



Do economic development and disaster adaptation measures reduce the impact of natural disasters? A district-level analysis, Odisha, India

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Abstract

Natural disasters are a regular phenomenon in Odisha due to its unique geo-climatic conditions. Frequent occurrences of natural disasters affect different aspects of human life and cause huge damage to private and public property. We examine the effects of economic development, basic disaster adaptation measures, and exposure to disaster on disaster fatalities due to floods, heat-wave, and lightning. We use district-level panel data for 30 districts in Odisha over the period 1999–2011. The FE Poisson estimates suggest that economic development (proxied by per capita income) is not adequate to minimize fatalities from natural disasters. The results further confirm that better disaster adaptation measures such as better medical facilities, adequate road infrastructure, higher primary enrolment, village electrification, forest cover, and financial accessibility help in mitigating disaster fatalities to some extent. In addition, the estimates indicate that disaster-specific exposures such as high incidences of floods, excessive rainfall during monsoon, high temperature, and humidity lead to an increase in disaster fatalities. In sum, our results conclude that adequate disaster adaptation measures and better disaster management policies are essential to mitigate fatalities from natural disasters in the districts of Odisha, India.

Keywords Disaster fatalities · Economic development · Disaster adaptation · Count model · Odisha · India

JEL Classification O10 · C54

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1 Introduction

Natural disaster causes huge losses in terms of loss of human lives and damages to private and public property. The level of impact depends upon the types and magnitude of disaster occurrences in a particular region (Guha-Sapir et al. 2004). Moreover, disaster impact also depends on the geo-climatic condition, the size of the vulnerable population, level of economic development, and the role of government in mitigating the impact of natural disasters. Between 1985 and 1999, 65% of the world population was lost due to natural disasters, with the greatest impact in areas with per capita income less than \$760 (Intergovernmental Panel on Climate Change 2001).¹ The existing empirical studies suggest that developed nations experienced lower disaster fatalities compared to developing nations (Kahn 2005; Stromberg 2007; Toya and Skidmore 2007). Higher economic development and better disaster warning systems are required to prevent natural disaster impact in terms of losses of lives. Moreover, countries with stronger institutions and effective governance experience lower death from natural disasters (Anbarci et al. 2005; Kahn 2005; Escaleras et al. 2007; Stromberg 2007). In developing economies like India, natural disaster severely affects different sectors of the economy and various aspects of human life. Between 1970 and 2009, India experienced 371 natural disasters, which led to a 151,000 loss of lives and affecting 1.86 billion people. Moreover, 63% of economic losses were caused by floods, 19% caused by cyclones, 10% caused by earthquakes, and 5% caused by droughts (World Bank 2012). Such high exposure to disaster risks ranks India high in terms of overall Climate Risk Index globally (Kreft et al. 2017).²

Among Indian states, Odisha is highly vulnerable to natural disasters due to its unique geo-climatic conditions and has witnessed a rise in natural disaster trends. High degree of socioeconomic vulnerability, inadequate mitigation measures and low levels of economic development, has further accentuated the damages caused due to natural disasters (Annual Report on Natural Calamities 2012–2013, Government of Odisha). Natural disasters such as floods, droughts, cyclones, heat-waves, and lightning are a regular phenomenon in Odisha with adverse effects on human life and private and public capital in different parts of the state.³ Over the period, direct economic losses from natural disasters have increased in different districts of Odisha. Odisha lost around 11% of Gross State Domestic Product (GSDP) in 1970, approximately Rs. 10.5 billion, with a seven times increase in 1980 and ten times in 1990 (Human Development Report 2004, Government of Odisha). Between 1980 and 2011, Odisha lost around 1% of GSDP, with an average one death per year due to floods. Moreover, around 0.031% of GSDP loss due to fire and one death due to fire accidents over the same period were observed. Further, natural disaster leads to a significant increase in fiscal pressures on the state governments. On average, Government of Odisha (GoO) spends around 1.3% of GSDP for flood control and irrigation-related activities, and 0.44% for evacuation and relief distribution (Parida et al. 2019).

In Odisha, human capital is immensely affected due to natural disasters. Between 1999 and 2011, 730 people were killed due to floods, 858 due to the heat-wave, and 3456 due to

¹ In developing nations, natural disasters claimed lives to the extent of 90 percent because these nations experience higher poverty, higher population density, and unsafe building practice. Moreover, economically weaker sections generally live in highly disaster-prone areas in these nations (Secretary-General of the United Nations Kofi Annan, 1999).

² India's rank is 14th in terms of the overall Climate Risk Index (Kreft et al. 2017).

³ Annual Report on Natural Calamities 2012–13, Government of Odisha.

lightning (Annual Report on Natural Calamities 2012–13, Government of Odisha). Developing nations experience high human casualty from natural disasters due to severe poverty, high dependence on primary sectors, low per capita income, and inadequate physical and social infrastructure. This impact is further accentuated by the lack of ability to prevent and mitigate disaster impacts. Inadequate disaster preparedness, lack of awareness about the disaster's impacts, and conventional disaster warning systems are other factors that lead to an increase in human casualty from disasters, multiplicatively.

The above argument shows that the districts of Odisha are affected by multiple natural disasters, but floods, heat-wave, and lightning are most prevalent. To examine the adverse impact of these natural disasters in different districts of Odisha, we employ unconditional fixed effect (FE) negative binomial and FE Poisson estimation methods. We estimate the impact of basic disaster adaptation measures, level of economic development and exposure to disaster on fatalities from natural disasters such as floods, heat-waves, and lightning. First, we combine subregional unique development indicators, disaster exposure, and disaster fatality data for 30 districts in the state of Odisha for the period 1999–2011. Second, we employ unconditional FE negative binomial and FE Poisson estimations because our outcome variable is the number of disaster fatalities due to flood, heat-wave, and lightning. The 'disaster fatalities' variables are rare events, non-negative integers, and unlikely to follow a normal distribution. Given the nature of the data, the ordinary least square (OLS) estimation method is not an appropriate estimation strategy because it may generate biased results. Moreover, the outcome variable does not satisfy the necessary OLS assumptions of the variable to be normally distributed because the variance of the outcome variable exceeds its means (see Table 6).⁴ In addition, Parida (2019) used both unconditional FE negative binomial and FE Poisson estimation methods using state-wise flood fatalities dataset in the Indian context.⁵ The literature provides limited evidence on the role of development indicators such as per capita income, literacy levels, financial development, infrastructure, and health care facility to prevent disaster fatality in subregional levels in Odisha. The current study contributes significantly to the economics of disaster literature and proposes suitable disaster policy devices to mitigate the impact of disasters in Odisha.

The rest of the paper is framed as follows: Overview of natural disasters is discussed in Sect. 2. Review of previous literature is presented in Sect. 3. Section 4 analyzes data sources and econometric methodology. Empirical results are presented in Sect. 5. Overall empirical findings are discussed in Sect. 6. Finally, conclusion and policy implications are discussed in Sect. 7.

2 Overview of natural disaster in Odisha

The state of Odisha is situated in the eastern part of India. This state is highly prone to natural calamities such as cyclones, floods, droughts, and lightning due to its unique geo-climatic conditions. Because of the geographical location, the coastal areas in Odisha remain

⁴ Kindly see Sect. 4 for a detailed discussion of the count data model used in this study.

⁵ Previous studies have used both FE negative binomial and FE Poisson model in country-wise flood fatalities data (Ferreira et al. 2013). Moreover, a few studies used the FE negative binomial model in country-wise earthquake fatalities data (Anbarci et al. 2005; Escaleras et al. 2007). Bahinipati, and Patnaik (2015) and Das (2016) used FE negative binomial and FE Poisson estimates in district-wise disaster data in Odisha. Therefore, we use the FE negative binomial and FE Poisson model in our study.

vulnerable to storms and floods in comparison with other non-coastal regions. According to the Human Development Report (2004), the destruction of coastal mangroves, soil salinity, and degradation of forests has probably increased susceptibility to natural calamities. Some areas in Odisha are also prone to droughts due to the increased moisture stress. Disasters such as floods, droughts, and lightning have posed serious constraints to productivity and growth by causing widespread human and environmental losses.

