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RESEARCH ARTICLE

Economic impact of floods in the Indian states

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Abstract
We examine the impact of economic development and the role of political alignment on the fatalities and damages due to floods using state-level panel data for 19 Indian states over the period 1980–2011. The empirical results confirm that economic development leads to a decline in flood fatalities and damages due to floods across Indian states. This study also examines the role of politics in the prevention of flood fatalities. We find that both state election years and political alignment influence the extent of flood fatalities. The results suggest that not only economic development but also healthy political coordination between the central government and the states is essential to mitigate the impact of floods.

Keywords: economic development; flood fatalities; IV-Poisson model; IV-Tobit model; political alignment

JEL Classification: O1; Q54; P16

1. Introduction

The impact of natural disasters and their intensity are similar across developed and developing countries, but developed nations experience fewer deaths from natural disasters compared to developing nations (Kahn, 2005; Stromberg, 2007; Toya and Skidmore, 2007; Keefer *et al.*, 2011). Evidence shows that the US experienced the greatest number of natural disasters compared to any other country, but with fewer fatalities in the various natural disaster events over the period 1974–2003 (506 natural disasters reported that killed 4.5 million people). On the other hand, developing countries such as India and Bangladesh experienced 303 and 174 disaster events, respectively, but the number of people killed stood at 1,832 million and 375 million, respectively, over the same period (Guha-Sapir *et al.*, 2004). Additionally, some studies have also argued that stronger institutions and better governance help minimize disaster fatalities (Anbarci *et al.*, 2005; Kahn, 2005; Escaleras *et al.*, 2007; Stromberg, 2007; Raschky, 2008).

Among the developing countries, India's geo-climatic conditions and high degree of socioeconomic vulnerability have led to an increase in the frequency, damages and fatalities due to natural disasters (Government of India, Ministry of Home Affairs, 2011). In a global ranking, India is 14th in the overall Climate Risk Index, second in annual average disaster fatalities, and third in average disaster damages (Kreft *et al.*, 2017). Every year, different regions of the country experience natural disasters in varying magnitudes, but flooding is one of the most alarming. India is the most flood-affected nation in the world (Government of India, Ministry of Home Affairs, 2011). Between 1953 and 2011, India experienced 192 floods that killed 97,557 people, with an additional 1,913 million impacted, resulting in an economic loss amounting to Indian rupees (Rs) 2,131 billion (Central Water Commission, 2012).[1]

Thus, the above analysis suggests that developing economies like India have experienced more human casualties and greater damage from frequent flood disasters due to an inability to prevent disasters, severe poverty, a high dependency on primary sectors, a low per capita income and inadequate physical and social infrastructure. Moreover, inadequate disaster preparedness and a lack of awareness about the disaster's impact and conventional disaster warning systems have led to an increase in the impact of floods over the years. Much of the existing empirical literature has evaluated the economics of natural disasters and their impact by considering only cross-national comparisons. In contrast, the objective of our study is to examine the impact of economic development and the role of political alignment[2] on flood fatalities and economic losses at the regional level, controlling for direct spending on disaster relief and expenditure on flood control measures using state-level panel data for 19 states over the period 1980–2011.

In India, political lobbying between the centre and the state governments plays an important role in minimizing flood fatalities because the central government often releases differential grants to various states. Notably, the grants from the central government to a state are more favorable if both the centre and state governments belong to the same political party or coalition political parties.[3] Additionally, the study also examines whether the casualty rate due to floods is lower during the years when the state election is due. Intuitively, the success of the incumbent state government during disaster management activities helps the government during an election.

Before discussing the empirical estimations, we show that the states with higher per capita income experience fewer flood fatalities (figure 1). We employ fixed effect (FE) Poisson, FE negative binomial and FE Tobit techniques for estimation purposes. Also, we use instrumental variables (IV) Poisson and IV Tobit models to control endogeneity issues between per capita income and the impact of floods in terms of flood fatalities and damages. In the Indian context, no such empirical work has been undertaken to study the economic impact of floods across Indian states. Our study attempts to make

[1] Between 1970 and 2009, India experienced 193 major floods (World Bank, 2012: 65). Around 12 per cent of the land in India is exposed to floods (Government of India Planning Commission, 2011).

[2] Political alignment is defined as the presence of the same political or coalition parties in both the centre and the state.

[3] There are several similar pieces of anecdotal evidence in the context of India. For instance, after the Gujarat earthquake in 2001, the Congress party claimed that the Bharatiya Janata Party (BJP)-led coalition government was discriminating against the Congress state government in releasing relief funds (Tribune News Service, 2001). Further, the central government had declared the Gujarat earthquake as a national calamity due to the presence of the same political party in the state and centre. On the other hand, in 1999 when Odisha was hit by a super cyclone, the central government did not declare it a national calamity due to the presence of an opposing ruling party in Odisha. Similarly, the BJP demanded that the Kosi floods in Bihar be declared a national calamity, but the centre did not agree because the National Democratic Alliance led by the Janta Dal United government was the ruling party in Bihar, and the Congress-led United Progress Alliance-1 was ruling at the centre (Indo-Asian News Service, 2008).

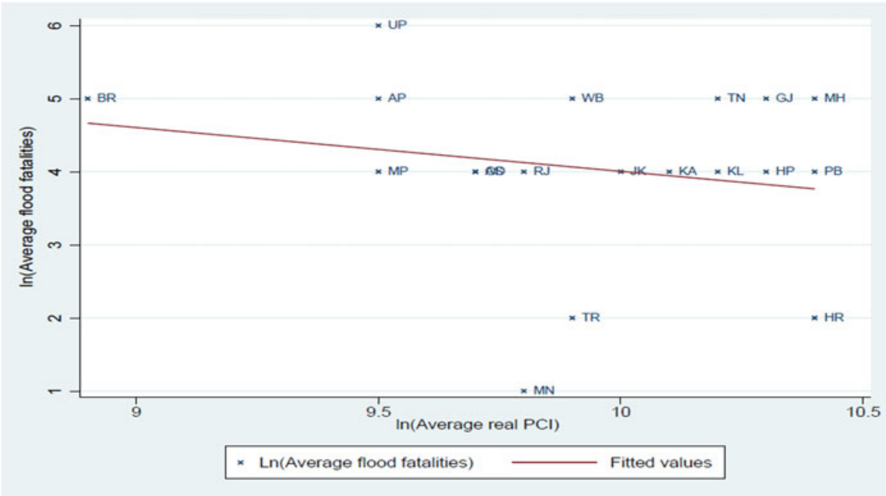

Figure 1. Relation between average flood fatalities and average real per capita income for 19 states over the period 1980–2011.
Notes: Author's own calculation. Andhra Pradesh (AP), Assam (AS), Bihar (BR), Gujarat (GJ), Haryana (HR), Himachal Pradesh (HP), Jammu and Kashmir (JK), Karnataka (KA), Kerala (KL), Madhya Pradesh (MP), Maharashtra (MH), Manipur (MN), Odisha (OD), Punjab (PB), Rajasthan (RJ), Tamil Nadu (TN), Tripura (TR), Utter Pradesh (UP), West Bengal (WB).

a substantive contribution to the existing empirical literature. Based on the empirical results, we provide some useful policy implications for enhancing the role of the state in mitigating the impact of disasters.

