences, illustrating how certain regions may face disproportionately severe impacts due to pre-existing economic disparities and weaknesses in governance. The regional fiscal impacts of natural disasters can exacerbate these pre-existing fiscal imbalances and economic disparities, as observed by Cavallo and Noy (2011).

Motivated by these insights, this study aims to empirically assess the fiscal implications of flood disasters in India, focusing on regional variations in fiscal resilience and vulnerabilities. Despite the prevalence of floods in India (Parida *et al* 2022), there is a notable lack of studies exploring their fiscal repercussions. By analyzing flood damage as a shock variable, we investigate its impact on key fiscal indicators—such as fiscal deficit, tax revenue, public debt, and flood control expenditure—across 19 major flood-affected states from 1980 to 2017. Employing a panel VAR methodology, we estimate Impulse Response Functions using the Choleski Decomposition method, providing valuable insights for policymakers and disaster management authorities.

Table 1. Description of the variables and data sources.

Name	Description	Source
DAMGD	Total flood damage as percent of GSDP	CWC
FISGD	Gross Fiscal Deficit as percent of GSDP	EPWRPF
FLCGD	Flood Control Expenditure as percent of GSDP	CWC
AREVGD	Aggregate Revenue Receipts as percent of GSDP	EPWRPF
DEBGD	Total Public Debt as percent of GSDP	EPWRPF
TRGD	Tax Revenue as percent of GSDP	EPWRPF
NTRGD	Non-Tax Revenue as percent of GSDP	EPWRPF

CWC = Central Water Commission; EPWRPF = Economic and Political Weekly Research Foundation.
Source: Author's estimation.

Exploring the mechanisms through which different regions absorb and respond to the fiscal shocks induced by natural disasters is essential for a deeper understanding of their impacts. This includes examining regional financial preparedness, such as the existence and efficacy of disaster relief funds and insurance mechanisms in alleviating adverse fiscal outcomes. Kousky and Shabman (2015) explore these aspects, shedding light on the importance of having robust systems in place to mitigate the financial fallout from disasters. Additionally, the role of intergovernmental fiscal transfers and international aid should be scrutinized for their potential to protect regions from the immediate and long-lasting fiscal distress that follows disasters. This underscores the necessity for a coordinated approach to disaster mitigation and recovery efforts, as emphasized by AghaKouchak *et al* (2018).

Through a systematic analysis of the varied regional fiscal impacts of natural disasters, this study aims to contribute significantly to the ongoing discourse on enhancing fiscal resilience and developing targeted disaster preparedness and response strategies. It highlights the need for a nuanced understanding of regional vulnerabilities and capacities, informing the formulation of fiscal policies and mechanisms that are better equipped to withstand the economic shocks brought about by natural disasters. Such an approach is crucial for policymakers, who must navigate the delicate balance between immediate disaster response needs and the long-term imperatives of fiscal sustainability and economic recovery, as illustrated by Hallegatte (2017) and Kunreuther and Michel-Kerjan (2017).

The remainder of this paper is structured as follows: Section 2 outlines the methods, Section 3 presents the results, Section 4 discusses the findings, and Section 5 concludes the study.

2. Methods

2.1. Data

Based on the data availability, we use annual panel data for 19 major flood-affected states[6] from 1980 to 2017. For our empirical analysis, we separate the 19 states into General Category States (GCS) and Special Category States (SCS) based on economic development (level of income) and their geographical characteristics.[7] Specifically, we have used seven variables, i.e., 'total flood damage' as percent of GSDP (DAMGD), 'gross fiscal deficit' as percent of GSDP (FISGD), 'flood control expenditure' as percent of GSDP (FLCGD), 'aggregate revenue receipts' as percent of GSDP (AREVGD), 'total public debt' as percent of GSDP (DEBGD), 'tax revenue' as percent of GSDP (TRGD), and 'non-tax revenue' as percent of GSDP (NTRGD), for our empirical analysis. The DAMGD and FLCGD data are obtained from the Central Water Commission (CWC), Government of India. The rest of the variables, i.e., FISGD, AREVGD, DEBGD, TRGD, and NTRGD are sourced from the Economic and Political Weekly Research Foundation (EPWRPF) database. The details of these variables are explained in table 1.

[6] These states are Andhra Pradesh, Assam, Bihar, Gujarat, Haryana, Himachal Pradesh, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Manipur, Meghalaya, Odisha, Punjab, Rajasthan, Tamil Nadu, Tripura, Uttar Pradesh, and West Bengal. We had to exclude Arunachal Pradesh from our empirical analysis because of incomplete data availability.

[7] 'Special Category States (SCS) require special attention while framing their economic policies due to the geographical and demographical disadvantage such as hilly and difficult terrain, low population density, a sizable share of tribal population, strategic location along borders with neighbouring countries, economic and infrastructural backwardness and non-viable nature of state finances, etc Due to the above characteristics, these states have a low resource base'. However, 'the General Category States (GCS) do not face these problems'. In our sample, there are 14 GCS (Andhra Pradesh, Bihar, Gujarat, Haryana, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Odisha, Punjab, Rajasthan, Tamil Nadu, Uttar Pradesh, and West Bengal) and 5 SCS (Assam, Manipur, Meghalaya, Tripura, Himachal Pradesh).

Table 2. Descriptive statistics.

Overall states	DAMGD	FISGD	FLCGD	AREVGD	DEBGD	TRGD	NTRGD
Mean	0.60	3.35	1.11	21.15	28.39	9.28	6.98
Maximum	14.44	15.37	7.08	57.11	61.15	21.46	39.19
Minimum	0.00	−2.89	0.06	−44.61	9.21	2.85	1.34
Std. Dev.	1.35	2.01	0.90	8.86	11.14	3.07	6.80
Observations	722	722	722	722	722	722	722
General Category States							
Mean	0.49	3.36	1.20	18.06	27.35	9.53	3.73
Maximum	14.44	12.30	7.08	35.03	61.06	20.13	13.08
Minimum	0.00	−0.98	0.13	7.05	10.61	5.53	1.34
Std. Dev.	1.24	1.62	0.92	5.20	10.80	2.96	1.73
Observations	532	532	532	532	532	532	532
Special Category States							
Mean	0.90	3.34	0.87	29.80	31.29	8.57	16.09
Maximum	8.34	15.37	4.52	57.11	61.15	21.46	39.19
Minimum	0.00	−2.89	0.06	−44.61	9.21	2.85	3.55
Std. Dev.	1.58	2.83	0.80	11.04	11.59	3.27	7.41
Observations	190	190	190	190	190	190	190

Source: Author's estimation.