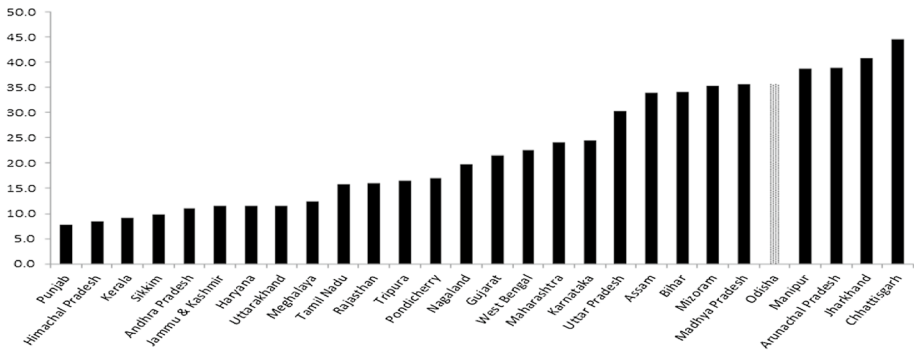
The critical condition of Odisha is accentuated due to the high incidence of poverty, food insecurity, poor health regime, and low education levels. Figure 1 (a) to (c) demonstrates the poor ranking of the state on these socioeconomic parameters. As shown in Fig. 1a, Odisha lies in the upper distribution of a percentage of the rural population living below the poverty line. The state also scores relatively low on the human development index (HDI) in comparison with other states of India, as shown in Fig. 1b. It is evident in Fig. 1c that Odisha ranks lowest with respect to literacy rate amongst the other states of India, as per the 2011 census.⁶ Many epidemic diseases, including cholera, measles, dysentery, respiratory infections, and malaria, are highly widespread due to the frequent occurrence of natural disasters (Human Development Report 2004, GoO). The occurrence of natural disasters coupled with the poor socioeconomic status of the state enhances the impact of disasters to a large extent. It generates a vicious cycle of low economic growth, high occurrences of natural disasters, and an increased burden on state expenditure for reconstruction. This further constrains investment for human capital and infrastructural growth that could mitigate the effects of disasters in the future.

Between 1900 and 2011, Odisha experienced different forms of natural disasters with high magnitudes, such as 59 incidences of high floods, 24 cyclones, 42 occurrences of severe droughts, 14 severe heat-waves, and 7 tornadoes. Since the nineteenth century, Odisha experienced 1.3 natural calamities per year (Annual Report on Natural Calamities 2006–07, Government of Odisha; Roy et al. 2002). Table 1 shows that the impact of natural disasters in terms of deaths per million of population in Odisha for the period 1999–2011. Between 1999 and 2011, 730 people died due to floods, 858 people due to the heat-waves, and 3456 people killed due to lightning. The number of deaths due to floods was highest in 2003 and the lowest in 2002. The state witnessed the highest heat-wave-related fatalities in 2005 and the lowest in 2002. Similarly, lightning caused the highest number of casualties in 2001 and 2008, respectively, and lowest in 2000. On average, floods claimed 56 lives, followed by 66 lives lost due to heat-waves, and 266 lives lost due to lightning. Overall, Table 1 shows that lightning caused the highest impact on lives with an average of 7 deaths per million of population, followed by heat-waves with an average of 2 deaths, and floods with 1 death per million population over the period 1999–2011.

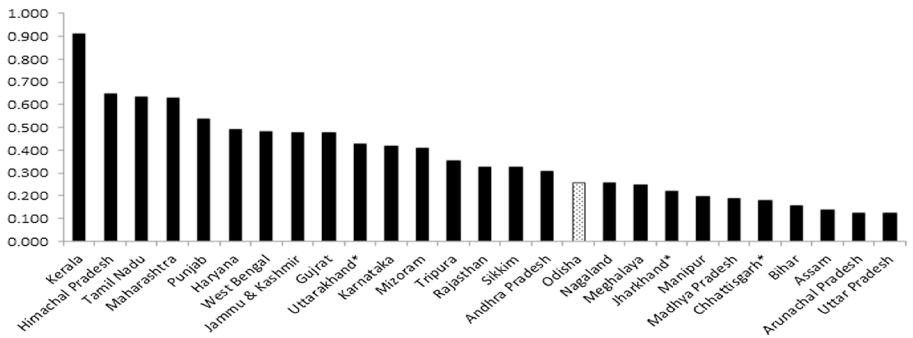
Figure 2 shows trends in disaster fatalities due to floods, heat-waves, and lightning per million population in the state of Odisha over the period 1999–2011. In 1999, around 7 people were killed due to lightning, and 2 people were killed due to heat-waves and floods

⁶ National Sample Survey (NSS) survey report titled 'Income, Expenditure, Productive Assets and Indebtedness of Agricultural Households in India, 2012–13' estimated average monthly income per agricultural households in all 28 India states. Odisha's average monthly income per agricultural household's income is Rs. 4976 in 2012–2013, which is below the average monthly income of 22 states in India. Regarding the health index, Odisha's rank is 24th out of 28 states in India (Mukherjee and Chakraborty 2011). Similarly, in terms of rural inequality, Odisha's rank is 21st out of 28 states in India (Databook for PC; 22nd December 2014, Planning Commission, Government of India). In terms of infant mortality rates, Odisha's rank is highest among the Indian states (Economic Survey 2009–10). In terms of liability to flood-prone area, Odisha ranks 20th out of 28 states in India (Page No-95, Government of India 2011).

(a) Percentage of rural population below the poverty line for all states in 2011-12



(b) Human Development Index for all states in 2011-12 (Rural & Urban Combined)



(c) Percentage literate population for 2011-12

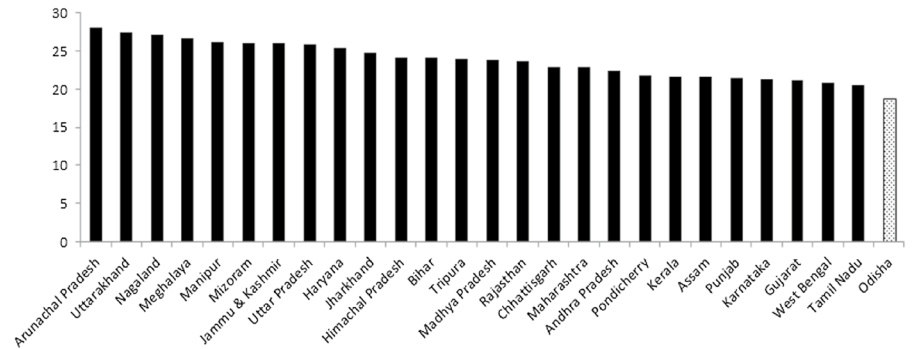


Fig. 1 a Percentage of rural population below the poverty line for all states in 2011–12. *Note:* Authors’ own compilation. Data Source: Report of the Expert Group to Review the Methodology for Measurement of Poverty, 2014, Planning Commission, Government of India. b Human Development Index for all states in 2011–12 (Rural & Urban Combined). *Note:* Authors’ own compilation. Data Source: Mukherjee et al. (2014). c Percentage literate population for 2011–12. *Note:* Authors’ own compilation. Data Source: Census of India, 2011

each, respectively, per million population. In 2001, the highest number of people were killed due to lightning, followed by floods and heat-waves. Moreover, in 2005, deaths due to heat-waves almost equalled deaths due to lightning. In sum, the figure shows that deaths

Table 1 Deaths due to natural disasters in Odisha over the period 1999–2011

Year	Flood	Heat-wave	Lightning
1999	60	81	268
2000	2	38	71
2001	113	26	362
2002	0	20	247
2003	124	70	288
2004	10	43	274
2005	19	235	235
2006	105	21	204
2007	60	47	351
2008	110	68	362
2009	59	87	214
2010	14	100	227
2011	54	22	353
Average	56	66	266
Total	730	858	3456
Average death per million population	1	2	7

Authors’ own estimates. Data source: Various Annual Reports on Natural Calamities, Government of Odisha

