Rakshit, B. (2021). Impact of Natural Disasters on Energy Consumption: Evidence From Indian States. *Energy RESEARCH LETTERS*, *2*(3). https://doi.org/10.46557/001c.27017

Energy and Environment

Impact of Natural Disasters on Energy Consumption: Evidence From Indian States

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Keywords: system gmm, energy consumption, natural disaster

https://doi.org/10.46557/001c.27017

Energy RESEARCH LETTERS

Vol. 2, Issue 3, 2021

This study investigates the impact of natural disasters on energy consumption across selected Indian states from 1996 to 2019. Using the system generalized method of moments, we examine whether the frequent occurrence of floods and droughts alters India's energy demand. Our findings show considerable variation in the relation between natural disasters and energy consumption. Generally, we find that natural disasters, as measured by the magnitude of floods and a drought dummy, have an adverse impact on per capita energy consumption.

I. Introduction

Several studies have theoretically and empirically documented the relation between natural disasters and economic growth across developing and advanced economies (Brown et al., 2018; Deuchert & Felfe, 2015; Lee & Chen, 2020). Noy (2009) finds that the damage caused by disasters is multidimensional. The differentiated effects of natural disasters on social, economic, and psychological aspects and the quality of a country's infrastructure are well researched (Deuchert & Felfe, 2015; Escaleras & Register, 2016; Fomby et al., 2013). However, the literature documenting the impact of natural disasters on energy consumption is scant.

Lee et al. (2021) draw international evidence on the natural disaster–energy consumption nexus and find natural disaster to have a significant negative impact on oil, renewables, and nuclear energy consumption. Doytch & Klein (2018) examine the impact of infrastructure-damaging natural disasters on energy consumption for 80 countries from 1961 to 2011. They confirm the positive finding of renewable energy use five years after geographical disasters. Nevertheless, we find limited evidence on the effects of natural disasters on energy consumption from a single-country perspective. Our study therefore explores the nexus between natural disasters and energy consumption in India, one of the disaster-prone countries of South Asia.

A theoretical understanding of the intricacies of the relation between disasters and energy demand can be obtained through the following channels. **First**, natural disasters and reduced energy consumption are crucial in regions of severe and recurring natural disasters. Several characteristics, such as higher population density, vulnerable land, and the total population affected by a disaster, are likely to influence an area's energy demand (Sultan, 2013). **Second,** the energy industry is the industry most affected by frequent natural disasters. Schwarz & Cochran (2013) examine the cost efficiency conflict regarding nuclear energy due to natural disasters, which affect the risk management of the energy industry in terms of future disaster mitigation.

India provides an exciting setting for exploring the relation between disaster and energy consumption, for the following reasons. The National Disaster Management Authority reports that 8% of India's total geographical area is susceptible to cyclones, 12% of the land is prone to flooding, and 60% of the landmass and 68% of the cultivable land are vulnerable to earthquakes and drought, respectively (Parida et al., 2018). Moreover, due to changes in geoclimatic conditions, natural disasters have become more frequent throughout Indian over the years. India's gross domestic product (GDP) declined by 0.46% due to natural disasters between 1980 and 2011 (Parida, 2020). On the other hand, as one of the fastest-growing emerging economies, India's reliance on energy resources has increased many times and continues to rise. Since 2000, India alone has increased global energy demands by 10% and is expected to surpass China, to become Asia's largest energy consumer (International Energy Agency, 2015; Mahalik & Mallick, 2014).

Among commercial sources of energy in India, the production of electricity has the highest compound annual growth rate (5.71%), followed by lignite (3.62%), coal (3.20%), and crude oil (0.63%). Panel A of Table 1 shows the compound annual growth rates of the states' GDP and the electricity consumption for selected states. Interestingly, these selected states' power consumption growth rate is higher than the average rate of economic growth. Eight states record growth in electricity consumption above the national average. Given this background, we attempt to investigate the dynamic relation between natural disasters and energy consumption across 18 Indian states from 1996 to 2019. Panel B highlights the ranks of the states in terms of their ratio of drought-prone areas to their total geographical area.