The descriptive statistics of the selected variables are displayed in table 2. It shows that the mean of total flood damage (DAMGD) for all states is 0.60, while it is higher in the Special Category States (0.90) compared to general category states (0.49). It implies that the total average damage due to flood is higher for special category states than other categories. The average flood control expenditure (FLCGD) is relatively higher in GCS than SCS and overall states. The mean of aggregate revenue receipts, total public debt, and non-tax revenue (AREVGD, DEBGD, NTRGD) are also observed to be higher in SCS as compared to GCS and overall states. However, the difference in the mean of fiscal deficit (FISGD) as well as 'tax revenue' as percent of GSDP (TRGD) in our sample across groups is not prominent. In our sample, the standard deviation of debt and aggregate revenue is larger than other variables across all states implying these two variables are volatile. The least variation is observed for flood control expenditure.

2.2. Variable selection criteria

In this study, we consider damage from floods as one of the key outcome variables for several compelling reasons. First, according to the Central Water Commission report, flood damages encompass destruction to houses, crops, and public utilities, all quantified in monetary terms. By including economic losses due to floods, we aim to illustrate how such losses significantly impact fiscal variables over a medium-term horizon of 3–5 years. Few studies have specifically focused on economic losses from floods, despite its importance as an impact measure in India (Parida 2020, Chowdhury *et al* 2022). Thus, incorporating economic losses due to floods allows us to fill this gap in the empirical literature and provides a critical measure for our analysis.

However, accurately measuring flood damage in India poses several challenges. Parida and Prasad Dash (2020) highlight that flood damage figures are often not accurately reported due to inadequate insurance facilities to protect private and public properties, including crops and houses, against natural disasters. Insurance facilities are vital for the accurate estimation of flood damages. Additionally, state governments tend to submit inflated flood damage figures to the central government to secure higher disaster grants for reconstruction and flood mitigation measures. The world's largest disaster database, 'The Emergency Events Database (EM-DAT)', also tends to underreport disaster damages and smaller natural disaster events (Dilley 2005, Rasmussen 2006). Despite these issues, extensive empirical literature relies on EM-DAT to study the socioeconomic impact of natural disasters (Cavallo and Noy 2011). Consequently, economic damages from floods in India may be either underreported or overreported, which could be a limitation of our study.

Understanding the interplay between various fiscal variables, such as fiscal deficit, public debt, flood control expenditure, tax revenue, non-tax revenue, and aggregate revenue, is crucial for comprehending fiscal dynamics, especially in the context of natural disasters like floods. Our theoretical framework is based on several key considerations. Tax revenue, derived from various forms of taxation (e.g., income tax, corporate tax, sales tax), is directly influenced by economic activity. Flood disasters disrupt economic activities, leading to declines in income, production, and consumption, which in turn reduce tax collections. Non-tax revenue includes government income from sources other than taxes, such as fees, fines, charges for services, and dividends from public sector enterprises. Floods can reduce the earnings of public enterprises and lower the collection of fees and charges, as well as lead to concessions or deferments on non-tax obligations.

Aggregate revenue receipts, which comprise both tax revenue and non-tax revenue, are affected by floods. A decline in revenue receipts due to floods compels the government to rely more on capital receipts to finance immediate relief and reconstruction efforts, affecting public debt and overall fiscal balance. The fiscal deficit widens during disasters due to increased expenditure on relief and reconstruction combined with reduced revenue collections. This deficit often needs to be financed through increased borrowing, leading to higher public debt. Public debt increases in the aftermath of floods, as the government may need to borrow more to cover the fiscal deficit and fund flood control and recovery efforts. Flood control expenditure includes spending on infrastructure and measures to prevent and mitigate flood damage. Post-disaster, this expenditure rises significantly to rebuild and strengthen infrastructure. While necessary, it further strains the fiscal balance, especially when financed through additional borrowing.

This paper has followed Panwar and Sen (2020) paper provide a significant contribution to understanding the fiscal impacts of natural disasters using an advanced PVAR-X framework. The robustness tests enhance the credibility of their findings. Further the varible selection was based Panwar and Sen (2020). They used endogenous variables such as government expenditure, revenue, and fiscal deficit. The choice of these variables is motivated by their direct relevance to fiscal health and their responsiveness to shocks from natural disasters added certain exogenous Variables that influence the endogenous variables but are not influenced by them within the model. In this study, exogenous variables include measures of disaster intensity, state-level GDP, population density, and infrastructure quality. However, the paper would benefit from clearer acknowledgment of previous related work and a more thorough discussion of potential methodological issues related to variable selection and model specification.

By analyzing these variables, we aim to provide a comprehensive understanding of the fiscal impact of floods and the economic losses they cause. This analysis will help to highlight the critical areas that need attention to improve disaster response and fiscal resilience in the face of natural disasters.

2.3. Econometric methodology

To examine the interaction between flood damage shocks and selected fiscal variables, we employ a panel Vector Autoregression (VAR) methodology, complemented by Impulse Response Functions (IRFs) derived using Cholesky Decomposition. The dynamic relationship between these fiscal variables is inherently interdependent. For instance, a reduction in tax and non-tax revenues leads to a decline in aggregate revenue receipts, while an increase in flood control expenditures widens the fiscal deficit. In response to this fiscal shortfall, the government borrows more, thereby increasing public debt. The panel VAR model is designed to capture these intricate interactions, allowing for mutual influences and feedback mechanisms between variables, without imposing restrictive assumptions on exogeneity or endogeneity.

The reduced form of the chosen panel VAR models can be represented as follows:

$$z_{i,t} = \alpha_i + \sum_{k=1}^{n} \beta_j z_{i,t-k} + \sum_{k=0}^{m} \delta_j x_{i,t-k} + \varepsilon_{i,t} \tag{1}$$

Where z and x represent the vectors of endogenous and weekly exogenous variables, respectively; i (1, 2, ….19) refers to selected major states; t stands for the time (1980, 1981,…..2017); ϵ represents the error term of the system, which is assumed to be independent within equations, $\mathrm{E}(\varepsilon_{i,s}\epsilon'_{i,p}) = 0,\ \ s \neq p$, and across equations, $\mathrm{E}(\varepsilon_{i,s}\epsilon'_{j,p}) = 0$, for any s & p where i ≠ j. The vector $z_{i,t}$ includes 6 × 1 endogenous variables, and the vector $x_{i,t}$ includes 1 × 1 weekly exogenous variables. These variables are as follows:

$$z_{i,t} = \begin{bmatrix} FISGD_{i,t} \\ FLCGD_{i,t} \\ AREVGD_{i,t} \\ DEBGD_{i,t} \\ TRGD_{i,t} \\ NTRGD_{i,t} \end{bmatrix}; x_{i,t} = [DAMGD_{i,t}] \tag{2}$$

Where:

FISGD: Fiscal deficit (as a percentage of GSDP).
FLCGD: Flood control expenditure (as a percentage of GSDP).
AREVGD: Aggregate revenue receipts (as a percentage of GSDP).
DEBGD: Public debt (as a percentage of GSDP).
TRGD: Tax revenue (as a percentage of GSDP).
NTRGD: Non-tax revenue (as a percentage of GSDP).