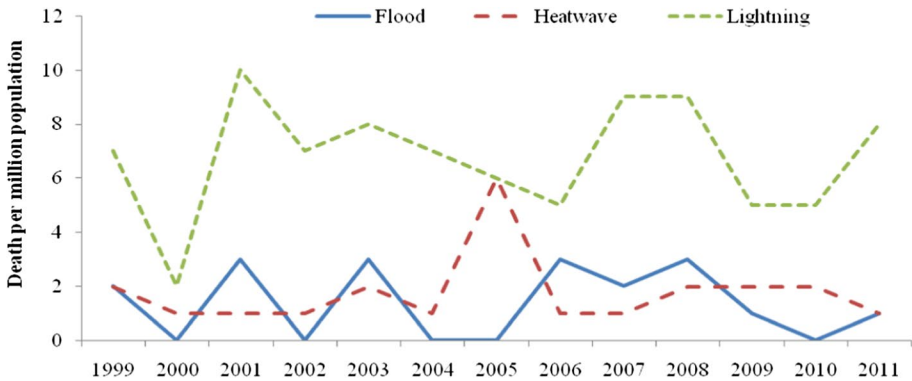


Fig. 2 Disaster fatalities per million of population. *Note:* Authors’ own estimates. *Data source:* Various Annual Report on Natural Calamities, Government of Odisha

due to lightning are the highest compared to deaths due to heat-waves and floods over the period 1999–2001.

3 Review of literature

The bulk of empirical studies confirm that not only economic development [proxied by per capita income (PCI)], but also better institution and better governance minimize fatalities resulting from natural disasters. Anbarci et al. (2005) examine the role of economic

development (proxied by PCI) and inequality on earthquake fatalities using country-wise earthquake fatalities over the period 1960–2002. The results based on fixed effect (FE) negative binomial estimates suggest that higher per capita income leads to a decline in fatalities from earthquakes, while higher inequality increases earthquake fatalities. Toya and Skidmore (2007) examine the effect of economic development on human and physical capital losses from natural disasters for 153 nations over the period 1960–2003. The empirical results based on the ordinary least squares (OLS) estimation confirm that countries with higher economic development, better financial markets, greater openness, and better educational attainment have experienced a lesser number of deaths and economic losses from natural disasters. Moreover, they confirm that developed nations suffer lower disaster losses in terms of human and physical capital compared to developing nations. Kahn (2005) examines the role of government, geographical location, and level of economic development on disaster fatality using data for 73 nations from 1980 to 2002. The empirical results based on zero-inflated negative binomial estimates show that economic development is better insurance against disaster shocks. Moreover, the study also confirms that countries with a democratic government and better institutions experience lower death rates. In addition, the study contemplates that developed nations experience lower deaths due to natural disasters.

Escaleras et al. (2007) employ the negative binomial estimation method to examine the relationship between corruption and earthquake fatality using 344 major earthquakes over the period 1975–2003. They confirm that a country with higher public sector corruption also experienced higher earthquake fatality. Stromberg (2007) employs OLS and instrumental variable (IV) estimation methods to examine the role of economic development and better governance on fatalities using country-wise natural disaster data. The author confirms that country with higher per capita income and better governance has experienced lower fatalities. Fankhauser and McDermott (2014) evaluate the relationship between per capita income and disaster fatality due to two extreme weather events (floods and cyclones) using negative binomial estimate. They find that a country with higher per capita income helps to reduce disaster fatality, but results do not hold after controlling country-specific fixed effects. Moreover, the study also shows that government expenditure for disaster adoption measures weakly prevents disaster fatality.

Apart from the impact of economic development (proxied by PCI) on fatalities from natural disasters, a few sets of empirical studies also argue that there exists a non-linear relationship between per capita income and disaster fatality. Ferreira et al. (2013) employ the FE Poisson and FE negative binomial estimation methods to evaluate the effect of economic development on flood fatality using cross-country flood dataset for 92 countries over the period 1985–2005. The econometric results suggest that higher per capita income and better governance reduce flood fatality without taking into account unobserved country-specific effects. The results further confirm that there exists a little evidence of higher per capita income on flood fatality after controlling unobserved country-specific effects. Schumacher and Strobl (2011) have used FE Tobit estimates to examine disaster exposure and per capita income on disaster risk in terms of human capital losses. They confirm that disaster risk in terms of fatalities increases with initial economic development (proxied by PCI) and declines further with an increase in economic development.

Raschky (2008) has applied the OLS method to examine how institutional quality and economic development minimize fatalities from natural disasters. The author states that countries with better institutions experience lower deaths from natural disasters. In addition, the study suggests that there exists a non-linear relation between per capita income and disaster risk in terms of fatalities. Kellenberg and Mobarak (2008) examine the role of per capita income and disaster exposure (number of disasters) on disaster fatalities using country-wise

disaster fatalities data for 133 countries. The results based on negative binomial and generalized least squares (GLS) methods show that economic development is a better measure to mitigate disaster risk in terms of fatalities. In addition, the study shows that there exists a non-linear relation between PCI and disaster fatalities (inverted U-shape) that means initially, disaster fatalities increase with an increase in PCI; after some point, it declines when PCI increases, and further, Padli et al. (2010) also confirm that there exists a non-linear relation between per capita GDP and deaths from disasters after controlling government consumption, financial market, school attainment, country land area, and size of the population.

Apart from the cross-country analysis, a few empirical studies confirm that states with higher economic development, better disaster adaptation measures, and the active role of media are better equipped to prevent disaster fatalities in India. Parida (2019) examines the impact of economic development and the role of political alignment on fatalities from floods for 19 Indian states over the period 1980–2011. The empirical results based on the FE Poisson and FE negative binomial estimates confirm that states with higher economic development experience lower deaths from floods. In addition, the result also suggests that political alignment minimizes flood fatalities. Bahinipati and Patnaik (2015) have used the OLS and FE negative binomial estimates to examine the impact of disaster-specific and adaptation measures on population and village affected by floods and cyclones in Odisha. They show that exposure to disasters and disaster adaptation measures reduce the population and villages affected by floods and cyclones in districts of Odisha. Das (2016) evaluates the role of electronic and print media on heat-wave fatality using district-wise socioeconomic data in Odisha. The results based on the FE Poisson estimates confirm that television and newspaper play a significant role in minimizing heat-wave fatality, but radio has limited impact.

Next, a few studies have constructed socioeconomic and infrastructural vulnerability indices for all districts of Odisha and other Indian districts. Sharma and Patwardhan (2008) compute components of vulnerability such as hazard, exposure, impact, and composite vulnerability index using the Human Development Index proposed by UNDP (2006) in coastal districts in India. They identified that few districts are most vulnerable based on various components of vulnerability indices compared to other districts. Bahinipati (2014) measures vulnerability by using exposure, sensitivity, and adaptation indices across 30 districts in Odisha. He finds that some districts are more vulnerable compared to other districts. In addition, he suggests that the socio-economic condition of the districts is a major cause of increasing vulnerability. Mazumdar and Paul (2016) measure the district-wise socioeconomic and infrastructural vulnerability due to cyclones in the eastern coastal states of India. They have identified that few districts are more vulnerable towards cyclones than other districts. Those districts also face enormous challenges in terms of socio-economic and infrastructural vulnerability to coping with cyclones. Mazumdar and Paul (2018) estimate socio-economic and infrastructural vulnerability indices using principal component analysis for various blocks in Odisha, and those blocks are seen to be likely affected by cyclones. They also identified highly vulnerable blocks that are affected by cyclones. Also, we summarize the literature review in Table 5.