The rest of the study is structured as follows. Section 2 presents a detailed literature review of country-specific and cross-country studies that analyze the impact of economic development on disaster fatalities and damages. Section 3 analyzes the identification strategy and major data sources used in this study. The empirical results are presented in section 4. Finally, the conclusion and discussion of the results are presented in section 5.

2. Review of literature

A few empirical studies have evaluated the impact of economic development and the role of the institution on disaster impact. Anbarci *et al.* (2005) uses a theoretical model to show that earthquake fatalities and per capita income are inversely related, whereas higher income inequality and earthquake fatalities are positively correlated. Kahn (2005) confirms that elevation (1000 m above sea level) reduces mortality from wind storms, and the distance from the Equator increases the chances of earthquake mortality. Kahn (2005) further shows that countries with higher economic development, lower income inequality, and the presence of a vibrant democratic government experience less natural disaster risk. The study also indicates that both richer and poorer countries face the same number of natural events, but more prosperous nations suffer fewer disaster-related deaths than poorer nations. Toya and Skidmore (2007) examine the impact of the level of economic development on natural disaster fatalities and damages in the Organisation for Economic Co-operation and Development (OECD) and developing countries using a cross-country dataset. The level of development is inversely related to disaster

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mortality and damage in both OECD and developing countries. The study shows that the estimate of the income coefficient is greater in OECD countries than in developing countries, which means that OECD countries are better prepared to mitigate disaster risk compared to developing nations.

Stromberg (2007) examines the relationships among natural disasters, economic development and humanitarian aid in high-, low- and middle-income countries. He finds that high-income countries experience 70 per cent lower fatality rates than low-income countries from the same type of disaster in the same year. Moreover, the study also shows that countries with more effective government suffer fewer fatalities, whereas more democratic countries suffer more. Escaleras *et al.* (2007) suggest that countries with high corruption in the public sector witness more earthquake fatalities while controlling for other factors such as the country's level of development, earthquake magnitude and population density. Keefer *et al.* (2011) suggest that the effect of earthquake propensity varies across countries depending on income and political characteristics. If the earthquake propensity is low, the government lacks incentives to implement an effective earthquake mortality prevention system because of the high opportunity costs involved in investing in equipment related to earthquake preparedness.

A few cross-country studies have examined the nonlinear relationship between economic development and natural disasters in terms of loss of human life and disaster damages. Raschky (2008) confirms that there exists a nonlinear relationship between economic development and disaster damage. The empirical findings further show that better institutions and higher economic development reduce disaster mortality and damage. Kellenberg and Mobarak (2008) find that disaster risk initially increases with an increase in wealth, but then begins to decline as wealth increases further. Schumacher and Strobl (2011) examine the relationship between wealth and disasters. Their simple analytical model shows that countries with a lower likelihood of disasters are likely to see an initial increase in disaster losses followed by a decrease with increasing economic development. Ferreira *et al.* (2013) indicate that there exists an inverted U-shaped relationship between income and flood fatalities. They also point to the role of better governance in reducing fatalities during flood events.

A few empirical studies have analyzed the relationship between the political economy of disaster expenditure and disaster impact. Downton and Pielke (2001) find that presidential flood declarations are greater in election years, when the president is running for re-election. Garrett and Sobel (2003) explain that the states that are politically important to the president and that have more representatives on the Federal Emergency Management Agency (FEMA) oversight committees are the recipients of more generous disaster relief compensation. Chang and Berdiev (2015) show that the occurrence of a disaster and its concomitant damage has the most impact on changes in the incumbent government. Besley and Burgess (2002) argue that political institutions, as well as economic development, affect government responsiveness in the Indian context. Interestingly, they find that calamity relief is most responsive to needs in states where more people are well informed about the latest developments by reading newspapers.

3. Data sources and empirical identification

The state-wise flood data used in this study were obtained from the Central Water Commission (2012) report. This dataset provides different flood disaster-related information such as area affected, the population affected, the number of human lives lost, the number of houses damaged and economic losses due to floods. However, the Central

Water Commission (CWC) data do not provide important flood-related information such as the magnitude and duration of floods, but these variables are crucial for determining the impact of floods. Hence, we matched the state-wise flood magnitude and duration of floods variables obtained from the Dartmouth Flood Observatory (DFO) dataset with the CWC dataset. However, in the CWC dataset, some information is missing. For instance, data on human lives lost are reported for some states for the respective years, but other variables such as area affected and population affected by floods are not reported. To account for the missing data, we have used the DFO and Emergency Events Database (EM-DAT).[4] Also, there are cases of missing observations for the two important outcome variables – flood fatalities and damages due to floods in the CWC dataset. For the flood fatality variable, we matched only an 8 per cent sample of the CWC dataset with the DFO and EM-DAT dataset. Similarly, for the damages due to floods variable, only 6 per cent of the observations of the CWC dataset were matched with the DFO and EM-DAT dataset.

Concerning various explanatory variables used in our study, the gross state domestic product (GSDP), both at current and constant prices, is available from the Ministry of Statistics and Program Implementation, Government of India (GoI). The state government expenditures on irrigation and flood control, expenditures on social security and welfare, relief aid because of natural calamities, and total expenditures are taken from the various volumes of State Finance Reports published by the Reserve Bank of India. The state-wise total population, literate population, and adult population data are taken from various census years, such as 1971, 1981, 1991, 2001, and 2011. The state-wise total populations, literate population, and adult population are linearly interpolated for the years when no census was conducted.

The state-wise drought-prone area is taken from the Department of Labour Resources, Ministry of Rural Development, GoI.[5] The government of India has identified 74.6 million hectares of land as the drought-prone area in 17 states, which accounts for 23 per cent of the total geographical area. Moreover, the state-wise liable to flood-prone area is taken from the *Report of Working Group on Flood Management and Region-Specific Issues for XII Plan* (Government of India Planning Commission, 2011). Around 40 million hectares of land is liable to flood, which accounts for 12 per cent of the total geographical area.[6] The state and national election data are taken from the Election Commission of India. The coalition and political scenarios of different states are adopted from Sridharan (1999). For empirical estimation, we have normalized the variables used in this study. The summary statistics of all variables, along with their definitions, are described in appendix table A1.