To achieve the proposed objective, first, we select 18 Indian states for which we have time-consistent data on natural disasters and energy consumption from 1996 to 2019. Second, since natural disasters are expected to have an im-

Table 1. CAGR in SGDP growth and energy consumption

States	Net SGDP	Electricity consumption	Rank	Drought prone area over state geographical area
Andhra Pradesh	6.03	9.88	4	36.1
Assam	5.54	8.25	10	6.2
Bihar	5.27	5.76	16	10.1
Chhattisgarh	5.82	7.01	17	6.4
Gujarat	6.61	8.96	9	22.4
Haryana	6.84	9.12	12	18.7
Karnataka	5.89	8.34	1	44.0
Kerala	6.15	6.92	3	25.2
Madhya Pradesh	5.87	9.73	5	28.9
Maharashtra	6.54	7.88	2	63.2
Odisha	5.54	7.84	13	16.8
Punjab	6.89	7.41	14	0.2
Rajasthan	5.74	10.57	11	9.3
Tamil Nadu	6.16	7.54	7	22.6
Tripura	4.97	8.01	6	3.0
Uttar Pradesh	5.74	8.95	15	14.5
West Bengal	6.05	5.87	8	13.1
All states	5.78	7.98		

The table shows CAGR in SGDP growth and energy consumption in Indian states. Source: Author's calculations from states of India, CMIE. Data on the drought-prone area were obtained from the Department of Land resources, Ministry of Rural Development, Government of India.

pact on energy consumption after a certain period, we consider the lagged effects of the disaster variables. Third, we consider the potential endogeneity of some of the explanatory variables, reverse causality between natural disasters and energy consumption, and simultaneity bias. Therefore, we apply the two-step system generalized method of moments (GMM) to the dynamic panel data model in our empirical specification. Finally, we test the robustness of our main findings. Our findings reveal that the frequent occurrence of natural disasters affects energy consumption demand after a time lag, but the effect is not uniform, and the effects of disasters and energy demand dynamics are differentiated across states.

The main contributions of this study are summarized as follows. This study adds to the current literature on energy consumption by incorporating the dimension of natural disasters in a disaster-prone country. While previous studies shed light on this issue from a cross-country perspective, our study is undertaken within the context of a single country. The use of state-level information is expected to provide better insights for policymakers in formulating energy policies. Finally, the dataset used in this study is very current.

The remainder of the paper is structured as follows. Section II presents the data and methodology. Section III reports the findings. Section IV concludes the paper.

II. Data and Methodology

For this study, we collected data from different sources. State data on energy demand were collected from the states of India and the Centre for Monitoring Indian Economy. Data on disaster variables such as droughts were obtained from the Department of Land Resources, Ministry of Rural Development, Government of India. For a few states, particularly Haryana and Assam, we obtained data on drought from the *Agriculture Research Data Book* (Haryana) and Agriculture and Irrigation in Assam, Government of Assam. State flood data was compiled from Rashtriya Barh Ayog (National Commission on Floods). Other state-specific characteristics were collected from the Reserve Bank of India. Data were collected for the period 1996 to 2019, based strictly on availability. The definitions of the variables and their descriptive statistics are presented in Table 2.

Following Doytch & Klein (2018), we employ the following empirical model to determine the impact of natural disasters on energy consumption across the Indian states:

$$\begin{aligned}\ln\left(Energy\ cons_{i,t}\right) =& \beta_o \\ &+ \beta_1 \ln\left(Energy\ cons_{i,t-1}\right) \\ &+ \beta_2(y_{i,t}) + \beta_3 d_{i,t-1} + \eta_t \\ &+ \mu_i + \varepsilon_{i,t}\end{aligned} \quad (1)$$

where $u_i \sim i.i.d.\ (0,\ \sigma_{\mu,i})\ \varepsilon_{\ i,t} \sim i.i.d.\ (0,\ \sigma_\varepsilon)$, and $E[\mu_i \varepsilon_{i,t}] = 0$, with $Energy\ cons_{i,t}$ denoting the per capita energy consumption, $y_{i,t}$ the growth of the per capita GDP in state *i* at time *t*, $d_{i,t-1}$ represents the lagged disaster variables, η_t is the (annual) time dummy, and μ_i is an idiosyncratic state-specific effect. We estimate Equation (1) by the system GMM, because it is considered superior to a static panel model. Blundell and Bond's (1998) system GMM is appropriate when some of the explanatory variables are lagged and endogeneity could be present.