4 Data sources and econometric methodology

The district-wise natural disaster data for Odisha on death due to floods, heat-waves, and lightning are taken from the various volumes of 'Annual Report on Natural Calamities,' which are published by Special Relief Commissioner, Revenue and Disaster Management

Department, Government of Odisha (GoO). Since the *Annual Report on Natural Calamities* does not provide district-wise data of flood events, we have compiled the district-wise number of flood occurrences from Sendai Framework for Disaster Risk Reduction database.⁷ The district-wise monthly temperature, humidity, rainfall, and forest cover data are taken from various volumes of 'Statistical Abstract of Odisha,' 'Economic Survey of Odisha,' and 'District Statistical Handbooks.' Data on district-wise road length, number of villages electrified, number of hospitals, and enrollment in primary schools are also obtained from the same sources. The district-wise population is taken from the 'Primary Census Abstract,' which is published by the Census of India. In India, the census is a decadal exercise since 1961. Data are available from 1961 until 2011, with a decadal gap. We linearly interpolated the population data to fill the gap years where no census was conducted. The district-wise real Gross District Domestic Product (GDDP) is leveraged from the Directorate of Economics and Statistics (DES), GoO. The district-wise credit sanction (outstanding amount) is taken from the Economic and Political Weekly Research Foundation (EPWRF), India Time Series database.

For the empirical exercise, we have normalized the variables using suitable indicators (see Table 6). Table 6 also presents the definition of all variables, summary statistics, and respective data sources. Between 1999 and 2011, on average, Odisha experienced 2 fatalities due to floods, 2 people killed due to heat-waves, and 7 deaths due to lightning. On average, Odisha experiences at least one incident of flood per year; the average maximum temperature in the state is as high as 32 degrees in Celsius with an average relative humidity of around 75%. In addition, the average annual per capita income is Rs. 22,255, around 31% of land as a percentage of district geographical area is covered with forest, on average, 76% of villages are electrified, and around eight government hospitals are available per lakh population. The expected signs of explanatory variables are also discussed in Table 6. For example, disaster adaptation measures such as annual per capita income, number of government hospitals, forest cover, villages electrified, bank credit, enrollment in primary schools, and road infrastructure are negatively related to fatalities due to floods, heat-waves, and lightning. Moreover, the number of floods and rainfall are positively associated with flood fatalities, whereas high temperature, relative humidity, and rainfall lead to higher deaths due to heat-waves and lightning. Table 7 provides the correlation between the variables of the study.⁸

We examine the effect of basic adaptation measures and specific disaster exposure on disaster fatality using district-level data for 30 districts in Odisha over the period 1999–2011. We employ an unconditional fixed effect (FE) negative binomial and FE Poisson models to estimate the following equations.⁹

⁷ <https://www.desinventar.net/DesInventar/profilatab.jsp?countrycode=019&continue=y> (Data was collected 2nd May 2017).

⁸ The correlation only shows the relationship between the variables, but it cannot capture the true cause and effect relationship between variables. In Table 7, per capita income is negatively correlated with flood fatalities, while it is positively related to heat-waves and lightning fatalities. In regression analysis, per capita income is negatively related to flood fatalities, heat-waves, and lightning fatalities, respectively (see Tables 2, 3 and 4). The results show that correlation does not estimate the sign of the coefficient correctly, whereas regression estimates provide correct signs of coefficients because it controls for cause and effect of the variables.

⁹ Hilbe (2011: 474) argued that the conditional FE negative binomial model 'is not a true fixed-effects model,' and it is unable to control time-invariant fixed effects robustly (Allison and Waterman 2002). Moreover, it controls for fixed effects with a very specific set of assumptions (Guimaraes 2008).

$$FF_{it} = \beta_0 + \beta_1 PCI_{it-1} + \beta_2 NF_{it} + \beta_3 RF_{it} + \beta_4 FC_{it} + \beta_5 Z_{it} + \mu_r + \gamma_t + \mu_{1it} \quad (1)$$

$$HWF_{it} = \alpha_0 + \alpha_1 PCI_{it-1} + \alpha_2 MT_{it} + \alpha_3 RH_{it} + \alpha_4 CR_{it} + \alpha_5 Z_{it} + \mu_r + \gamma_t + \mu_{2it} \quad (2)$$

$$LD_{it} = \vartheta_0 + \vartheta_1 PCI_{it-1} + \vartheta_2 MT_{it} + \vartheta_3 RH_{it} + \vartheta_4 PE_{it} + \vartheta_5 Z_{it} + \mu_r + \gamma_t + \mu_{3it} \quad (3)$$

where i represents the district {1 to 30}, t denotes time period {1999 to 2011}, dependent variables { FF_{it} is the number flood fatalities HWF_{it} is the number of heat-wave fatalities, LD_{it} is the number of deaths due to lighting}, NF_{it} is the number of floods that occurred in different districts in the respective years, PCI_{it-1} is the natural logarithm of per capita income in the previous period, RF_{it} is the natural logarithm of average rainfall July to September, FC_{it} is the forest cover, MT_{it} is the maximum temperature, RH_{it} is the relative humidity, CR_{it} is the credit ratio, PE_{it} is the primary enrollment, Z_{it} denotes other explanatory variables {percentage of village electrified, number of hospitals, and road density}, γ_t is the year-specific effects, μ_r is the district unobserved time-invariant region effects, and μ_{it} is the error term.

In Eqs. (1) to (3), the outcome is a count variable that measures the number of deaths due to floods, heat-waves, and lightning. The variance of the outcome variable exceeds the mean implying that the outcome is over-dispersed, and it violates the assumption of normal distribution (as shown in Table 6). In this case, the ordinary least squares (OLS) estimation method generates biased estimates. Several empirical studies have used unconditional FE negative binomial and FE Poisson estimates in count dataset (Anbarci et al. 2005; Kahn 2005; Escaleras et al. 2007; Parida (2019); Parida et al. 2018). Therefore, our study employs unconditional FE negative binomial in consideration of the following summary and test statistics. First, the variance of the outcome variable exceeds the mean (see Table 6). Second, the Wald test states that alpha that accounts for unobserved heterogeneity is significantly different from zero, suggesting the appropriateness of unconditional FE negative binomial model (see Models 5 and 6 of Tables 2, 3 and 4). Third, Akaike's information criterion (AIC) and Schwarz's Bayesian information criterion (BIC) are lower for FE negative binomial model compared to the Poisson regression model (see Models 1, 2, 5, and 6 of Tables 2, 3 and 4). Fourth, the FE negative binomial estimates consistent parameters and controls for time-invariant unobserved region factors efficiently when cross-sectional units are less than 20 (Hilbe 2011: 473). Fifth, Pearson goodness-of-fit test suggests that the unconditional FE negative binomial model is appropriate for this dataset because it suffers from an overdispersion problem (Models 1 and 2 of Tables 2, 3 and 4). However, Cameron and Trivedi (1998: 282) argued that in a short panel, the unconditional FE negative binomial model produces biased estimates, and it suffers an incidental parameter problem. To overcome the biased results, we apply FE Poisson estimation and base our findings from this model for the following reasons. First, it controls for fixed effect (region) and does not suffer from the incidental parameter problem (Wooldridge 2002: 674–676). Second, Cameron and Trivedi's (2010, 575) overdispersion test suggests that FE Poisson is preferred over unconditional FE negative binomial estimates since it controls for unobserved fixed effect (region) efficiently (see Models 1 and 2 of Tables 2, 3 and 4). Finally, the above argument shows that both unconditional FE negative binomial and FE Poisson estimation methods are suitable for our dataset. Recently, Parida (2019) and Ferreira et al. (2013) have used both FE Poisson and FE negative binomial methods in the flood fatalities dataset. In the regression models, we control for time-invariant region effects for

Table 2 Effect of economic development and incidence of the flood on flood fatalities