The state-wise flood impact in terms of human lives lost and economic losses due to floods for 19 states over the period 1980–2011 are shown in appendix A, figures A1 and A2. The state-wise average flood fatalities per million population are highest in Himachal Pradesh, followed by Jammu and Kashmir, Gujarat, Utter Pradesh, Bihar and Kerala while the lowest are in Haryana (figure A1). Moreover, the frequent occurrence of floods adversely affects human capital and causes damage to private and public properties, including damage to crops. Figure A2 shows that average annual flood damage as

[4]The country-wise, all forms of natural disaster data are collected by the EM-DAT database, the collection of which follows a criterion, such as 10 or more people killed and 100 or more people affected.

[5]See Drought-Prone Areas Program, available at http://www.dolr.nic.in/dpap_annex.htm.

[6]In 1980, the National Flood Commission of India estimated state-wise liable to flood-prone area for all states.

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a percentage of GSDP is highest in Bihar (3.04 per cent), followed by Himachal Pradesh (2.73 per cent), Andhra Pradesh (1.95 per cent), and Odisha (1.03 per cent), with the lowest damage being in Madhya Pradesh (0.04 per cent). For estimation purposes, the outcome variables are the number of human lives lost and damages caused due to floods. The following functions explain the impact of economic development on flood fatalities and damages in Indian states:

$$\begin{aligned}\mathrm{FF}_{it} = \beta_0 + \beta_1 \ln \mathrm{PCI}_{it-1} + \beta_2 \ln \mathrm{FM}_{it} + \beta_3 \mathrm{PAD}_{it} + \beta_4 \mathrm{SED}_{it} \\ + \beta_5 \ln \mathrm{SSE}_{it-1} + \beta_6 Z_{it} + \theta_{\mathrm{r}} + \gamma_t + \mu_{1it},\end{aligned} \tag{1}$$

$$\begin{aligned}\ln (\mathrm{damages/GSDP})_{it} = \alpha_1 + \alpha_2 \ln \mathrm{PCI}_{it-1} + \alpha_3 \ln \mathrm{FM}_{it} \\ + \alpha_4 \ln \mathrm{SSE}_{it-1} + \alpha_5 Z_{it} + \theta_r + \gamma_t + \mu_{2it}\end{aligned} \tag{2}$$

where i indicates states and t denotes year; FF_{it}. is the flood fatalities; ln(damages/ GSDP)$_{it}$. is the natural logarithm of damages due to floods over GSDP; $\ln\mathrm{PCI}_{it-1}$. is the natural logarithm of lag of real per capita income (PCI); PAD_{it}. is the political alignment dummy; SED_{it}. is the state election dummy; is the natural logarithm of lag of government expenditure for social security a welfare; Z_{it} denote the obseed time-varying control variables, which include flood disaster exposure measured as the tural logarithm of flood magnitudes, and disaster adoption measures such as direct spendfor irrigation and flood control and expenditures on disaster relief; θ_{r} account for unobserved time-invariant region effects; γ_t denote the year-specific effects; and μ_{it} is the error term.

The dependent variable in equation (1) is flood-related fatalities, i.e., the number of people killed during the flood events in different years in various states. This is a non-negative count variable. The conditional variance of the flood fatality variable exceeds the mean, which means the ‘flood fatalities’ variable is overdispersed (see table A1 in the appendix). Hence, it is suitable to apply the FE negative binomial over the FE Poisson model.[7] Therefore, we employed the unconditional FE negative binomial model to evaluate the effect of economic development on flood fatalities across Indian states, controlling for socioeconomic factors. In the regression analysis, we have controlled unobserved time-invariant region effects, which are correlated with the outcome variables such as flood fatalities and damages due to floods and correlated with variables of interest such as per capita income and other control variables. For example, a few regions in India are vulnerable to floods and droughts, and other regions are vulnerable

[7] The Pearson goodness-of-fit test confirms that the FE Poisson model is not suitable for our dataset, and it suffers from an overdispersion problem. In contrast, Cameron and Trivedi (2010: 575) overdispersion test of the FE Poisson model with region and state fixed effects does not reject the null hypothesis, which suggests that the FE Poisson model is appropriate for our dataset because it controls the unobserved time-invariant region and state effects completely. The FE negative binomial model controls for time-invariant unobserved effects efficiently when the cross-sectional units are less than 20 (Hilbe, 2012: 473). Moreover, the zero-inflated negative binomial model is not appropriate because only 11 per cent of observations amount to zero flood fatalities. Kellenberg and Mobarak (2008) employed the conditional FE negative binomial model in a cross-country panel dataset and found it controls for unobserved time-invariant country effects, which ‘is not a true fixed-effects model’ (Hilbe, 2012: 474) because it does not control for all stable covariates completely (Allison and Waterman, 2002).

to earthquakes, landslides and cold waves. These unobserved factors do not change over time and could be considered as omitted variables in our model. Therefore, we eliminate the omitted variables bias problem by including region dummies in the regression analysis.

Moreover, Ravallion (2008) argues that inadequate control for unobserved time-invariant characteristics generates inconsistent and biased estimations. A few empirical studies have controlled for the time-invariant unobserved region (or continent) fixed effects instead of a country or state fixed effects (Anbarci *et al.*, 2005; Kahn, 2005; Escaleras *et al.*, 2007; Parida *et al.*, 2018). In addition to unobserved time-invariant characteristics, we also control for unobserved time-variant factors that are common for all states. For example, in the method of estimating flood damages, the technology used for forecasting floods and the central government's policy changes regarding disaster management and so forth can be considered as unobserved time-variant factors. In the regression model, these unobserved factors affect the outcome variable and other variables of interest included in the model. We used the year dummy to control unobserved time-variant factors in our models.

The FE model solves the problems resulting from omitted variable bias that are unobserved and constant over time, but it cannot control other types of bias. First, the FE model produces biased results in the presence of unobserved time-varying variables that are omitted but correlated with the explanatory variables included in our models (Wooldridge, 2013: 512). Second, the FE model does not solve the endogeneity problem due to the occurrence of reverse causality among the variables. Therefore, we have used IV Poisson and IV Tobit models to address the endogeneity problem caused by omitting time-varying variables or reverse causality between variables of interest and outcome variables. Finally, the FE model generates biased and inconsistent results in the presence of a lag-dependent variable (Nickell, 1981). This specific problem does not occur in our dataset. Also, we used the FE Poisson model because it fully controls for time-invariant unobserved region effects (Wooldridge, 2002: 674–676). Additionally, the standard errors are clustered in all regressions at the region level. We estimate equation (2) using the FE Tobit model to examine the impact of economic development on economic losses due to floods across Indian states. The reason for using the FE Tobit model is that the outcome variable, 'damages due to floods', has many zero observations and therefore our data are truncated from below.