Table 2. Definition of variables and summary statistics

Variables	Definition	Obs	Mean	SD	Min	Max
Energy consumption	The logarithm of per capita power (electricity) consumption at the state level is considered to proxy energy consumption.	432	5.739	0.932	3.908	6.673
Flood magnitude	Following Parida (2020), we define flood magnitude as the area affected by flood in sq km * severity* duration in days. We take the natural logarithm of flood magnitude.	432	2.05	2.85	0.01	8.25
Flood duration	Following Parida (2020), we define flood duration [(End days – beginning days +1)+0.01]	432	0.68	3.47	1.61	5.08
Drought dummy	We assign drought dummy 1 if the state faced drought situation in respective years, 0 otherwise	432	0.30	0.45	0	1
Population affected	State-wise population affected by flood/ Total population	432	5.761	3.51	2.34	12.5
Economic growth	Per capita growth defined as as ln (GSDPit)-ln (GSDPit−1)	432	5.741	4.54	-2.54	18.54

The table shows definition of variables and summary statistics. The statistics, Obs, SD, Min, and Max denote, respectively, observations, standard deviation, minimum, and maximum. Source: Author's calculation from different sources.

Table 3. Impact of natural disaster on energy consumption

	Model 1	Model 2	Model 3	Model 4	Model 5
Lagged PCEC	0.341*** (0.0547)	0.337*** (0.0471)	0.391*** (0.0522)	0.384*** (0.0487)	0.541*** (0.0618)
Flood magnitude	-0.004*** (0.0024)	-0.034*** (0.0174)	-0.007*** (0.0114)	-0.052** (0.0231)	-0.067*** (0.0514)
Flood duration		-0.001 (0.0021)	-0.003 (0.0011)	-0.0009 (0.0005)	-0.0011 (0.0041)
Drought dummy			-0.251** (0.2214)	-0.271*** (0.2647)	-0.294*** (0.3214)
Population affected				0.674 (0.8841)	0.714 (0.9147)
Per capita growth					0.023*** (0.0232)
Observations	432	432	432	432	432
Number of states	18	18	18	18	18
Num of instruments	14	14	13	13	12
AR (1)	0.001	0.001	0.002	0.001	0.003
AR (2)	0.654	0.691	0.724	0.784	0.841
Hansen P value	0.884	0.865	0.872	0.897	0.921

This table shows the impact of natural disaster on energy consumption. Note: *, ** and *** represents level of significance at 10%, 5% and 1% respectively. Estimations were performed using SYS-GMM. Two steps results have been reported only. Figures in the parentheses represent robust standard error. Arellano-Bond test p-value that average autocovariance in residuals of order 1 is 0 (H_0: no autocorrelation). Arellano-Bond test p-value that average autocovariance in residuals of order 2 is 0 (H_0: no autocorrelation). In all our model number of instruments were less than the number of cross-sections.

III. Empirical Findings

Table 3 presents the results estimated by two-step system GMM regression for five different models, with sample data for 18 states over the period 1996 to 2019. The estimated coefficients of per capita energy consumption across all the models are positive and significant at the 1% level, ranging between 0.341 and 0.541. This implies that energy consumption in the current period is affected by energy consumption in the previous year. This finding is consistent with recent empirical research, such as that of Berk et al. (2020) and Blazquez et al. (2013), who find similar results. To avoid instrumental proliferation, we do not add all the explanatory variables in one model.