Table 3. The result of panel unit root tests.

Variable	LLC	Breitung	IPS	ADF - fisher	pp - fisher
DAMGD	-16.79^{***}	-14.03^{***}	-15.55^{***}	274.09^{***}	363.24^{***}
FISGD	-8.51^{***}	-5.67^{***}	-7.55^{***}	129.01^{***}	134.52^{***}
FLCGD	-6.34^{***}	-3.09^{***}	-5.48^{***}	119.87^{***}	94.13^{***}
AREVGD	-7.33^{***}	-2.59^{**}	-7.99^{***}	149.21^{***}	153.88^{***}
DEBGD	-2.08^{**}	0.04	-1.24^{*}	39.25	28.62
TRGD	-3.83^{***}	-2.78^{***}	-2.83^{***}	70.62^{***}	66.55^{***}
NTRGD	-5.55^{***}	-6.26^{***}	-5.94^{***}	101.42^{***}	103.40^{***}

LLC represents Levin *et al* panel unit root tests (2002). The Breitung test is proposed by Breitung and Das (2005) and the IPS test is by Im *et al* (2003). The ADF-Fisher and PP-Fisher unit root tests are proposed by Maddala and Wu (1999). The Schwarz Information Criterion (SIC) is used to select the lag length. All the tests have the null hypothesis that the data contains unit root. ***, **, and * denotes significance level at 1%, 5%, and 10% respectively.
Source: Author's estimation.

DAMGD: Flood damage (as a percentage of GSDP, used as an exogenous variable).

The panel VAR methodology requires validating the stationarity of the selected variables. Therefore, in the subsequent section, we perform unit root tests to confirm the stationary properties of these variables before analyzing the impulse response functions.

The use of the panel VAR model offers several key contributions to our analysis. First, it captures the dynamic and interdependent relationships between fiscal variables—such as the fiscal deficit, public debt, flood control expenditure, tax revenue, non-tax revenue, and aggregate revenue receipts—especially in the context of natural disasters like floods. Unlike traditional models that require prior assumptions about the exogeneity or endogeneity of variables, the panel VAR model allows for a more flexible approach, accommodating the mutual feedback between fiscal variables as they evolve over time in response to flood shocks.

Second, the panel VAR model accounts for heterogeneity across states. By classifying the 19 Indian states into General Category States (GCS) and Special Category States (SCS), based on their economic development and geographical characteristics, we can investigate whether fiscal responses to flood events vary according to these categorizations. This aspect of the model allows us to explore state-specific fiscal dynamics, reflecting the differing vulnerabilities and capacities of states in managing flood-induced fiscal pressures.

Third, the panel VAR model facilitates the analysis of time-dependent fiscal impacts by employing impulse response functions. These functions help quantify the effects of shocks to one variable (e.g., flood damage) on other variables over time, providing a detailed understanding of the transmission of fiscal shocks in disaster-prone regions. This methodology offers deeper insights than simpler econometric models, enabling a more comprehensive exploration of fiscal dynamics.

Finally, the panel VAR approach is a well-established method for addressing endogeneity issues, particularly in macroeconomic contexts (Noy and Nualsri 2011, Fomby *et al* 2013). This makes it an ideal choice for studying the fiscal responses to natural disasters like floods, where the interaction between fiscal variables and external shocks is complex and evolving over time.

3. Results

3.1. Unit root tests

The study has used various well-known crucial panel unit root tests (see Levin *et al* 2002, Maddala and Wu 1999, Im *et al* 2003, Breitung and Das 2005) to check the stationarity of the selected variables. The results of these panel Unit root tests are reported in table 3. All unit root tests show that all these variables (except DEBGD) are stationary at their levels, i.e., I (0). The variable DEBGD is stationary by LLC & IPS Unit root test but non-stationary by other selected unit root tests. However, based on LLC & IPS unit root tests, we believe the stationarity assumption is probably warranted for all variables.

3.2. Results of impulse response functions

A priori, natural disasters such as floods have long lasting impacts on geography, ecology and economy. An attempt is made in this study to empirically analyze whether floods have long term impact on fiscal variables. IRFs (or Impulse Response Functions) are used to analyze the impact of flood shock on several fiscal variables. The effect of one SD (standard deviation) shock to flood damage is to be seen in all endogenous variables, that is, FISGD, FLCGD, AREVGD, DEBGD, TRGD and NTRGD. Since floods in India are a recurrent phenomenon (NDMA- National Disaster Management Authority), we take one SD shock as opposed to a two SD shock which is taken as a large disaster shock in the literature (see Noy and Nualsri 2011). Here, we trace out the IRFs for flood damage shock for 19 overall states, 14 General Category States as well as 5 Special Category States. Our results will be useful in understanding how the variables behave dynamically in response to disaster shocks and whether there is any difference between GCS and SCS (as these are characterized by hilly terrains and infrastructural bottlenecks). Before running the VAR model, we conducted several pre-estimation tests including panel cointegration test, VAR lag order selection, and VAR roots test. The results can be found in the appendix. In our case, we chose to use 3 lags based on AIC, LR, and FPE as the majority of criteria suggested 3 lags (see appendix table A2). We found that our variables are cointegrated for the long run (refer to appendix table A1). Furthermore, the VAR roots for the characteristics polynomial indicate that all inverse roots lie within the unit circle. This satisfies the stability condition (see appendix figure A1).

3.2.1. Results for all states

3.2.1.1. Impulse response functions

The impulse response graphs can be seen in figure 1. The six figures ranging from (a) to (f) show the response of multiple fiscal variables i.e., FISGD, FLCGD, AREVGD, DEBGD, TRGD, and NTRGD to one SD shock to DAMGD. The horizontal axis shows the number of periods (years) that have passed after the impulse or one SD shock in DAMGD. The vertical axis shows the response or change in the mentioned fiscal variables. If the confidence band contains the horizontal axis, then the IRF is statistically insignificant.