In the regression estimation, we introduce the lag of real PCI to control for the endogeneity issue because the previous period's PCI is exogenous to the current disaster impact, but the contemporaneous PCI is endogenous to the present disaster impact. Moreover, there exists bi-directional causality between PCI and flood impact in terms of flood fatalities and damages due to floods. States that have experienced a higher severity of floods have also seen a steeper decline in PCI. On the other hand, higher PCI also helps alleviate the impact of floods. Thus, to control for the problem of endogeneity, we have used state-wise '*liable to flood-prone area*' and '*drought-prone area*' as instruments for current PCI. An inverse relationship exists between the state-wise '*liable to flood-prone area*' and real PCI, implying that states with a greater proportion of area marked as liable to flood experience lower PCI. A similar inverse relationship exists between the '*drought-prone area*' and PCI such that states with a larger share of the drought-prone area also experience lower PCI. Much of the cross-national empirical literature does not address economic development as an endogenous variable (see section 2). To control for the problem of endogeneity, we employ an IV Poisson model to estimate equation (1), and an IV Tobit model to estimate equation (2).

4. Empirical results: impact of economic development and political alignment on flood fatalities

Estimates of equation (1) using the FE Poisson model are presented in table 1. In model 1, the coefficient of lagged real PCI is negative and statistically significant. The result indicates that states with higher PCI have witnessed fewer flood fatalities. In model 7, the coefficient of lag real PCI is still negative and statistically significant after adding the control variable, such as direct spending on flood control measures and expenditures for natural calamity. However, the magnitude of real PCI is marginally reduced from 0.732 to 0.587 throughout the models. Hence, the estimate is robust throughout the models, even after adding the control variables. These findings are consistent with those of Ferreira *et al.* (2013) and mirror the results for earthquake fatalities (Anbarci *et al.*, 2005; Kahn, 2005; Escaleras *et al.*, 2007; Keefer *et al.*, 2011).

The result confirms that economic development (proxied by real PCI) is one of the key determinants to minimizing flood fatalities across Indian states, controlling for socioeconomic and political factors. The reasons behind this are that the individual states that have higher real PCI are capable of spending more on disaster risk reduction measures (disaster safety and securities, rehabilitation, reconstruction and emergency responses) to mitigate flood fatalities. The demand for safety or disaster preparedness increases with an increase in the level of per capita income (Horwich, 2000). In other words, a state with higher economic development can invest more for flood risk prevention and preparedness measures, such as flood-resilient infrastructure and better disaster management.

In the case of developing economies like India, the economic development of the states does not always help mitigate flood risk in terms of flood fatalities. For example, apart from heavy rainfall, unplanned urbanization, rapid urban growth, and inadequate health and housing services were the major causes for the 2015 Chennai flood, which claimed 354 human lives (Szynkowska, 2016). We also argue that there exists reverse causality between per capita income and flood fatalities. On the one hand, a state with higher per capita income experiences lower flood fatalities, but on the other hand, higher human death also adversely affects per capita income of the states. Therefore, we employed IV Poisson estimates to solve the reverse causality problem (see table 2).[8]

The coefficient of flood magnitude is positive and significant from models 2 to 7, which shows that flood magnitude has significantly increased the flood death toll. This finding is consistent with the findings of Ferreira *et al.* (2013). Also, damage to homes is positively correlated with flood mortalities, which are shown in models 4 to 7. This result implies that more flood fatalities occur because of the damage to homes during floods. The population affected by the flood and flood fatalities are positively correlated, which shows that the greater the population affected by a flood, the higher the death toll. Similarly, population density increases flood fatalities, as shown in models 5 to 7. The states with higher population density also have a higher probability of flood fatalities. Furthermore, literacy rate and expenditures for irrigation and flood control do not significantly minimize flood fatalities, but expenditures for social security and welfare and expenditures for natural calamity are positive and insignificant.

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[8]Historical tsunami deaths in Japan led to a decline in the 2011 Tohoku tsunami mortality (Plümper *et al.*, 2017). We could not address in our empirical exercise how historical flood events across Indian states help to reduce flood fatalities.

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Table 1. Impact of PCI, flood magnitude and political alignment on flood fatalities: FE Poisson model

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
lag of ln(per capita income)	−0.7323*** (0.1250)	−0.5982*** (0.1265)	−0.4987*** (0.0987)	−0.4638*** (0.1060)	−0.4963*** (0.0537)	−0.5408*** (0.0528)	−0.5876*** (0.2006)
ln(flood magnitude)		0.1707*** (0.0386)	0.0897*** (0.0176)	0.0811*** (0.0160)	0.0779*** (0.0134)	0.0842*** (0.0127)	0.0855*** (0.0123)
ln(population affected by floods)			0.2216*** (0.0568)	0.1346*** (0.0349)	0.1359*** (0.0355)	0.1443*** (0.0348)	0.1419*** (0.0339)
ln(number of houses damaged)				0.0981** (0.0381)	0.0907*** (0.0330)	0.0858*** (0.0302)	0.0870*** (0.0304)
ln(population density)					0.3616 (0.2386)	0.3692 (0.2285)	0.3905 (0.2604)
State election dummy						−0.4236*** (0.1105)	−0.4192*** (0.1283)
Political alignment dummy						−0.3274*** (0.0752)	−0.3250*** (0.0754)
Literacy rate						−0.0033 (0.0044)	−0.0039 (0.0038)
lag of ln(expenditure of social security and welfare)							0.0547 (0.0344)
lag of ln(expenditure of irrigation and flood control)							−0.0999 (0.1539)
lag of ln(expenditure of natural calamity)							0.0934 (0.0642)
Observations	589	589	589	589	589	589	589
No. of states	19	19	19	19	19	19	19

Notes: Clustered standard errors in parentheses.
Significance: ***$p < 0.01$, **$p < 0.05$. The dependent variable is flood-related fatalities. All models include time-invariant region and year fixed effects.

Table 2. Impact of PCI and political alignment on flood fatalities: IV Poisson model

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
ln(per capita income)	−2.0368*** (0.3815)	−1.3159*** (0.3021)	−0.9810*** (0.3148)	−1.0984*** (0.3045)	−1.0111*** (0.3042)	−1.0984*** (0.3013)	−1.9405*** (0.5470)
ln(area affected by floods)		0.1692*** (0.0246)	0.1022*** (0.0342)	0.0489 (0.0385)	0.0501 (0.0371)	0.0525 (0.0376)	0.0594 (0.0373)
ln(number of houses damaged)			0.1260*** (0.0431)	0.0926** (0.0386)	0.0884** (0.0367)	0.0830** (0.0358)	0.0775** (0.0352)
ln(population affected by floods)				0.1250*** (0.0275)	0.1161*** (0.0270)	0.1174*** (0.0288)	0.1323*** (0.0296)
ln(flood duration)					0.0555*** (0.0170)	0.0616*** (0.0166)	0.0601*** (0.0180)
State election dummy						−0.4522*** (0.1305)	−0.3823*** (0.1426)
Political alignment dummy						−0.2957* (0.1539)	−0.2152 (0.1630)
Literacy rate						0.0019 (0.0049)	−0.0053 (0.0055)
lag of ln(expenditure of social security and welfare)							0.0044 (0.0582)
lag of ln(expenditure of irrigation and flood control)							−0.6029** (0.1946)
lag of ln(expenditure of natural calamity)							0.0475 (0.0574)
Hansen's J chi2(1) *p*-value				1.3323 (0.2484)	0.9685 (0.3250)	1.0714 (0.3006)	0.0042 (0.9483)
Observations	608	608	608	608	608	608	589
No. of states	19	19	19	19	19	19	19

Notes: Robust standard errors in parentheses.
Significance: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. The dependent variable is flood-related fatalities. All models include time-invariant region and year fixed effects. *Instrument*: state-wise ln(*liable to flood-prone area)* and ln(*drought-prone area*) as an instrument for ln(per capita income). Hansen's J chi2(1) overidentifying restriction tests fail to reject the null hypothesis, which implies that the model is correctly specified. In other words, instruments satisfied the relevance and exogeneity conditions.

