Flood Shocks and Rural Out-migration: Evidence from Uttar Pradesh and Bihar, India

EC428 Structured Essay

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Abstract

This essay investigates the propensity of households to migrate out of rural regions in response to recurring flood shocks, employing an innovative metric of flood exposure— state-level flood damage. I use a logistic regression model with annual rainfall intensity as an instrument for flood damage. Analyzing a nationally representative household survey dataset, that longitudinally tracks 2,610 migrant households from 1980 to 2007 in Uttar Pradesh and Bihar states of India, I document three key findings. First, a one percent increase in flood damage elevates the likelihood of rural household out-migration by 82.1%, when holding other factors constant. Second, an in-depth analysis of the migration mechanism reveals that affected population density in respective flooding regions is a predominant driver of this impact. This study also attempts to capture the inter-generational altruism factor influencing households' decisions to migrate permanently and ascertains the loss of cattle lives due to floods as the most significant precursor. Third, the effects are more pronounced among socio-economically disadvantaged households and those with female heads, highlighting the compounded vulnerabilities they face during extreme flooding events. Finally, I project migration patterns from 2007 to 2017 and observe a general trend of stability of historical impact. This hints at a 'learning effect'— resilience or adaptation of the population to existing flood risks, and/or effective flood management and mitigation strategies in severely affected regions.

KEYWORDS: flash flood, rural-total out-migration, livelihood risk

1 Introduction

In his seminal article "A Theory of Migration," Lee, 1966 laid the foundation for understanding push factors that drive migration, such as economic hardships, lack of job opportunities, political instability, and environmental stress. Climate change-induced migration is increasingly perceived as a strategic measure for self-protection, mitigating exposure to disaster risks, and associated uncertainties (Banerjee et al., 2011). Individuals displaced by environmental stress factors are referred to in migration literature as 'environmental refugees' (Bates, 2002). This term encompasses two categories: those compelled to relocate by sudden, irreversible environmental changes, and those who migrate due to long-term, gradual climatic changes that degrade living conditions. This essay focuses on the latter definition, in the context of rural out-migration due to flood shocks in India, where two-thirds of the population resides in rural areas, with over half of them dependent on agriculture for livelihood[1].

According to the Global Report on Internal Displacement[2], as of 31 December 2023, more than 7.7 million people in 82 countries and territories displaced due EWEs. The "State of India's Environment-2023" reports[3] India as the fourth most severely affected country in terms of climate-induced migration, with over three million individuals forced to leave their homes between 2020 and 2021. Since the 1950s, flooding events in India have increased, partly due to a rise in localized, short-duration intense rainfall events, and have cost India \$26.3 billion, with damages exceeding 0.5% of its GDP[4]. Long-term, gradual climatic changes in severely affected areas trigger livelihood risks, leading to multi-directional mobility responses, including rural-to-urban, rural-to-rural, urban-to-urban, and urban-to-rural migration (Boustan et al., 2012). Recurring shocks including climate change-induced produce and maintain poverty traps, especially for those who cannot adapt, impeding low-income households from accumulating

[1] The Economic Survey of India 2022- 2023, Press Information Bureau, Government of India
[2] Global Migration Data Portal
[3] Centre for Science and Environment, India
[4] State of the Climate in Asia 2020

assets that can enhance their security (Hallegatte and Rozenberg, 2017, Hsiang and Jina, 2014, Stern, 2007).