A look at the figure 1(a) shows that the IRF is insignificant till period 3 but significant thereafter. Response (change) of FISGD (in percent points) following one SD shock displays an initial rising trend and peaks around the fourth period. This reflects the expected expansionary fiscal reaction to unexpected damage shock. After the fourth period, 'change in FISGD' starts to decrease but remains above zero for the remaining observed periods. This shows that following the flood disaster damage shock, the 'change in FISGD' increases, reaches a peak and thereafter declines but is still positive. It implies that flood shocks have a lasting impact on fiscal deficits. There is a lingering effect of the shock on the fiscal position of the government, which raises concerns about fiscal sustainability.

Figures 1(b) to (f) shows that the IRF is insignificant for all periods since the confidence band contains the horizontal axis. However, we may briefly interpret the trends. In figure 1(b), 'change in FLCGD' (in percent points) dips below zero immediately following one standard deviation shock in flood damage. *A priori*, flood control expenditure should rise following the flood shock as there is immediate reallocation of funds to more urgent or unexpected needs arising from the damage. However, quite on the contrary, we observe that 'change in FLCGD' dips below zero. The 'change in FLCGD' moves from negative and into positive territory between periods 3 and 4, which implies the recognition of the need for increased investment in flood control measures to mitigate the impact of similar future shocks. Subsequently, the trend persists throughout the remaining observed periods and stabilizes at a positive level. This response pattern suggests a sustained policy response aimed at committing more resources to flood control and strengthening the resilience against future floods.

In figure 1(c), the impulse response graph of AREVGD (aggregate revenue receipts as a percent of GDP) dips below zero right after the shock, which indicates that 'change in AREVGD' (in percent points) displayed a reduction right after the damage shock. Consequently, this response becomes less negative and crosses the zero line between periods 2 and 3, which could indicate a rebound in economic activity, possibly owing to recovery aid and increased economic activity in the reconstruction phase. Finally, from period 3 onwards, the response of AREVGD fluctuates around the zero line, but remains mostly positive. This positive response is because of the resilience of the tax revenue systems (figure 1(e)) or the effectiveness of policy measures to restore and possibly enhance revenue streams during the post-shock period.

In figure 1(d), 'change in DEBGD' (in percent points) is not instantly affected by the damage shock, possibly because debt issuance and repayment are not immediately responsive to such shocks. Subsequently, the response of DEBGD indicates a gradual and sustained increase to finance the recovery efforts throughout ten years following the shock, but the slope appears to flatten out. The analysis of the impact of damage shock on public debt highlights the importance of considering shock impacts in debt management and fiscal planning to maintain long-term fiscal sustainability.

Figures 1(e) and (f) present contrasting responses of tax and non-tax revenue following the flood shock. The 'change in TRGD' (in percent points) shows an immediate rise, suggesting immediate policy reactions such as tax increases or better collection to finance emergency spending or it may reflect an increase in certain taxes owing to the damage (e.g., import tariffs on goods to replace damaged infrastructure). After the initial response, the 'change in TRGD' stabilizes slightly above zero line. This response pattern implies the stabilization of tax revenue and the resilience of the tax system to flood damage shock. However, the impulse response graph of NTRGD, as shown in figure 1(f) displays a sharp decline in the solid line, indicating that 'change in NTRGD' (in percent points) becomes negative immediately after the damage shock. This reflect the direct impact of the flood