Another interesting finding of our study is that the coefficient of state election year dummies is negative and significant in models 6 and 7. The estimates show that in the state election years, flood fatalities are lower when compared to the non-state election years, as the incumbent state government tries to minimize flood fatalities with the help of flood disaster funding, which in turn increases the state government's chances of returning to power in the next election term as well. Moreover, the coefficient of political alignment dummy is negative and significant, which implies that when both centre and state have the same political or coalition party in power, the respective states experience lower flood fatalities when compared to non-alliance political parties in power in both centre and states. This political bias could be because the central government is more reluctant to release disaster funding to states that have a non-alliance political party in power. Evidence suggests that the central government is often not willing to declare a specific natural disaster as a national disaster due to the presence of the non-alliance political party in the state government.

Next, we estimate the marginal effects at the mean for the FE Poisson models for comparing the effects of the size stability of the coefficients; the estimates are shown in table 3.[9] In model 1, the marginal effect at the mean of the lag of real PCI is negative and significant, which shows the probability of 5 fewer people being killed due to floods when per capita income increases by 10 per cent at the mean.

Similarly, in model 7, the marginal effect at the mean of the lag of real PCI is also negative and significant, which means that controlling for other explanatory variables at their mean, the probability is that 3 fewer people will be killed due to floods when the lag of real PCI increases by 10 per cent at the mean. Also, flood magnitude and population affected by floods follow the same pattern. Another interesting finding of the study is that, in the year when the state election is due, the probability is that 21 fewer people will be killed due to floods when compared to a non-election year, whereas the probability is that 16 fewer people will be killed due to the same political alignment at centre and state as compared to the case of non-alignment (model 7 of table 3).

To check the robustness of the results, we estimate equation (1) using the unconditional FE negative binomial model. The estimates are shown in appendix table A2. The coefficient of lag real PCI is negative and significant after adding all control variables, as shown in model 7. The coefficient of flood magnitude, house damages and population affected by flood are positively associated with flood fatalities, whereas state election year and political alignment are negatively correlated with flood fatalities. Also, literacy rate, expenditure on social security and expenditure on flood control are negatively correlated with flood fatalities, which shows that the current expenditure directed to social sector development is inadequate to prevent flood fatalities across Indian states.

Additionally, we estimate a marginal effect at the mean of the FE negative binomial model; the results are shown in table A3 of the appendix. Again, the marginal effect at the mean of the lagged real PCI is still negative and statistically significant, whereas the magnitude of the lag of real PCI marginally varies from 53.228 to 53.042 throughout the models after adding the control variables at their mean.

[9]We have computed marginal effect at the mean using the ((margins, dydx (*)) atmean) command in Stata 13 (see Cameron and Trivedi, 2010: 343–350). For nonlinear models, marginal effects for continuous variables measure the instantaneous rate of change. For the Poisson model, the marginal effect at mean gives the change in predicted probabilities of the dependent variable when the independent variable changes at the sample mean. For the indicator variable, the marginal effect measures discrete change, i.e., predicted probabilities change when the indicator variable changes from 0 to 1.

Table 3. Marginal effect at the mean: FE Poisson model

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
lag of ln(per capita income)	−53.821*** (8.385)	−40.038** (8.126)	−28.015*** (4.152)	−23.871*** (4.339)	−25.218*** (6.566)	−27.052*** (6.845)	−28.978** (11.618)
ln(flood magnitude)		11.426*** (1.943)	5.039*** (0.672)	4.174*** (0.970)	3.960*** (0.705)	4.214*** (0.790)	4.218*** (0.719)
ln(population affected by floods)			12.451*** (1.499)	6.931*** (1.091)	9.909*** (0.977)	7.222*** (0.841)	7.000*** (0.724)
ln(number of houses damaged)				5.049** (1.247)	4.609*** (1.220)	4.292*** (1.090)	4.290*** (1.077)
ln(population density)					18.372 (1.424)	18.463* (10.689)	19.258 (12.217)
State election dummy						−12.190*** (4.186)	−20.672*** (4.872)
Political alignment dummy						−16.377*** (4.098)	−16.028*** (4.008)
Literacy rate						−0.167 (0.222)	−0.196 (0.189)
lag of ln(expenditure of social security and welfare)							2.698 (1.769)
lag of ln(expenditure of irrigation and flood control)							−4.928 (7.570)
lag of ln(expenditure of natural calamity)							4.608 (3.417)
Observations	589	589	589	589	589	589	589
No. of states	19	19	19	19	19	19	19

Notes: Delta-method standard errors in parentheses.
Significance: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. The dependent variable is flood-related fatalities.

In model 7, the marginal effects of the state election year and political alignment are negative and statistically significant, whereas the magnitude of the coefficients varies from FE Poisson to FE negative binomial estimates (model 7 of table 3 and model 7 of appendix table A3). Overall, the marginal effect of both estimates produces consistent results, but there are large differences in the magnitude of the coefficients (see table 3 and appendix table A3).

Next, we estimate the IV Poisson model using equation (1); results are shown in table 2. The coefficient of real PCI is still negative and significant throughout the models, but the magnitude of coefficients greatly decreases, from 2.03 in model 1 to 1.94 in model 7 after adding the control variables.[10] Additionally, the coefficients of house damages, duration of floods and population affected by the flood are positively correlated with flood fatalities, whereas state election year and political alignment are negatively correlated with flood fatalities. Overall, IV Poisson model estimates produce similar results, but the magnitude of the coefficients varies between FE Poisson and FE negative binomial estimates (see table 1 and appendix table A2). We also perform the overidentifying restriction test for the instruments. Hansen's J chi2(1) test fails to reject the null hypothesis, which implies that the model is correctly specified. In other words, the instruments have satisfied the relevance and exogeneity conditions.