Independent variables	Dependent variable (flood fatalities): FE Poisson				Dependent variable (flood fatalities): FE negative binomial			
	Coefficients		Incident rate ratio (IRR)		Coefficients		Incident rate ratio (IRR)	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Lag of ln (Per capita income)	-0.279 (0.257)	-0.330 (0.263)	0.756 (0.194)	0.719 (0.188)	-0.086 (0.287)	-0.055 (0.279)	0.916 (0.263)	0.945 (0.263)
ln (Number of floods)	0.541*** (0.093)	0.505*** (0.084)	1.717*** (0.159)	1.656*** (0.139)	0.617*** (0.079)	0.606*** (0.076)	1.853*** (0.147)	1.833*** (0.139)
ln (Rainfall July to September)	2.061*** (0.449)	2.817*** (0.437)	7.854*** (3.525)	16.720*** (7.316)	2.321*** (0.473)	2.660*** (0.470)	10.190*** (4.818)	14.294*** (6.715)
Forest area coverage (%)		-0.002 (0.008)		0.997 (0.008)		-0.006 (0.007)		0.993 (0.007)
Primary enrollment (%)		-0.104* (0.055)		0.901* (0.050)		-0.081 (0.063)		0.922 (0.058)
Bank credit over district GDP (%)		-0.032*** (0.011)		0.968*** (0.011)		-0.027** (0.013)		0.972** (0.013)
Village electrified (%)		-0.001 (0.006)		0.998 (0.006)		-0.008 (0.007)		0.991 (0.007)
Number of hospital per lakh population		-0.178** (0.080)		0.837** (0.067)		-0.150** (0.074)		0.8609** (0.063)
χ^2 (d.f.)	1081.8 (23)	1156.64 (28)	1081.8 (23)	1391.29 (28)	917.07 (23)	925.07 (28)	917.07 (23)	925.07 (28)
log-likelihood	-548.19	-572.94	-548.19	-524.6	-441.58	-437.48	-441.58	-437.48
Wald test					36.22	38.68		
(P-value)					(0.000)	(0.000)		
AIC	1144.39	1107.20			933.16	934.96		
BIC	1237.66	1219.90			1030.31	1051.54		
Pearson goodness of fit	860.505	803.894						
(P-value)	(0.000)	(0.000)						

Table 2 (continued)

Independent variables	Dependent variable (flood fatalities): FE Poisson				Dependent variable (flood fatalities): FE negative binomial			
	Coefficients		Incident rate ratio (IRR)		Coefficients		Incident rate ratio (IRR)	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Cameron and Trivedi's (2010, 575) <i>t</i> -value and (<i>P</i> -value)	2.21 (0.028)	1.55 (0.122)						
No. of districts	30	30	30	30	30	30	30	30
Observations	360	360	360	360	360	360	360	360

Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ denote 1%, 5%, and 10% levels of significance, respectively. We control region and time fixed effects in all models

controlling unobserved heterogeneity that may be correlated with both the outcome and explanatory variables in our models.¹⁰

5 Empirical results

5.1 Effect of economic development and flood occurrences on flood fatalities

In this section, we employ an FE Poisson model to examine the effects of economic development and occurrences of floods on flood fatalities using Eq. (1). The FE Poisson estimates are shown in Models 1 and 2 of Table 2. In Model 1, the coefficient of lag per capita income (PCI) is negative and insignificant, which shows that economic development (proxied by PCI) helps in reducing the flood fatalities rate, although the relationship is statistically weak. This result is consistent with Ferreira et al. (2013) and Fankhauser and McDermott (2014) findings. In addition, results imply that the contemporary level of economic development of districts is not adequate to mitigate flood fatalities. Therefore, the lack of resilience is observed in terms of levels of economic development and effective implementation of preemptive and corrective measures to minimize flood fatalities. Moreover, development measures fail to translate into lower spending toward flood control measures such as construction and maintenance of river embankment, rehabilitation centers in low lying areas, flood warning, and flood forecasting that are essential to mitigate the flood impact.

The disaster-specific exposures, such as frequent floods and excess rainfall during monsoon months, increase the flood risk in terms of flood fatality (see Model 1). In Model 2, the coefficient of lag PCI remains negative and insignificant, while the number of floods and rainfall is found to be positive and significant after controlling for disaster adaptation measures. Moreover, disaster adaptation measures, such as the area covered under forests and villages electrified, minimize the flood fatalities marginally. An interesting finding of the study is that the basic disaster adaptation measures such as higher primary enrollment rate, better financial markets, and the availability of hospitals lead to a decline in the flood fatality.

The study also estimates the incidence rate ratios (IIRs) for Poisson regression, and the results are presented in Models 3 and 4. In Model 3, the estimates confirm that a one percent increase in PCI would result in only 75% of flood fatalities, that is, there would be 25% lesser fatalities. Moreover, frequent floods and high rainfall increase the flood fatality by 1.71 times and 7.85 times, respectively. In Model 4, the estimates are robust to the inclusion of control variables such as forest coverage, primary enrollment rate, village electrification, and bank credit. Estimates from Model 4 with the inclusion of other control variables are close and indicate only 72% of flood fatalities with a percentage rise in PCI. Further, higher occurrences of flood lead to 1.65 times higher flood fatalities. Furthermore, estimates show that a percentage rise in rainfall during flood months accounts for 16.7 times higher fatalities. Other control variable, such as the primary school enrollment rate shows a positive impact in reducing the flood fatalities by 10%. Education is not only indicative of awareness levels and ease of dissemination of information during times of crisis, but it is also a measure of development and has direct and indirect effects on reducing fatality rates.

¹⁰ We have divided 30 districts into 10 agro-climatic regions.

Table 3 Effects of economic development and specific disaster exposure on heat-wave fatalities

Independent variables	Dependent variable (heat-wave fatalities): FE Poisson				Dependent variable (heat-wave fatalities): FE negative binomial			
	Coefficients		Incident rate ratio (IRR)		Coefficients		Incident rate ratio (IRR)	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
lag of ln (per capita income)	-0.059 (0.198)	-0.163 (0.196)	0.943 (0.187)	0.849 (0.167)	-0.152 (0.221)	-0.429* (0.226)	0.859 (0.190)	0.651* (0.147)
Maximum temperature (degree in C)	0.190*** (0.062)	0.105 (0.072)	1.209*** (0.075)	1.111 (0.080)	0.245*** (0.073)	0.216*** (0.077)	1.278*** (0.093)	1.241*** (0.096)
Relative humidity (%)	0.040*** (0.013)	0.040*** (0.013)	1.041*** (0.013)	1.041*** (0.014)	0.044*** (0.015)	0.044*** (0.015)	1.045*** (0.016)	1.046*** (0.016)
Forest area coverage (%)		0.003 (0.005)		1.003 (0.005)		-0.002 (0.005)		0.997 (0.005)
Primary enrollment (%)		-0.306*** (0.070)		0.736*** (0.051)		-0.342*** (0.077)		0.710*** (0.054)
Road density		0.000 (0.002)		1.000 (0.002)		-0.003* (0.002)		0.996* (0.002)
Credit (sanction) by deposit ratio (%)		-0.004 (0.004)		0.995 (0.004)		-0.009** (0.004)		0.990** (0.004)
χ^2 (d.f.)	305.82 (23)	317.55 (27)	305.82 (23)	317.55 (27)	172.98 (23)	249.65 (27)	172.98 (23)	249.65 (27)
log-likelihood	-734.3	-690.23	-734.3	-690.23	-586.59	-569.14	-586.59	-569.14
Wald test					19.66 (0.000)	32.90 (0.000)		
(P-value)								
AIC	1516.60	1436.76			1223.18	1196.29		
BIC	1609.87	1545.28			1320.33	1308.99		
Pearson goodness of fit	1332.44 (0.000)	1159.89 (0.000)						
(P-value)								
Cameron and Trivedi's (2010, 575)	0.80 (0.425)	1.58 (0.115)						
t-value and (P-value)								

Table 3 (continued)

Independent variables	Dependent variable (heat-wave fatalities): FE Poisson				Dependent variable (heat-wave fatalities): FE negative binomial			
	Coefficients		Incident rate ratio (IRR)		Coefficients		Incident rate ratio (IRR)	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
No. of districts	30	30	30	30	30	30	30	30
Observations	360	360	360	360	360	360	360	360

Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ denote 1%, 5%, and 10% levels of significance, respectively. We control region and time fixed effects in all models

Table 4 Effects of economic development and basic disaster adaptation measures on lightning fatalities