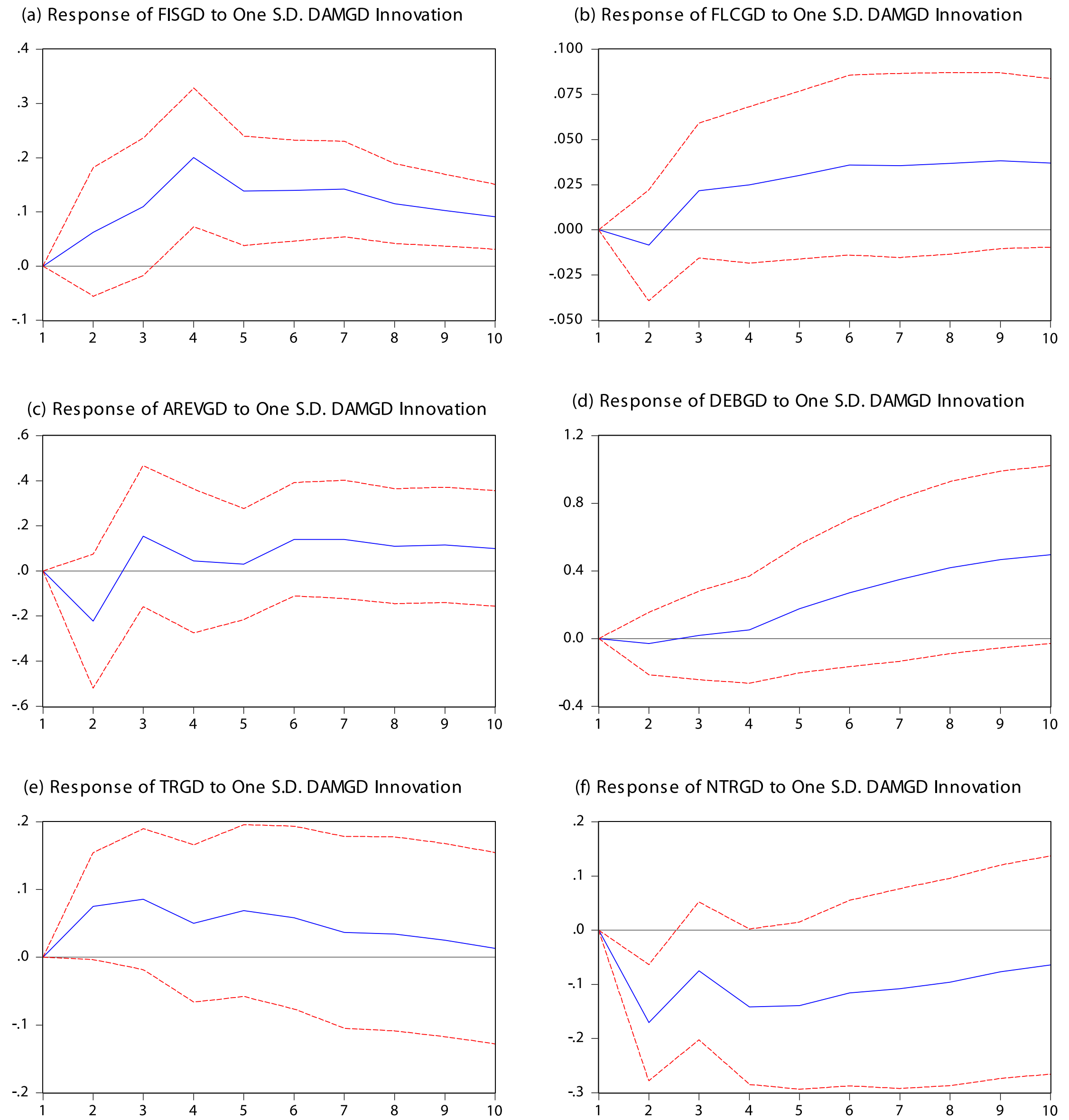

Figure 1. Impulse response graphs of selected variables to total damage shocks (Overall States). Source: Author's estimation.

damages on the sources of non-tax revenue, such as profits from state-owned enterprises, fees, and other government services that may be disrupted. After the initial drop, the response rises back towards zero, but remains slightly negative, indicating a partial but not complete recovery of 'change in NTRGD'. Finally, the solid line stabilizes below zero throughout the remainder of the periods, suggesting a sustained negative impact on non-tax revenue. This reflects upon the fact that first, non-tax revenue is more vulnerable to damage shocks compared to tax revenue, potentially because of its reliance on economic activities and services that can be directly affected by such shocks; and second, unlike tax revenue, non-tax revenue may not have mechanisms to immediately compensate for the shock, such as increased rates or improved collection.

3.2.1.2. Cumulative impact of flood damage shock

Notwithstanding the dynamic fiscal impacts, we also estimate the cumulative fiscal effects of one standard deviation shock to flood damage over time. Table 4 delineates a mixed fiscal response to flood damage over time. Out of the six variables., viz., FISGD, FLCGD, AREVGD, DEBGD, TRGD, and NTRGD, the cumulative impact on AREVGD, DEBGD are statistically insignificant even considering longer horizons such as 5–10 years. The 'change in FISGD' is 0.062 by the end of period 2 and 0.172 by the end of period 3 (statistically significant at 10 percent). However, considering the cumulative effect over 5–10 years, the 'change in FISGD' is insignificant. The 'change in FLCGD' is negative (−0.009) by the end of period 2 and 0.013 by the end of period 3 (statistically significant at 5 percent). Even when considering the cumulative effect over 5 years, the 'change in FLCGD' is significant. Hence, 'flood control expenditure increase' following a flood shock may be seen cumulatively over 5

Table 4. Impulse response functions to a one standard deviation shock to flood damage (Overall States).

Time period	FISGD	FLCGD	AREVGD	DEBGD	TRGD	NTRGD
Period 1	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Period 2	0.062*	−0.009**	−0.222	−0.030*	0.075**	−0.171*
	(0.059)	(0.015)	(0.148)	(0.092)	(0.039)	(0.054)
Period 3	0.172	0.013**	−0.068	−0.011	0.161*	−0.246
	(0.102)	(0.030)	(0.236)	(0.204)	(0.084)	(0.103)
Cumulative Effect (5 years)	0.510	0.068*	0.005	0.218	0.279	−0.528
	(0.186)	(0.070)	(0.423)	(0.516)	(0.191)	(0.233)
Cumulative Effect (10 years)	1.010	0.252	0.609	2.219	0.446	−0.990
	(0.355)	(0.187)	(1.011)	(1.697)	(0.529)	(0.684)

*$p < 0.01$.
**$p < 0.05$.
***$p < 0.01$.
Source: Author's estimation.

years. The 'change in TRGD' is positive by the end of period 2 and period 3 (statistically significant). The 'change in NTRGD' is negative by the end of period 2 (statistically significant) and negative by the end of period 3 (statistically insignificant). Hence, both tax and non-tax revenue increase at least till 3 years following the shock which implies how the government tries to increase tax collections to compensate for fiscal expenses or increase interest rates on loans which leads to increase in non-tax revenue receipts.

3.2.2. Results for general category states

3.2.2.1. Impulse response functions

In its extension, specifically, we further investigate whether the flood-induced fiscal impacts follow a similar pattern across states with differential socioeconomic conditions and differing geographical characteristics. Specifically, we divide our sample of states into two categories: general category states (GCS) and special category states (SCS). Figure 2 presents the dynamic fiscal impacts of flood damage shocks on endogenous fiscal variables for the general category states (GCS). A glance at the six figures show that only in (b), the IRF is statistically significant as the confidence band does not contain the horizontal axis. For all other figures, the IRFs are found to be statistically insignificant over all the periods. In figure 2(b), the IRF is insignificant until period 3, thereafter, the 'change in FLCGD' (in percent points) is positive and increasing slightly until it stabilizes. That is, the flood control expenses following the shock increases and becomes almost stable at the increased level. This response pattern suggests a commitment to enhanced flood control measures in the general category states following damage shock, thereby reflecting proactive fiscal policy in disaster management and mitigation.

3.2.2.2. Cumulative impact of flood damage shock

Apart from the dynamic fiscal impacts, we also estimate the cumulative fiscal effects of one standard deviation shock to flood damage over time for GCS. Table 5 delineates a mixed fiscal response to flood damage over time. Out of the six variables., viz., FISGD, FLCGD, AREVGD, DEBGD, TRGD, and NTRGD, the cumulative impact on DEBGD is statistically insignificant even considering longer horizons such as 5–10 years. The 'change in FISGD' (in percent points) is −0.047 by the end of period 2 (statistically significant at 5 percent) and −0.015 by the end of period 3 (statistically significant at 10 percent). However, considering the cumulative effect over 5–10 years, the 'change in FISGD' is insignificant. The negative change or the decline in FISGD is not subject to economic interpretation as typically in the aftermath of a disaster, revenue collections fall and expenditures increase *a priori*. The 'change in FLCGD' (in percent points) is negative (−0.013) by the end of period 2 and positive (0.031) by the end of period 3 (statistically significant at 5 percent). Hence, 'flood control expenditure increase' following a flood shock may be seen cumulatively over 3 years. The 'change in AREVGD' is negative by the end of period 2 at −0.028 (statistically significant at 10 percent) which implies that revenue receipts decline until period 2 following a disaster shock. The 'change in TRGD' (in percent points) is 0.034 by the end of period 2 and 0.076 by the end of period 3 (statistically significant). The 'change in NTRGD' (in percent points) is −0.006 by the end of period 2 and 0.019 by the end of period 3 (statistically significant). Hence, both tax and non-tax revenue increase at least till 3 years following the shock. These are consistent results as aggregate revenue receipts (as a percent of GSDP) are found to scale up until period 3 following a disaster shock, but both tax and non-tax revenue (as a percent of GSDP) are found to increase till 3 years following the shock. However, keeping aside