4.1 Impact of economic development and flood magnitude on damages due to floods

This study examines the impact of economic development and flood magnitude on flood damages, controlling for expenditures on irrigation and flood control and direct spending on disaster relief. The study estimates the FE Tobit model using equation (2), the results of which are presented in table 4.[11] In model 1, the coefficient of lagged PCI is negative and statistically significant, which shows that higher PCI reduces flood damages. Again, the coefficient of lagged real PCI is still negative and statistically significant in model 4 after adding control variables such as direct spending on disaster relief and irrigation and flood control measures, but the magnitude of the coefficient varies marginally from 1.87 to 1.39 throughout the models. These findings are mirror results of disaster damages (Toya and Skidmore, 2007; Neumayer *et al*., 2014).

The econometric results confirm that the states that are more economically developed can spend more on creating flood-resilient infrastructure and flood control measures

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[10] We have addressed the dependent variable issues empirically. First, we removed the 8 per cent sample of the 'flood fatalities' variable which is matched from DFO and EM-DAT dataset. Then we re-estimated the FE Poisson and IV Poisson using original data of the dependent variable 'flood fatalities', which are taken from the Central Water Commission (2012) report only. The estimate based on the FE Poisson and IV Poisson models produced the same results (see tables B1 and B2 in the online appendix). Moreover, these results are also consistent with earlier findings, as shown in tables 1 and 2, respectively. Second, we removed the 6 per cent sample of the 'damages due to floods' variable which is matched from DFO and EM-DAT dataset. Then we re-estimated the FE Tobit and IV Tobit models using original data on 'damages due to floods', which are taken from the CWC (2012) report. The estimates based on the FE Tobit and IV Tobit models produce similar results (see tables B3 and B4 in the online appendix). Moreover, these results also consistent with earlier findings, as shown in tables 4 and 5, respectively.

[11] In the FE Tobit and IV Tobit models, we have normalized the government expenditure variables with total government expenditure. Also, we re-estimated the baseline econometric models such as the FE Poisson and FE Tobit models after taking into account unobserved time-invariant state-fixed and time effects. Also, we have clustered the standard errors at the state level. The FE Poisson and FE Tobit estimations produce the same results, but the lagged real PCI becomes negative and insignificant after clustering standard errors at the state level (see tables C1 and C2 in the online appendix).

Table 4. Impact of PCI and flood magnitude on damages: FE Tobit model

	Coefficients				Average marginal effect (AME)			
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
lag of ln(per capita income)	−1.8787*** (0.6560)	−1.4632** (0.5700)	−1.1402* (0.6164)	−1.3901** (0.5965)	−0.0310** (0.1033)	−0.0243** (0.0117)	−0.0197 (0.0128)	−0.0251** (0.0124)
ln(flood magnitude)		0.6268*** (0.1125)	0.1855* (0.1094)	0.1036 (0.1263)		0.0104*** (0.0033)	0.0032* (0.0018)	0.0018 (0.0023)
ln(population affected by floods)			1.1014*** (0.1010)	0.5575*** (0.0818)			0.0191*** (0.0038)	0.0100*** (0.0014)
ln(number of houses damaged)				0.5364*** (0.0909)				0.0096*** (0.0023)
Literacy rate				−0.0167** (0.0094)				−0.0003* (0.0001)
lag of ln(expenditure of social security and welfare)				−0.0451 (0.2851)				−0.0008 (0.0051)
lag of ln(expenditure of irrigation and flood control)				0.0824 (0.6074)				0.0014 (0.0115)
lag of ln(expenditure of natural calamity)				−0.3218 (0.3610)				−0.0058 (0.0061)
Observations	589	589	589	589	589	589	589	589
No. of states	19	19	19	19	19	19	19	19

Notes: Clustered standard errors in parentheses.
Significance: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. The dependent variable is ln(damages/GSDP). All models include time-invariant region and year fixed effects.

that help to mitigate damages due to floods across Indian states if the severity of flooding remains in the expected range. On the other hand, a state with higher economic development can experience higher damages due to flood through damages caused to private and public infrastructures if the severity of the flooding exceeds certain levels.

Additionally, we also argue that frequent flooding poses a serious threat to economic development across Indian states. For example, rapid urbanization and unauthorized construction increased exposure to flood hazards in terms of economic losses in the 2015 Chennai flood that totalled Rs. 84,810 million, according to the *Joint Needs Assessment Report Tamil Nadu Floods – 2015* (available at https://reliefweb.int/sites/reliefweb.int/files/resources/jna-report-tamilnadu-december-2015.pdf) which was prepared by a coalition of agencies. Moreover, India lost around 0.46 per cent of GDP, including crop loss of 0.18 per cent of GDP, damage to homes of 0.07 per cent of GDP, and damage to public utilities at 0.21 per cent of GDP annually due to floods over the period 1980–2011.[12] This flood impact increases fiscal pressure on the federal government because of the costs of mitigation and prevention.[13]

In sum, we conclude that a state's economic development enhances its adaptive capacity to mitigate economic losses and, at the same time, it increases potential damages. Therefore, there exists a causality between economic development and flood impact in terms of economic losses. We therefore employed an IV Tobit model to solve the reverse causality problem (see table 5 and table B4 in the online appendix). Our result suggests that more severe flooding is associated with great damage. However, higher expenditures on different social security and welfare programs lead to a decline in flood damage, possibly because social security serves as long-term insurance against flood disaster damages. Higher literacy leads to a decline in flood disaster damages because educated people can adopt more precautionary measures against disasters to minimize concomitant damage.

Next, we estimate the average marginal effect of the FE Tobit model; the results are shown in table 4.[14] In model 5, the coefficient of the lag of real PCI is negative and statistically significant, confirming that a 10 per cent increase in the lag of real PCI leads to a 0.31 per cent decline in damages due to flooding. Similarly, in model 8, the coefficient of the lag of real PCI is still negative and statistically significant, and it marginally declines from 0.0310 in model 4 to 0.0251 in model 8 after adding the control variables. This result implies that damage due to flooding declines by 0.25 per cent when the lag of real PCI increases by 10 per cent.

The next regression specification shows the result obtained from the IV Tobit model. As shown in table 5, the coefficient of real PCI is negative and statistically significant in all models, but the magnitude of the coefficient of real PCI is greatly reduced after adding the control variables. Overall, this finding is consistent with the earlier findings of our study, but the magnitude of the coefficients greatly varies between the IV Tobit and FE Tobit estimated models, as explained in tables 4 and 5. The tests confirming the validity of instruments are shown in table 2.

[12] Author's own estimates using the CWC (2012) report.

[13] A World Bank study indicated that direct economic losses are caused by all types of natural disasters up to 12 per cent of combined centre and state revenues (World Bank, 2003: 8).

[14] The study calculates average marginal effect (AME) using the 'margins, dydx(*)' command. AME first calculates the marginal effect for each state with their observed level of covariates and then takes an average across all states. In the case of nonlinear models, marginal effects at the mean (MEM) produces a smaller marginal effect than AME due to the fact that the exponential function is globally convex (Cameron and Trivedi, 2010: 350).