Independent variables	Dependent variable (lightning fatalities): FE Poisson				Dependent variable (lightning fatalities): FE negative binomial			
	Coefficients		Incident rate ratio (IRR)		Coefficients		Incident rate ratio (IRR)	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
lag of ln (per capita income)	-0.274** (0.111)	-0.296*** (0.112)	0.760** (0.084)	0.744*** (0.083)	-0.245** (0.117)	-0.341*** (0.127)	0.783** (0.091)	0.711*** (0.090)
Maximum temperature (degree in C)	0.207*** (0.041)	0.194*** (0.045)	1.230*** (0.051)	1.214*** (0.055)	0.192*** (0.038)	0.188*** (0.040)	1.211*** (0.047)	1.206*** (0.048)
Relative humidity (%)	0.010 (0.007)	0.0161** (0.007)	1.010 (0.007)	1.016** (0.007)	0.009 (0.007)	0.014* (0.007)	1.010 (0.007)	1.015* (0.007)
Forest area coverage (%)		-0.006* (0.003)		0.993* (0.004)		-0.007** (0.003)		0.993** (0.003)
Primary enrollment (%)		-0.096*** (0.027)		0.908*** (0.025)		-0.135*** (0.033)		0.874*** (0.029)
Road density		-0.001 (0.001)		0.999 (0.001)		-0.000 (0.001)		0.999 (0.000)
Credit (sanction) by deposit ratio (%)		0.000 (0.002)		1.001 (0.002)		-0.001 (0.002)		0.999 (0.002)
χ^2 (d.f.)	308.59 (23)	299.42 (27)	308.59 (23)	299.42 (27)	269.03 (23)	290.07 (27)	269.03 (23)	290.07 (27)
log-likelihood	-1401.41	-1991.8	-1401.41	-1991.8	-1080.85	-1068.24	-1080.85	-1068.24
Wald test					199.49	219.66		
(P-value)					(0.000)	(0.000)		
AIC	2850.82	2774.78						
BIC	2944.09	2883.59			2211.70	2194.48		
Pearson goodness of fit	1560.661	1469.711			2308.86	2307.18		
(P-value)	(0.000)	(0.000)						
Cameron and Trivedi's (2010, 575)	0.92	1.41						
t-value and (P-value)	(0.356)	(0.159)						

Table 4 (continued)

Independent variables	Dependent variable (lightning fatalities): FE Poisson				Dependent variable (lightning fatalities): FE negative binomial			
	Coefficients		Incident rate ratio (IRR)		Coefficients		Incident rate ratio (IRR)	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
No. of districts	30	30	30	30	30	30	30	30
Observations	360	360	360	360	360	360	360	360

Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ denote 1%, 5%, and 10% levels of significance, respectively. We control region and time fixed effects in all models

Similarly, a percentage increment in bank credit leads to only 97 per fatalities, reducing the number by about 3%. The ease of availability of funds translates into being better financially equipped both at the time of disaster and building assets and resources in the aftermath of the disaster to combat any upcoming crisis.

Lower reliance on traditional money lenders strengthens the financial capability to reap a virtuous cycle of growth and the ability to self-sustenance even during disasters such as floods. Enhanced infrastructure measured by the number of hospital beds is estimated, and the result suggests 17% lesser number of flood fatalities. The proportion of villages electrified and the area under forest cover have significant but negligible impacts on flood fatalities.

For robustness checks, we employ the unconditional FE negative binomial estimated using Eq. (1), and estimates are shown in Models 5 and 7 of Table 2. In Model 5 and 6, the sign and significance levels of all coefficients are similar and consistent with the FE Poisson estimates. The IRR estimates from FE negative binomial in Model 4 suggest that a percentage increase in per capita income in the previous period causes flood fatalities in only 94% cases. Thus, an increased PCI leads to 6% lesser fatalities. Though the variable is statistically insignificant, directionally it points to a fall in fatality rate with higher economic growth. The rise in the number of floods, on the other hand, leads to increased flood fatalities by 83%. However, heavier rainfall causes 14.2 times greater fatalities, as indicated by the estimates. Other development indicators that significantly reduce flood fatalities are financial development and the number of hospitals per lakh population, which reduce fatalities by 3% and 14%, respectively.

5.2 Effect of economic development and role of the specific disaster exposure on heat-wave fatalities

Heat-waves, as discussed earlier, are the second largest cause of disaster deaths in the state of Odisha. Thus, it becomes highly imperative to study the causal relationship of the impacting variables and deaths due to high heat-waves. In this section, we estimate Eq. (2) using the FE Poisson model and estimates are shown in Models 1 and 2 of Table 3. Economic development is critical to the provision of immediate support and relief at the time of sudden struck of a natural calamity. Heat-waves have claimed a significant number of lives, mainly owing to the lack of preparedness both at the level of the administration and the individuals. Incidence rate ratio (IRR) results from Poisson regression in Model 4 of Table 3 suggest that higher development levels measured by PCI in the lagged period result in 15% lesser death fatalities due to heat-waves. Though the estimates are insignificant, however, they directionally indicate a reduction in heat-wave deaths. Hence, as discussed, levels of economic development generate a reducing effect on heat-wave fatalities but are not significant enough to cause a substantial impact. Relative humidity in the given model is expected to increase deaths in the category by about 4%. With the rise in temperature, humidity is observed to intensify the effect of heat-waves.

Moister laden heat has far more devastating effects than dry air because humans and other mammals cool down their body temperature through sweating. However, with high

levels of humidity, the natural process breaks down, destabilizing the body mechanism. In the districts of Odisha with lower levels of PCI, individuals possess lesser resources and minimal leisure to stay indoors and avoid the heat. Sufficient literature is available on the significance of education and awareness in the event of extreme climatic conditions. Education not only enables the required first aid at the onset of a disaster, but it is critical to precautionary measures by the individuals. In the case of strong heat-waves, cognizance about staying indoors, keeping hydrated, etc., is known to bring down the death fatality numbers significantly. The estimates show that a percentage increase in primary enrollment rate is found to be significant in causing heat-wave deaths in only 73% of the cases. The model does not indicate a substantive effect of other infrastructure variables such as road density or credit availability on such fatalities.

For robustness checks, we also estimate Eq. (2) using the unconditional FE negative binomial model and results are shown in Model 5 to Model 8 of Table 3. In Model 6, the coefficient of lag PCI is negative and significant, which shows that economic development estimate is not only significant but also has a larger impact on lowering heat-wave fatalities. The district with a higher per capita income witnesses 35% lesser fatalities owing to heat-waves (see Model 8). A unit rise in maximum temperature and relative humidity, on the other hand, leads to increased heat-wave deaths by 24% and 5%, respectively. Education causes a significant positive impact on lowering deaths by 29%. The model also indicates a significant positive effect of infrastructures, such as road density and financial development on heat-wave deaths. The estimates, however, are small, with the effect being negligible to reduce fatality by about 1%. Thus, economic development and education are seen to be the most important contributors and policy parameters in constraining heat-wave fatalities. An increase in income not only increases accessibility to better nutrition and health facilities, but it also reduces the opportunity cost of preventive measures against heat-waves, such as staying indoors and foregoing work in events of extreme weather.

5.3 Effect of economic development and role of the basic disaster adaptation measures on lightning fatalities

Lightning fatality accounts for the largest disaster fatality in Odisha. Increasing incidences of thunderstorm and occupation structure defined by farming and fishing in Odisha enhance outdoor exposure causing a rise in lightning deaths in the state.

As per the statistics, lightning led to a higher number of deaths in Odisha between 1999 and 2011. Therefore, it becomes imperative to restrain the figures with appropriate policy measures. In this section, we examine how economic development and basic disaster adaptation measures minimize lightning fatalities across districts in Odisha. We estimate Eq. (3) using the FE Poisson model, and estimates are shown in Models 1 and 2 of Table 4. In Model 2, the coefficient of the lag of PCI is negative and significant, which shows that higher PCI is significant in reducing fatalities due to lightning. The PCI should not only be seen as a factor that increases the capability to secure preventive resources and acquire timely information, but it also lowers the opportunity cost of staying indoors and refraining

from work at times of extreme weather events. Moreover, higher temperatures and high humidity increase fatalities due to lightning, while higher forest cover, higher primary enrolment rate, and better road infrastructure decline the same.