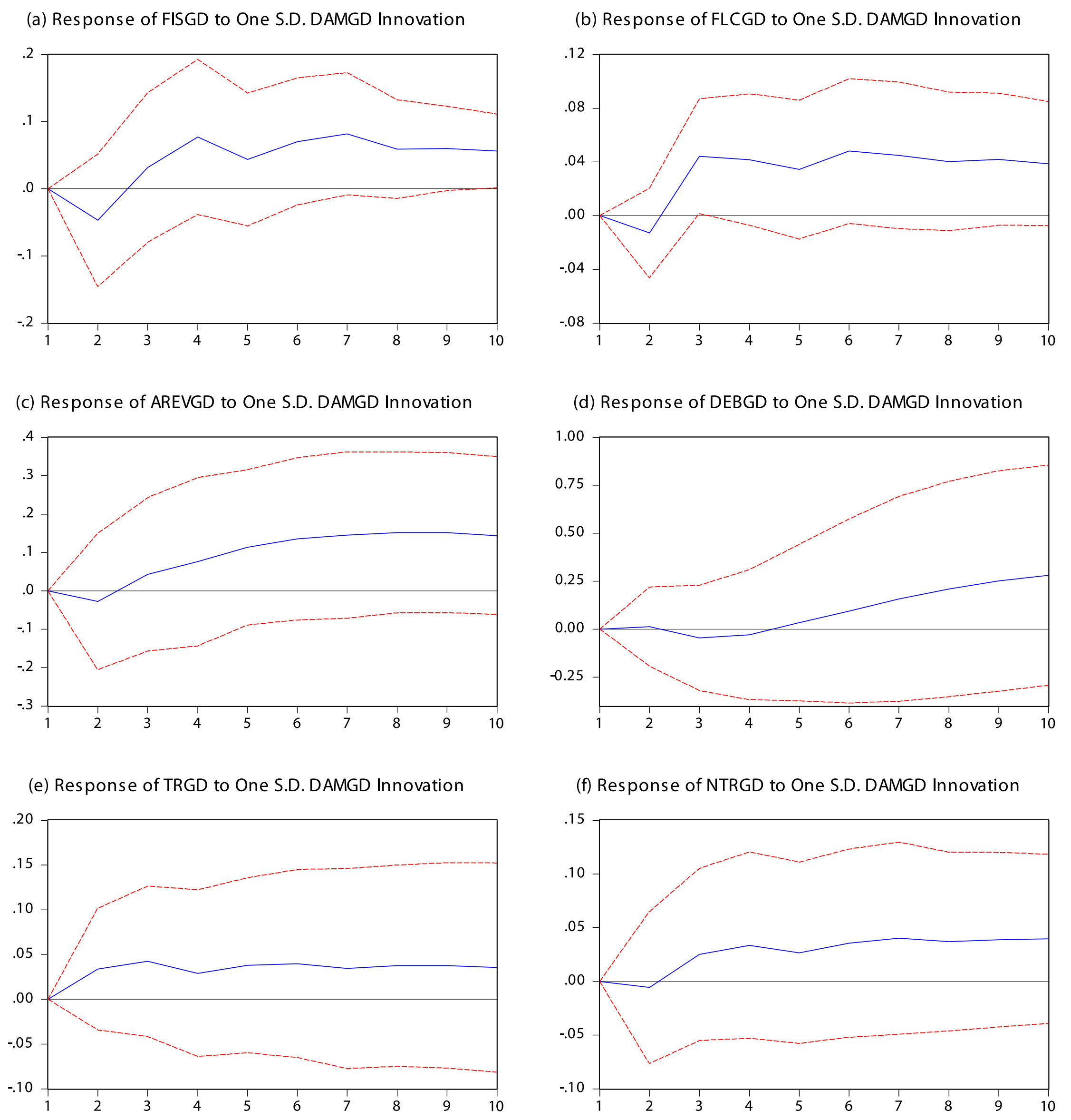

Figure 2. Impulse response graphs of selected variables to total damage shocks (General Category States). Source: Author's estimation.

Table 5. Impulse Response Functions to a one standard deviation shock to Flood Damage (General Category States).

Time period	FISGD	FLCGD	AREVGD	DEBGD	TRGD	NTRGD
Period 1	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Period 2	-0.047^{**}	-0.013^{**}	-0.028^{*}	0.013	0.034^{**}	-0.006^{**}
	(0.049)	(0.017)	(0.089)	(0.103)	(0.034)	(0.035)
Period 3	-0.015^{*}	0.031^{**}	0.015	−0.033	0.076^{*}	0.019^{*}
	(0.091)	(0.034)	(0.160)	(0.218)	(0.068)	(0.066)
Cumulative Effect (5 years)	0.105	0.107	0.204	−0.028	0.143	0.080
	(0.173)	(0.079)	(0.328)	(0.553)	(0.151)	(0.138)
Cumulative Effect (10 years)	0.432	0.321	0.932	0.966	0.328	0.271
	(0.341)	(0.200)	(0.817)	(1.853)	(0.421)	(0.338)

$^{*}p < 0.01$.
$^{**}p < 0.05$.
$^{***}p < 0.01$
Source: Author's estimation.