Table 5. Impact of PCI and flood magnitude on damages: IV Tobit model

Variables	Model 1	Model 2	Model 3	Model 4
ln(per capita income)	−4.3178* (2.2463)	−2.9158 (2.3709)	−3.0262*** (1.1500)	−3.0658** (1.2746)
ln(flood magnitude)		0.5035*** (0.0853)	0.1085 (0.0810)	0.1133 (0.0803)
ln(population affected by floods)			0.9782*** (0.1206)	0.9772*** (0.1184)
Literacy rate				−0.0042 (0.0128)
lag of ln(expenditure of social security and welfare)				−0.0213 (0.3595)
lag of ln(expenditure of irrigation and flood control)				0.0207 (0.4287)
lag of ln(expenditure of natural calamity)				−0.1049 (0.2060)
Observations	608	608	608	589
Wald test of exogeneity(chi2(1)) (*p*-value)	1.24 (0.266)	0.48 (0.48)	3.27 (0.070)	3.55 (0.056)
No. of states	19	19	19	19

Notes: Clustered standard errors in parentheses.
Significance: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. The dependent variable is ln(damages/GSDP). All models include time-invariant region and year fixed effects.
Instrument: state-wise ln(*liable to flood-prone area)* and ln(*drought-prone area*) as an instrument for ln(per capita income). In models 3 and 4, the Wald test of exogeneity shows that ln(per capita income) is an endogenous variable. First-stage regression of IV Tobit estimate confirms that ln(*liable to flood-prone area)* and ln(*drought-prone area*) is negatively related with ln(per capita income), which implies that states with higher *liable to flood-prone area and drought-prone area* experienced lower per capita income.

5. Conclusion and discussion

India's geo-climatic conditions, lack of coping ability, inadequate flood resilience infrastructure and socioeconomic heterogeneity lead to an increase in human fatalities and damages due to floods across Indian states (Central Water Commission, 2012). Moreover, lack of political coordination between the centre and states for the disbursement of disaster grants is also responsible for increasing the impact of floods (Tribune News Service, 2001). The existing literature argues that higher economic development is important in lowering natural disaster fatalities and damages (Anbarci *et al.*, 2005; Kahn, 2005; Stromberg, 2007; Toya and Skidmore, 2007; Ferreira *et al.*, 2013).

This study empirically examines the impact of economic development on, and the role of political institutions in, flood fatalities and damages across Indian states. Before describing the econometric exercise, we show that there exists an inverse relationship between average flood fatalities and real PCI over the period 1980–2011 (figure 1). Moreover, we estimate the average flood impact in 19 Indian states and confirm that some states are more vulnerable compared to other states in terms of flood fatalities

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and damages (figures A1 and A2). The econometric results based on FE Poisson and FE Tobit estimations suggest that economic development (proxied by real PCI) reduces flood fatalities and damages after controlling for direct spending on disaster relief and expenditures on flood control measures. Our results further confirm that flood fatalities are lower in a year when state elections are held compared to a non-election year. Moreover, the presence of political alignment between the centre and the states also minimizes the flood fatalities compared to non-political alignment. The results also confirm that more severe flooding increases flood fatalities and damages, whereas literacy rate reduces the impact of floods.

Next, we estimate the marginal effect obtained from FE Poisson and FE Tobit models and compare the magnitude of the coefficients across models. The result suggests the probability of 3 fewer people being killed due to flooding when real PCI increases by 10 per cent at the mean level, after controlling for other explanatory variables at their mean. Additionally, 21 fewer flood fatalities occurred in a year when state elections were held, whereas 16 fewer flood fatalities occurred due to the existence of the same political alignment between the centre and the states. The study also shows that a 10 per cent increase in real PCI leads to a decline in damages due to flooding by 0.25 per cent.

To obtain robust results, we estimate the FE negative binomial model and the corresponding marginal effects. Overall, the findings are consistent with FE Poisson estimates, but the magnitude of the marginal effects slightly varies across models. Besides, we argue that there exists reverse causality between PCI and flood impacts in terms of flood fatalities and damages. On the one hand, a state with higher PCI experienced lower flood impacts, but on the other hand, greater flood impacts adversely affect the PCI of the states.

We employed IV Poisson and IV Tobit estimations to take into account the reverse causality problem. These findings are largely consistent with FE Poisson and FE Tobit estimates, albeit with some differences in the magnitude of the coefficients. The empirical findings of the study are the following: first, economic development allows a state to invest in flood control measures such as the construction of flood-resilient infrastructure and better disaster management to mitigate the impact of floods across Indian states. Second, healthy political coordination between the centre and state governments is necessary in order to minimize flood fatalities. Third, government spending on irrigation and flood control and expenditures on social security and welfare is not adequate to mitigate the impact of floods. In sum, we conclude that economic development and political cooperation between the centre and states government play an important role in mitigating the impact of floods across Indian states.

Supplementary material. The supplementary material for this article can be found at https://doi.org/10.1017/S1355770X19000317

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Appendix A

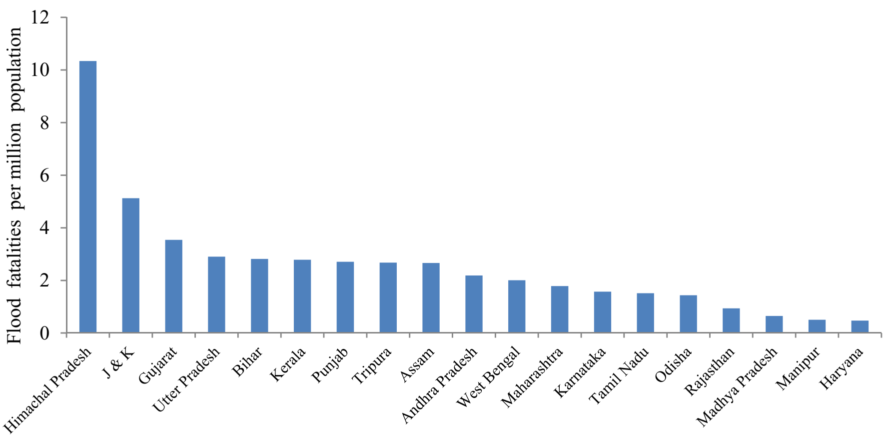

Figure A1. Average flood fatalities per million population over the period 1980–2011.
Note: Author's calculation.