Also, we estimate IRR of the FE Poisson models and estimates are presented in Models 3 and 4. The IRR in Model 4 shows that 26% lesser death fatalities with a percentage increase in PCI in the prior period. Similar to heat-wave fatality incidences, a unit increase in maximum temperature and relative humidity leads to a rise in lives lost by 21 percent and 0.016 percent, respectively. Lightning deaths are mostly recorded during monsoons that combine high heat with high levels of humidity. Among others, controls such as the area under forest cover and education are seen to reduce lightning deaths, though marginally by 1%. With major misconceptions on preventive measures during lightning, such as shelter under a tree, schooling becomes an important source of educating individuals toward appropriate precautionary measures. Infrastructure measured by road density and credit to deposit ratio is statistically insignificant in bringing down lightning deaths.

For robustness checks, we estimate Eq. (3) using the unconditional FE negative binomial model, and estimates are shown in Models 5 and 6 of Table 4. In Model 6, the coefficient of the lag of PCI is negative and significant, while maximum temperature and relative humidity are positively related to lightning fatalities. In addition, higher forest cover, higher primary enrolment, and better road infrastructure lead to a decline in lightning fatalities. In sum, FE negative binomial estimates produce the same result, but the magnitude of the coefficients slightly varies. The incidence rate ratio of the FE negative binomial model reported in Model 8 signifies fewer lightning deaths, reduced to 71 percent cases with a percentage increase in income in the previous period. The estimates are robust to the inclusion of other controls when compared to Model 7, which suggests lightning fatalities in 78% of cases with the rise in income. Moreover, maximum temperature and relative humidity add to the toll leading to rising in cases by 21% and 0.01%, respectively. Still, enrollment in primary education remains significant with a strong positive effect leading to 13% lesser fatalities due to lightning. As in the Poisson regression, infrastructure is not found to be statistically significant in lowering the toll due to lightning.

6 Discussion

Odisha's geographical conditions and a high degree of socio-economic vulnerability increase exposure to disaster losses in terms of physical and human capital. Natural disasters adversely affect different sectors of the economy and the socioeconomic condition of rural households through damage to crops, houses, and other private assets. Natural disasters also increase the fiscal burden through a rise in expenditure on disaster management, such as evacuation, relief distribution, rehabilitation, and construction of social and physical infrastructure. In this study, we empirically examine how disaster adaptation measures along with economic development (proxied by PCI) reduce natural disasters risk in terms of floods, heat-waves, and lightning fatalities at the subregional level in Odisha. We argue that districts with higher PCI experience lower fatalities from natural disasters. Basic disaster adaptation measures, such as forest cover, level of education, higher financial development, and basic health and infrastructure facilities, help to mitigate fatalities from natural

disasters to some extent. We have employed the FE Poisson estimation method to examine the above research objective. The FE Poisson estimates show that the lagged PCI is insignificant except for Table 4. The results imply that current economic development plays a marginal role in constraining the effects of natural disasters, if not on a larger scale. In addition, disaster adaptation measures such as better road infrastructure, better financial development, and higher village electrification minimize natural disaster fatalities. This result is consistent with the findings of Toya and Skidmore (2007), and we obtain mirror results in the case of the population affected and house damages due to floods and cyclones (Bahinipati and Patnaik 2017).

Interestingly, we find that districts with higher primary enrollment rates, higher forest cover, and better medical facilities have experienced lower fatalities from natural disasters. This finding is the mirror results of flood fatalities (Ferreira et al. 2013). Moreover, frequent occurrences of floods and higher rainfall during monsoon increase the flood risk in terms of flood fatalities, while higher temperatures and humidity increase fatalities due to heat-waves and lightning, respectively. For robustness checks, we employ FE negative binomial model to examine the same objective. The FE negative binomial model estimates produce similar results, and the findings are consistent with FE Poisson models (see Tables 2, 3 and 4). In sum, the results conclude that not only higher PCI, but adequate disaster adaptation measures are also essential to minimizing fatalities from natural disasters. Moreover, frequent occurrences of floods, unpredictable rainfall, higher temperate during summer, and high humidity are also responsible for increasing fatalities from natural disasters.

7 Conclusion and policy suggestions

Employing the FE Poisson model, this study examines the impact of disaster adaptation measures and specific-disaster exposure on disaster impact in terms of fatality. The findings of the study suggest that districts that lack disaster resilience in terms of lower economic development (proxied by PCI) and have inadequate infrastructure facilities are unable to mitigate disaster fatality. Second, increased exposure to disaster measures such as the number of floods, higher rainfall, maximum temperature, and humidity lead to increasing disaster fatality. Finally, disaster mitigation measures such as forest cover, primary enrollment, better road infrastructure, better financial markets, village electrification, and better medical facility tend to minimize the fatalities from the natural disaster. For robustness checks, we employ the unconditional FE negative binomial model to analyze the effect of disaster mitigation measures on disaster risk in terms of disaster fatality. The econometric results based on unconditional FE negative binomial estimates are found to be consistent with the FE Poisson estimates, but the magnitude of the coefficients marginally varies with the estimates.

Overall findings conclude that Odisha is highly sensitive to natural disasters' impact in reference to human capital losses for the following reasons. First, a high level of socio-economic vulnerability is due to low coping ability, higher poverty levels, heavy dependence on agricultural sectors, and low literacy rate. These conditions make Odisha highly susceptible to disaster losses. Second, the geographical location of the state is also responsible for

increasing the risk of natural disasters. Finally, climatic conditions such as heavy rainfall during monsoon and higher temperatures along with high humidity increase the risk of larger disaster-related losses. Based on empirical findings, this paper proposes the following policy suggestions and recommendations. First, greater spending by district disaster management authority on relief distribution, rehabilitation, and evacuation during flood disasters would help to mitigate flood fatalities. Second, the installation of flood warning systems by Odisha State Disaster Management Authority (OSDMA), particularly in coastal districts and accurate forecasting of rainfall and floods, might allow for timely measures and constrain disaster impacts. Third, the development of disaster-resilient infrastructures, such as construction and maintenance of river embankment, canals, roads, bridges, and construction of flood shelters in low-lying districts by the Government of Odisha (GoO) is some suggested possible measures. Fourth, OSDMA should create a massive community awareness campaign regarding natural disaster impact. Fifth, it is important to invest in the development of social and physical infrastructure such as better medical facilities and provision of 'pucca' house (made up of bricks) that helps to mitigate disaster fatality. Sixth, particularly the Ministry of Health department, GoO and OSDMA should provide specific guidelines on 'what to do' and 'what not to do,' particularly during periods of high heat, humidity, and excessive rains. Seventh, it is essential to create awareness about the impact of over-rearing and deforestation and its adverse impact on the environment. Therefore, the overall findings conclude that government intervention in terms of disaster management is important in constraining disaster risk.

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Appendix: A

See Tables 5, 6, and 7.

Table 5 Summary of the literature

Author(s)	Types of natural disasters	Econometric method	Sample	Results
<i>Review of literature in the global context</i>				
Anbarci et al. (2005)	Earthquakes	Fixed effect (FE) negative binomial	26 nations	The country with higher economic development (proxy by PCI) and lower inequality experienced lower earthquakes fatalities
Toya and Skidmore (2007)	Earthquakes, floods, volcanic eruptions, extreme winds, and waves	Ordinary least squares (OLS)	151 developed and developing nations	Per capita income and higher educational attainment are negatively correlated related to disaster fatalities
Kahn (2005)	Earthquakes, extreme temperature, floods, landslides, windstorms	Zero-inflated negative binomial estimates	73 nations	Higher per capita income and better institution reduce the fatalities from natural disasters
Stromberg (2007)	Volcanic, earthquakes, winds, floods, and landslides	Ordinary least squares and instrumental variable (IV) regression	High-, low-, and middle-income countries	The country with higher per capita income and better governance suffers lower fatalities from natural disasters
Escaleras et al. (2007)	Earthquakes	Negative binomial estimates	42 nations	Higher corruption in the public sector increases earthquakes fatalities, controlling for PCI and population density
Fankhauser and McDermott (2014)	Floods and tropical cyclones	Negative binomial regression	200 nations	Higher per capita income helps to reduce fatalities from floods and cyclones
Raschky (2008)	All types of natural disasters	Ordinary least squares	Selected developed and developing nations	There exists a nonlinear relation between economic development (proxy by PCI) and disaster fatalities
Kellenberg and Mobarak (2008)	All types of natural disasters	Negative binomial estimates and generalized least squares (GLS)	133 nations	Initially, disaster fatalities increase with an increase PCI; then, it declines when PCI increase further
Padli et al. (2010)	All types of natural disasters	Ordinary least squares	73 nations	There exists a nonlinear relation between per capita GDP and death from natural disasters
Schumacher and Strobl (2011)	Cyclones, droughts, earthquakes, floods, landslides, volcanoes	FE Tobit estimate	181 nations	The result confirms that disaster risk in terms of fatalities and losses increases with initial economic development and declines further with increase in economic development
Ferreira et al. (2013)	Floods	FE Poisson and FE negative binomial estimates	92 nations	Flood fatalities increase with an increase in PCI; then, it declines when PCI increase further
<i>Review of literature in the Indian context</i>				
Bahinipati and Patnaik (2015)	Cyclone and floods	Negative binomial and OLS estimates	30 districts in Odisha	Disaster adaptation and disaster-specific measures reduce population affected and village affected by floods and cyclone