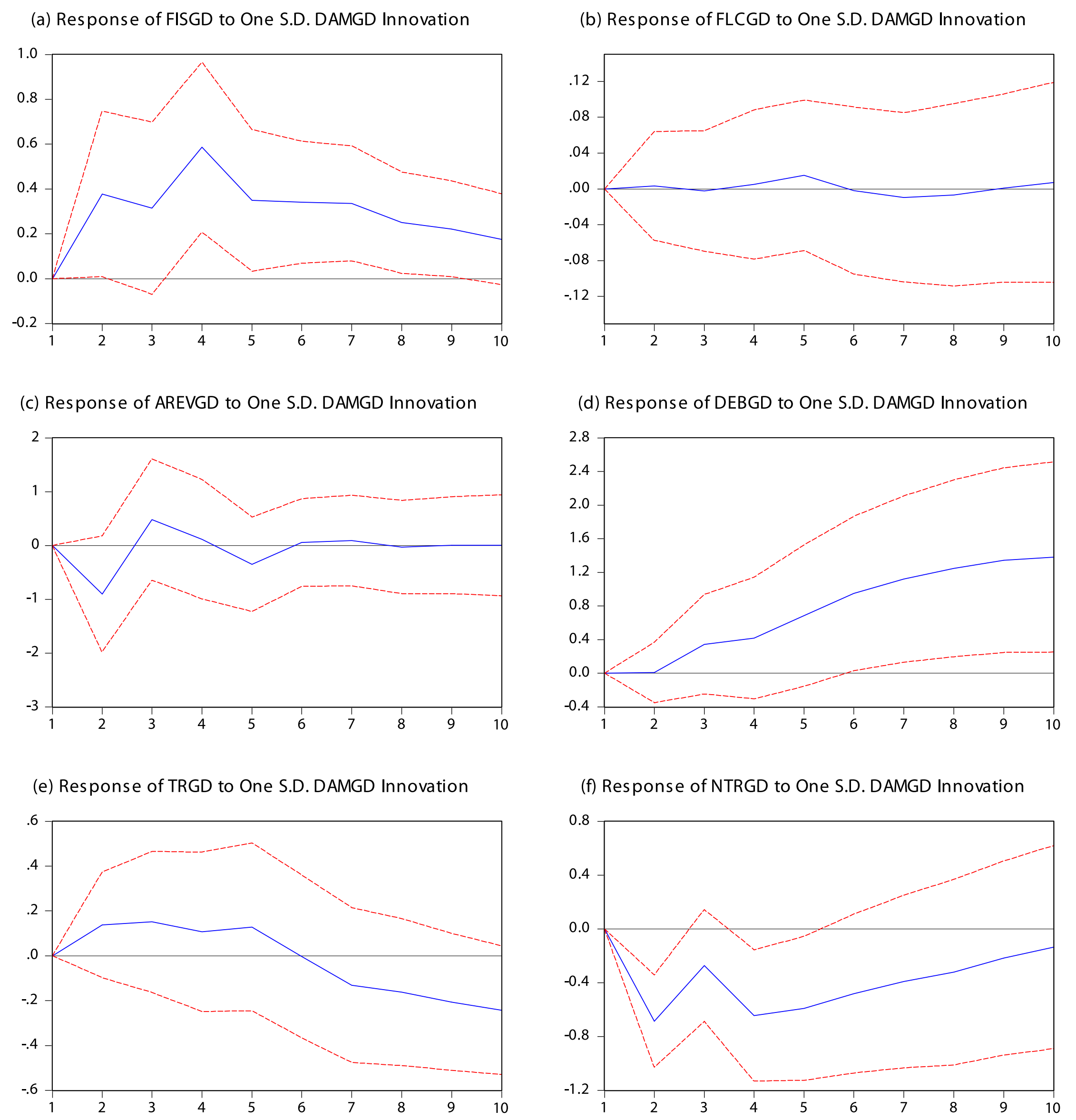

Figure 3. Impulse response graphs of selected variables to total damage shocks (Special Category States). Source: Author's estimation.

weakly significant results as that obtained for AREVGD, we can conclude that both tax and non-tax revenue increase at least till 3 years following the shock.

3.2.3. Results for special category states

3.2.3.1. Impulse response functions

Figure 3 presents the dynamic fiscal impacts of flood damage shocks on endogenous fiscal variables for the special category states (SCSs). A glance at the six figures shows that only in (a) and (f), the IRFs are statistically significant for certain periods, in rest of the figures, the IRFs are statistically insignificant as the confidence band contains the horizontal axis. In figure 3(a), the IRF is significant between periods 3 and 5. Response (change) of FISGD following one SD shock displays an initial rising trend and peaks at period 3. This reflects the expected expansionary fiscal reaction to unexpected damage shock. After the 3rd period, 'change in FISGD (in percent points)' starts to decrease but remains above zero in all periods. It implies that flood shocks have a lasting impact on fiscal deficits. When we look at figure 3(f), the IRF is significant till period 2 and thereafter it is insignificant. It shows that the 'change in NTRGD' (in percent points) is negative and decreasing until period 2 after which it increases and stabilizes, but remains negative throughout the period. This implies that non-tax revenue (as percent of GDP) decreases significantly in periods immediately after the flood shock.

Table 6. Impulse response functions to a one standard deviation shock to flood damage (Special Category States).

Time period	FISGD	FLCGD	AREVGD	DEBGD	TRGD	NTRGD
Period 1	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Period 2	0.377	0.003**	−0.902	0.009	0.137	−0.686
	(0.185)	(0.030)	(0.539)	(0.180)	(0.118)	(0.172)
Period 3	0.691	0.001*	−0.422	0.353	0.288	−0.959
	(0.301)	(0.054)	(0.823)	(0.445)	(0.252)	(0.328)
Cumulative Effect (5 years)	1.626	0.021	−0.656	1.456	0.523	−2.192
	(0.515)	(0.121)	(1.380)	(1.120)	(0.553)	(0.746)
Cumulative Effect (10 years)	2.950	0.012	−0.534	7.497	−0.223	−3.740
	(0.927)	(0.342)	(3.242)	(3.479)	(1.221)	(2.285)

*$p < 0.10$.
**$p < 0.05$.
***$p < 0.01$.
Source: Author's estimation.

3.2.3.2. Cumulative impact of flood damage shock

Apart from the dynamic fiscal impacts, we also estimate the cumulative fiscal effects of one standard deviation shock to flood damage over time for SCSs. Table 6 delineates a mixed fiscal response to flood damage over time. Out of the six variables., viz., FISGD, FLCGD, AREVGD, DEBGD, TRGD, and NTRGD, only the cumulative impact on FLCGD is found to be statistically significant. The 'change in FLCGD' is 0.003 by the end of period 2 and 0.001 by the end of period 3 (statistically significant at 10 percent). However, considering the cumulative effect over 5–10 years, the 'change in FLCGD' is insignificant. For the rest of the variables, the cumulative impact over 2–3 years or 5–10 years is found to be insignificant.