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Table A1. Summary statistics and the definition of variables

Variables	Definition of variables	Mean	Std. Dev	Min	Max
Dependent variables					
Flood fatalities	Number of people who died during flood events	99.55	182.91	0.0	1399
ln(damages/GSDP)	[(Damages due to flood includes crops, houses, and public utilities over GSDP at current price) + 0.01]	−9.38	5.94	−23.19	−0.37
Instrument variables					
ln(liable to flood-prone area)	*Rashtriya Barh Ayog* (RBA) has estimated state-wise liable to flood affected area in lakh hectares ‘by adding the maxima of flood affected area (1953–78) in any year to the area protected up to 1978 and then deducting portion of the protected area included in the flood affected area due to the failure of protection works’	2.02	1.57	−1.61	4.30
ln(drought-prone area)	State-wise drought-prone area in lakh hectares	−0.55	5.96	−9.21	5.27
Independent variables					
lag of ln(per capita income)	Real gross state domestic product (GSDP)/State-wise population	9.82	0.52	8.40	11.11
ln(flood magnitude)	(Area affected by flood in sq km × Severity × Duration in days)	2.03	2.98	0.0	8.28
ln(flood duration)	[(End days − beginning days + 1) + 0.01]	−0.78	3.49	−4.61	5.08
ln(total area affected by flood in lakh hector)	(State-wise total area affected by flood including crop area in lakh hectares + 0.0001)	−1.83	4.58	−9.21	4.60
ln(population affected by flood)	(State-wise population affected by flood + 0.01)/Total population	−5.67	3.41	−12.19	−0.52
ln(number of houses damaged)	State-wise number of houses damaged by floods + 0.01	6.95	6.00	−4.61	20.11
ln(population density)	State-wise population/State wise area in square km	5.61	0.80	3.27	7.01
Literacy rate	State-wise literate population as % of the adult population	55.13	11.95	22.70	94.0

(continued)

Table A1. Continued

Variables	Definition of variables	Mean	Std. Dev	Min	Max
lag of ln(expenditure of irrigation and flood control)	One-year lag of expenditure of irrigation and flood control by State government/GSDP	−4.59	0.72	−7.46	−2.60
lag of ln(expenditure of natural calamity)	One-year lag of revenue expenditure of natural calamities by State government/GSDP	−6.51	1.01	−12.58	−3.50
lag of ln(expenditure of social security and welfare)	One-year lag of expenditure on social security and welfare by State government/GSDP	−5.60	0.78	−12.29	−3.11
State election dummy	State election held in different years in different states is equal to 1, otherwise zero	0.22	0.41	0.00	1.0
Political alignment dummy	Centre and state have the same political party or coalition political party governments years and particulate states are equal to 1, otherwise zero	0.29	0.46	0.00	1.0

Table A2. Impact of PCI, flood magnitude and political alignment on flood fatalities: FE negative binomial model

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
lag of ln(per capita income)	−0.7373*** (0.1585)	−0.5600** (0.2283)	−0.6405* (0.3477)	−0.7162*** (0.1703)	−0.7366*** (0.1168)	−0.7755*** (0.1288)	−1.1522*** (0.2360)
ln(flood magnitude)		0.2086*** (0.0632)	0.1312*** (0.0401)	0.1418*** (0.0386)	0.1418*** (0.0386)	0.1429*** (0.0371)	0.1301*** (0.0279)
ln(population affected by floods)			0.2330*** (0.0311)	0.1361*** (0.0254)	0.1362*** (0.0253)	0.1385*** (0.0243)	0.1425*** (0.0235)
ln(number of houses damaged)				0.1040*** (0.0182)	0.1019*** (0.0197)	0.1007*** (0.0184)	0.0961*** (0.0144)
ln(population density)					0.0771 (0.3551)	0.0927 (0.3533)	0.0616 (0.2647)
State election dummy						−0.1943** (0.0912)	−0.1718* (0.0958)
Political alignment dummy						−0.2589** (0.1114)	−0.2136** (0.0973)
Literacy rate						−0.0027 (0.0054)	−0.0058 (0.0063)
lag of ln(expenditure of social security and welfare)							−0.2157 (0.1526)
lag of ln(expenditure of irrigation and flood control)							−0.4285* (0.2642)
lag of ln(expenditure of natural calamity)							0.2149* (0.1124)
Observations	589	589	589	589	589	589	589
No. of states	19	19	19	19	19	19	19

Notes: Clustered standard errors in parentheses.
Significance: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. The dependent variable is flood fatalities. All models include time-invariant region and year fixed effects.

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Table A3. Marginal effect at the mean: FE negative binomial model

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
lag of ln(per capita income)	−53.228*** (11.434)	−35.904** (14.657)	−34.060* (18.483)	−34.442*** (8.132)	−35.380*** (5.500)	−37.054*** (6.000)	−53.041*** (10.366)
ln(flood magnitude)		13.378*** (4.034)	6.976*** (2.112)	6.818*** (1.815)	6.814*** (1.816)	6.831*** (1.732)	5.990*** (1.230)
ln(pop affected by floods)			12.392*** (1.620)	6.544*** (1.210)	6.543*** (1.203)	6.620*** (1.146)	6.560*** (1.056)
ln(number of houses damaged)				5.002*** (0.847)	4.896*** (0.923)	4.812*** (0.855)	4.425*** (0.639)
ln(population density)					3.707 (17.060)	4.433 (16.884)	6.836 (12.182)
State election dummy						−9.284** (4.335)	−7.911* (4.400)
Political alignment dummy						−12.371** (5.271)	−9.834** (4.440)
Literacy rate						−0.131 (0.258)	−0.271 (0.289)
lag of ln(expenditure of social security and welfare)							−9.933 (6.973)
lag of ln(expenditure of irrigation and flood control)							−19.728* (11.973)
lag of ln(expenditure of natural calamity)							9.893* (5.095)
Observations	589	589	589	589	589	589	589
No. of states	19	19	19	19	19	19	19

Notes: Delta-method standard errors in parentheses.
Significance: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. The dependent variable is flood-related fatalities.

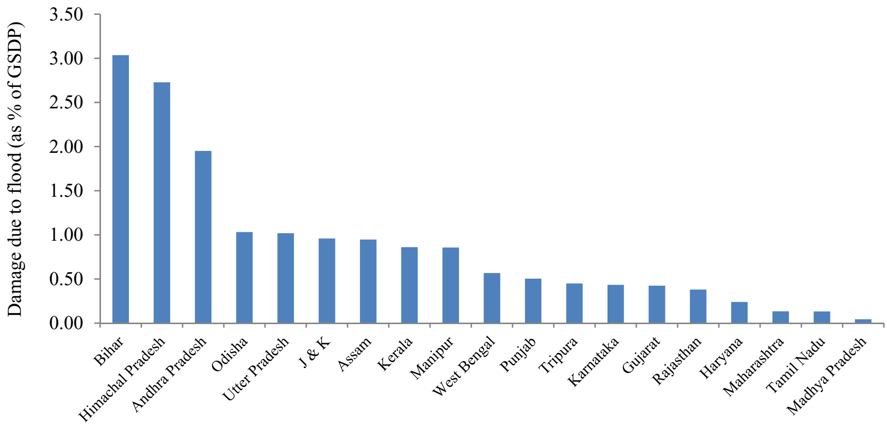

Figure A2. Average damages due to floods (as % of GSDP) over the period 1980–2011.
Note: Author's calculation.

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