Table 5 (continued)

Author(s)	Types of natural disasters	Econometric method	Sample	Results
Bahinipati (2014)	Cyclone and floods	HDI proposed by UNDP (2006)	30 districts in Odisha	Measured district-wise vulnerability indices in Odisha
Mazumdar and Paul (2018)	Cyclones	Principal component analysis (PCA)	477 blocks across 30 districts in Odisha	Measured vulnerability condition block across 30 districts in Odisha
Mazumdar and Paul (2016)	Cyclones	Principal component analysis (PCA)	Five eastern coastal states such as West Bengal, Odisha, Tamil Nadu, Andhra Pradesh, and Puducherry	Estimated socioeconomic and infrastructural vulnerability indices
Sharma and Patwardhan (2008)	Tropical cyclones	HDI proposed by UNDP (2006)	Coastal districts across India	Measures district-wise vulnerability index
Das (2016)	Heat-wave	FE Poisson and OLS	30 districts in Odisha	Electronic and print media play a significant role in minimizing heat-wave fatality, while radio has no impact on the same
Parida (2019)	Floods	FE Poisson and FE negative binomial estimates	19 states in India	Higher economic development (proxy by PCI) and political alignment between the center and state government help to minimize the flood fatalities

Authors' own compilation from various studies

Table 6 Definition and summary statistics

Dependent variable	Definition of variables	Mean	SD	Min	Max	Expected sign	Data sources
Flood fatality	Number of people killed due to floods in different districts in different years	1.87	3.86	0	27	NA	<i>Annual Report on Natural Calamities</i> , Revenue and Disaster Management Department, Government of Odisha https://srcodisha.nic.in/annual_report.php
Heat-wave fatality	Number of people killed due to heat-wave in different districts in different years	2.20	4.23	0	39	NA	
Lightning fatality	Number of people killed due to lightning in different districts in different years	8.86	13.39	0	216	NA	
<i>Independent variable</i>							
No of floods	Floods occurred in a different district in respective years	0.73	0.86	0	5	+	Sendai Framework for Disaster Risk Reduction https://www.desinventar.net/DesInventar/profietab.jsp?countrycode=019&continue=y

Table 6 (continued)

Dependent variable	Definition of variables	Mean	SD	Min	Max	Expected sign	Data sources
Maximum temperature (Degree C)	Yearly average maximum temperature (Degree C) in a different district in respective years	32.56	1.51	29	37	+	Various volumes of 'Statistical Abstract of Odisha' Directorate of Economics and Statistics, Odisha, Bhubaneswar. Various volumes of 'Economic Survey of Odisha' and 'District Statistical Handbooks' https://www.desorissa.nic.in/lates_t_publications.html
Relative humidity (%)	Yearly average relative humidity in a different district in respective years	74.67	7.73	53	87	+	
Rainfall July to September	Average rainfall (mm) during July to September in a different district in respective months of the year	1021.81	294.88	381	2183	+	
Forest area coverage (as % of district geographical area)	Forest cover in a different district in different year over district geographical area	33.07	18.09	0.80	71.19	-	
Primary enrollment (as % of district-wise population)	Enrolment in Primary or Junior Basic Schools over district-wise population	12.07	2.10	3.37	18.73	-	
Village electrified (as % of total villages in the districts)	Number of villages electrified over total villages	76.97	19.89	14.00	100	-	
Number of hospital per lakh population	Number of hospitals per lakh population	7.69	1.58	4.85	15.04	-	
Road density	The total length of road per 100 sq. km	151.99	52.23	55.19	575.52	-	
Credit (Sanction) by deposit ratio (%)	Credit (Sanction) by different commercial banks in different districts in different years over-deposit of the respective banks	52.29	18.29	15.60	119	-	Economic and Political Weekly Research Foundation India Time Series database, https://www.epwrfits.in/
Bank credit (as % of GDDP)	Credit sanction (amount outstanding) over district DGDP	11.94	6.99	2	54	-	

Table 6 (continued)

Dependent variable	Definition of variables	Mean	SD	Min	Max	Expected sign	Data sources
Per capita income (PCI)	Gross District Domestic Product (GDDP) at a constant price, 2004 in Rs over district-wise population	22,254.95	11,015.37	9437	72,250	-	The district-wise GDDP is taken from Directorate of Economics and Statistics, Odisha, Bhubaneswar. The district-wise population data are taken from <i>Primary Census Abstract</i> , Census of India

Authors' own estimates

Table 7 Correlation of the variables

	Flood fatality	Heat-wave fatality	Lightning fatalities	lag of ln (PCI)	ln (Number of floods)	ln (Rainfall July to September)	Forest area coverage	Primary Enrollment	Bank credit over district GDDP	Village electrified	Number of hospital per lakh population	Maximum temperature	Relative humidity	Road density	Credit (sanc-tion) by deposit ratio
Flood fatality	1														
Heat-wave fatality	-0.034	1													
Lightning fatalities	0.208	0.378	1												
lag of ln (PCI)	-0.028	0.168	0.133	1											
ln (Number of floods)	0.454	0.085	0.187	0.000	1										
ln (Rainfall July to fall)	0.289	-0.016	-0.019	0.013	0.377	1									
July to September)															
Forest area coverage	-0.140	-0.020	-0.085	0.104	-0.093	0.074	1								
Primary Enrollment	-0.041	-0.258	-0.249	-0.358	-0.068	0.021	0.286	1							

Table 7 (continued)

	Flood fatality	Heat-wave fatality	Lightning fatalities	lag off In (PCI)	In (Number of floods)	In (Rainfall July to September)	Forest area coverage	Primary Enrollment	Bank credit over district GDDP	Village electrified	Number of hospital per lakh population	Maximum temperature	Relative humidity	Road density	Credit (sanction) by deposit ratio
Bank credit over district GDDP	0.100	0.224	0.269	0.082	0.145	0.074	-0.397	-0.488	1						
Village electrified	0.098	0.193	0.251	0.087	0.082	-0.102	-0.611	-0.381	0.395	1					
Number of hospital per lakh population	-0.127	-0.160	-0.245	0.044	-0.083	0.102	0.579	0.397	-0.387	-0.527	1				
Maximum temperature	-0.180	0.074	0.043	0.191	-0.126	-0.085	0.023	-0.089	0.106	0.164	-0.177	1			
Relative humidity	0.181	0.107	0.136	-0.024	0.086	0.001	-0.032	-0.021	0.184	-0.010	-0.006	-0.302	1		
Road density	0.050	0.100	0.013	0.021	0.024	-0.044	-0.383	-0.330	0.395	0.363	-0.419	0.083	0.139	1	

Table 7 (continued)

	Flood fatality	Heat-wave fatality	Lightning fatalities	lag of In (PCI)	In (Number of floods)	In (Rainfall July to September)	Forest area coverage	Primary Enrollment	Bank credit over district GDDP	Village electrified	Number of hospital per lakh population	Maximum temperature	Relative humidity	Road density	Credit (sanction) by deposit ratio
Credit (sanction) by deposit ratio	-0.015	0.042	0.070	-0.107	0.107	0.211	-0.144	-0.154	0.304	0.176	-0.119	0.103	-0.182	0.066	1

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