We made our main results even stronger by adding another fiscal variable to the model: agricultural revenue (AGRDG). This addition helps us show the total impact of flood damage over time. You can find all our detailed findings in appendix table A3, and they match closely with the results of our main model (tables 4–6). Additional graphs showing the impact of the robustness test results are included in the appendix (figure A2–A5). Additionally, the impulse response graphs of selected variables to total damage shocks (overall states, general category states, and special category states) - robustness check (agriculture revenue (AGRDG)) are reported in the appendix (see figure A2–A4).

4. Discussion

The findings of this study contribute significantly to the understanding of the fiscal implications of flood shocks across different states in India, particularly by distinguishing between General Category States (GCS) and Special Category States (SCS). This differentiation reveals critical insights into the varying levels of fiscal resilience and vulnerabilities that exist within these regions, reflecting the nuanced challenges faced by state governments in managing disaster impacts.

Our results align with previous studies, such as Panwar and Sen (2020), which emphasize the persistence of flood shock impacts in the medium term, with a gradual decline over the long term. Additionally, Agarwal Goel *et al* (2024) documented increased fiscal pressure on governments following natural calamities, further highlighting the fiscal repercussions of disasters as context-dependent and varying across regions. By partitioning our dataset into GCS and SCS, we found that SCS experienced more pronounced and enduring adverse impacts from flood shocks, particularly in terms of fiscal deficits. This finding corroborates distinctions made by Suresh *et al* (2024), who classified states based on their susceptibility to disasters.

The analysis of impulse response functions (IRFs) demonstrated a complex landscape of fiscal responses post-disaster. For GCS, the IRFs indicate that flood control expenditures (FLCGD) significantly increase after a flood shock, peaking at higher levels before stabilizing. This suggests a proactive fiscal policy response aimed at enhancing flood management infrastructure, consistent with Benson and Clay (2004), who emphasized the necessity of government investment in disaster preparedness to mitigate future damages. However, the insignificant changes in other fiscal variables, such as tax revenue and public debt, imply that GCS may absorb the fiscal impacts of floods through existing mechanisms without experiencing substantial instability.

Conversely, the results for SCS indicate that the fiscal deficit (FISGD) exhibits a significant and lasting response to flood shocks, with immediate increases that persist over time. This persistent rise in fiscal deficits suggests that SCS governments face considerable challenges in balancing immediate recovery efforts with long-term fiscal sustainability. This aligns with Chen (2020), who highlighted the unique difficulties faced by regions with limited fiscal capacity in the aftermath of disasters. Furthermore, the significant decline in non-tax revenue (NTRGD) in SCS post-shock underscores the heightened vulnerability of these regions, likely due to economic disruptions that hinder revenue generation, as discussed by Hallegatte (2017).

The differential fiscal responses between GCS and SCS highlight the need for tailored fiscal policies to address the specific challenges faced by these regions. For GCS, continued investment in proactive flood control measures is essential to mitigate future risks. In contrast, SCS may require enhanced intergovernmental transfers and the establishment of robust financial preparedness mechanisms, such as disaster funds or insurance schemes (Kousky and Shabman 2015). Policymakers should also explore how international aid and federal support can buffer these states from the long-term fiscal distress caused by disasters.

To reduce long-term economic damage and fiscal strain, it is crucial for governments to strengthen regional disaster preparedness and resilience strategies. Investments in disaster risk reduction (DRR) and climate adaptation measures are vital, as supported by previous research (Atreya *et al* 2017, Davlasheridze *et al* 2017). Innovative financing mechanisms, including catastrophe bonds or insurance schemes, could also play a pivotal role in helping regions manage the fiscal impacts of future disasters (Aurangzeb and Stengos 2012).

Despite the valuable insights provided by this study, it is important to acknowledge its limitations. The analysis does not account for the broader efficacy of flood management practices in India, nor does it consider expenditures by various line departments such as water resources, disaster management, and urban development. This oversight may lead to an incomplete understanding of the total fiscal burden on state exchequers (Mohanty *et al* 2020). Moreover, the focus on flood damages neglects the necessity for a multi-hazard risk assessment, as states may also be vulnerable to cyclones, earthquakes, droughts, and landslides. A more comprehensive approach to disaster risk reduction could better inform fiscal policy and resource allocation strategies (Noy *et al* 2023).

Future research should include a detailed cost analysis of all departments involved in flood management and adopt a multi-hazard risk assessment framework. By doing so, researchers can provide a more holistic understanding of the fiscal impacts associated with disasters and contribute to more effective policy formulation in disaster-prone regions.

5. Conclusion

This study analyzed 19 Indian states to examine the fiscal impacts of flood shocks. The results indicate that flood shocks have a significant and lasting impact on fiscal deficits, especially in Special Category States (SCS), where fiscal deficits widen initially and remain elevated over time. The fiscal deficits in General Category States (GCS) showed a significant increase within the first three years following the flood shock but tended to stabilize over the longer term. Both tax and non-tax revenue increased in the medium term (3–5 years) as governments adjusted fiscal policies to offset disaster costs. However, SCS experienced a more substantial drop in non-tax revenue, highlighting their greater vulnerability and fiscal challenges in managing disasters.

Flood control expenditures also increased after flood shocks, with GCS showing a commitment to maintaining higher expenditure levels in the long term, reflecting proactive fiscal policies for disaster management. SCS, however, faced greater fiscal stress due to their limited ability to recover non-tax revenues and their dependence on external aid. These findings suggest that flood shocks result in medium-term fiscal challenges for both GCS and SCS, with more severe impacts observed in SCS. Policymakers need to focus on creating fiscal buffers, such as disaster relief funds, and on enhancing state-level disaster preparedness, particularly in vulnerable regions. Moreover, governments should strengthen revenue collection systems and explore sustainable debt management practices to ensure fiscal stability in the wake of natural disasters.

The study's results provide critical insights for fiscal policy design in disaster-prone areas, but further research is required. Future studies should incorporate a broader scope of natural hazards and engage more closely with the total fiscal management of flood-related expenditures across different government departments. A multi-hazard risk assessment approach will help in developing more comprehensive fiscal strategies to manage the fiscal shocks induced by natural disasters.

Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files).

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Competing interests

The authors have no relevant financial or non-financial interests to disclose.

Ethical approval

This study utilized publicly available secondary data and did not involve human participants directly; therefore, ethical approval was not required.

Author contributions

RKM, DKB, and YP conceptualized the idea and collected the data; RKM estimated the result; DKB and YPverified the results and analysis; PA and DS contributed to the research literature and analysis; All authors contributed to writing the draft the paper and all authors read and approved the final manuscript.

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