Table 4. Sensitivity Analysis

	Model 1	Model 2	Model 3	Model 4	Model 4
Lagged PCEC	0.412*** (0.0727)	0.430*** (0.0841)	0.386*** (0.0527)	0.419*** (0.0786)	0.441*** (0.0715)
Low flood magnitude dummy	-0.001 (0.0021)	-0.001 (0.0114)	-0.002 (0.0017)	-0.001 (0.0003)	-0.011 (0.0211)
Moderate flood magnitude dummy		-0.016 (0.0321)	-0.023** (0.0017)	-0.033** (0.0045)	-0.027** (0.0031)
High flood magnitude dummy			-0.052*** (0.2214)	-0.61*** (0.2632)	-0.64*** (0.3764)
Population affected				1.321 (1.0547)	1.614 (1.142)
Per capita growth					0.029*** (0.0342)
Observations	432	432	432	432	432
Number of states	18	18	18	18	18
Num of instruments	15	14	12	13	14
AR (1)	0.007	0.001	0.002	0.003	0.003
AR (2)	0.692	0.672	0.705	0.739	0.821
Hansen P value	0.832	0.846	0.887	0.912	0.934

The table shows the sensitivity analysis. Note: *, ** and *** represents level of significance at 10%, 5% and 1% respectively.

We find that the magnitude of floods has a negative and significant effect on per capita energy consumption. The estimated coefficients for flood magnitude are found to be significant at the 1% level. A plausible explanation of this finding is that the frequent occurrence of floods in India destroys infrastructure, power grids, and other electricity-generating machinery, affecting energy consumption at both the household and industry levels. Due to the growing incidence of floods and other natural disasters, Indian states are likely to face still greater economic damage that could exceed the country's capacity for reconstruction. Such a situation can reduce both renewable and nonrenewable energy consumption. This finding corroborates previous empirical evidence of Lee et al. (2021). In addition, we find no significant relation between flood duration and energy consumption. This result implies that, as long as the span of the flood does not cause any damage and contributes to natural disasters, it does not cause any reduction in energy consumption.

However, using the drought dummy as a proxy for natural disasters, we find that drought negatively affects India's energy consumption patterns. The economic implications can be attributed to the fact that metrological disasters such as storms and extreme temperatures, earthquakes, landmass movements, and volcanic activity adversely affect energy consumption requirements. Doytch & Klein (2018) suggest that the effect of energy consumption after disasters provides the scope to decouple economic activities from the carbon footprint for reconstruction.

When we measure natural disasters in terms of the people affected in each state, we find a positive but nonsignificant coefficient in Models 4 and 5. This result indicates that the total number of people affected by droughts, pandemics, floods, earthquakes, and landslides might not have any significant bearing on the country's energy consumption. Finally, with respect to economic growth, we find that, with the rapid expansion of economic activities, especially after the economic reforms, the demand for energy consumption has significant risen. This finding is confirmed by the positive and significant impact of the per capita energy consumption on energy consumption in Model 5. This finding is consistent with the results of Alam (2013) and Acheampong (2019).

We further conduct a sensitivity analysis of our main findings. The results are presented in Table 4. We split the magnitudes of the floods into three groups: low, moderate, and high. We set a low flood magnitude dummy equal to one if the state's total area affected by flooding is equal to or below the 49th percentile, and zero otherwise. We set a moderate and a high flood magnitude dummy equal to one if the state's total flooded area lies between the 50th to 74th percentiles and the 75th percentile and above, respectively. This classification helps us understand the differentiated effects of flood magnitudes on energy demand. We find that, in low flood magnitude states such as Punjab, Rajasthan, Haryana, and Uttar Pradesh, floods do not significantly affect energy consumption. On the contrary, in highly flood-prone states such as Assam, Kerala, Odhisa, and West Bengal, there is a positive and significant association between floods and energy consumption. Regarding the other state-specific variables, we note no significant changes in their signs or significance levels.

IV. Conclusion

Using the system GMM, this study investigates the impact of natural disasters on energy consumption across 18

Indian states from 1996 to 2019. The results indicate considerable variation in the relation between natural disasters and energy consumption. Broadly, we find natural disasters, as measured by a flood magnitude dummy and a drought dummy, to have an adverse impact on per capita energy consumption in India. To capture the differentiated effects of natural disasters on energy demand, we classify the 18 states into three groups, with low, moderate, and high flood magnitudes, respectively. The results show that, while states with a low flood magnitude do not affect energy consumption, states with a high flood magnitude significantly influence energy consumption across states. From a policy standpoint, we suggest that disaster mitigation policies should be implemented to ensure efficient energy consumption in India.

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