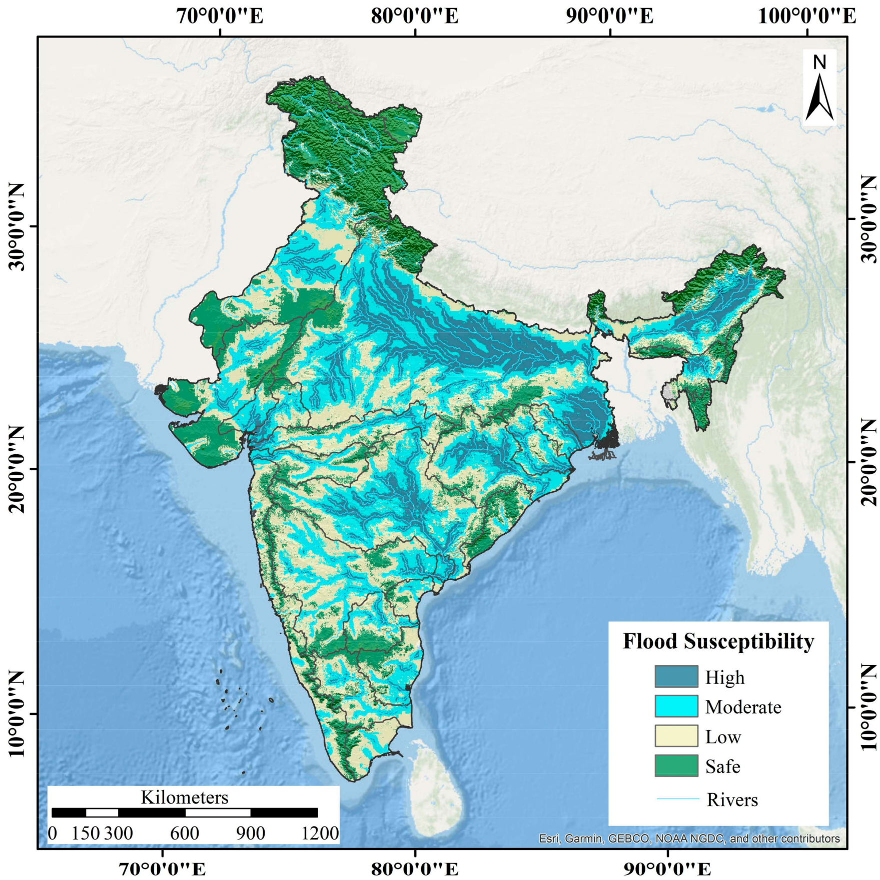


Figure 1: *Source: MDPI*[5] Flood Susceptibility Map of India

Uttar Pradesh (UP) and Bihar- two landlocked Indian states experience recurrent flooding, justifying the selection of studying these two states. Flooding in these two neighboring states—UP, situated between latitudes 23°52'N and 31°28'N and longitudes 77°3'E and 84°39'E, and Bihar, situated between latitudes 24°20'10"N and 27°31'15"N and longitudes 83°19'50"E and 88°17'40"E—is primarily characterized by flash floods.[6] (see Figure 1)

Areas where flood exposure is uniformly distributed, migrants incur both search and migration costs (Bazzi, 2017, Bryan and Morten, 2019) coupled with uncertainty regarding the

[6]Flash floods, also termed pluvial floods, occur due to intense rainfall rather than the overflow of a water body. In contrast, fluvial floods, or river floods, happen when rivers, lakes, or streams overflow onto nearby land due to heavy rain or snowmelt. Coastal floods arise when seawater inundates coastal land, typically caused by severe windstorms combined with high tides (storm surges) or tsunamis.

livelihood prospects at the destination (Bryan et al., 2012, Bryan et al., 2014, Bhavnani and Lacina, 2015). Rural households also face adaptation challenges due to credit constraints and social disadvantages. This will be investigated in the essay for the focus regions. Understanding this question has critical implications for development and growth economics, as it sheds light on how environmental stressors influence human mobility and resource allocation owing to bounded rationality, especially in rural regions. This knowledge can guide policymakers in designing interventions to support vulnerable populations and sustain economic growth in severely affected areas.

The structure of this extended essay is as follows: Section 1 provides background on flood-induced migration and migration statistics in India; Section 2 reviews the existing literature; Section 3 discusses the rationale for rural out-migration using a simple theoretical model; Section 4 details the datasets and methodology employed; Section 5 presents the results; and Section 6 offers a review discussion and concluding comments. Supporting evidence and auxiliary results are stored in Appendices A and B.

2 Literature Review

The contention in the existing literature[7] regarding whether flood shocks have a direct or indirect impact on migration, persists till date. Traditional migration models extrapolate migration patterns by incorporating various climate change indicators. Notwithstanding, limited empirical insights are available on migration induced by flood shocks. Direct impacts are observed in the USA during the 1920s and 1930s (Boustan et al., 2012), Bangladesh (Gray and Mueller, 2012), and Indonesia (Bohra-Mishra et al., 2014).

Barrios et al., 2006 exploit time series data on average annual rainfall for 76 develop-

[7]A substantial body of literature highlights the macroeconomic effects of climate change, revealing the impact of temperature and precipitation on economic activities, particularly in agriculture (Barreca et al., 2015, Barreca et al., 2016, Costello et al., 2012, Deschênes and Greenstone, 2007, Dell et al., 2012, Schlenker and Roberts, 2009), labor (Graff Zivin and Neidell, 2013), economic growth (Strömberg, 2007, Costello et al., 2012), and education (Maccini and Yang, 2009), and less direct impact on manufacturing sector (Smith et al., 2009). Given that the manufacturing sector is predominantly urban and agriculture is prevalent in rural regions; weather anomalies are likely to drive rural-to-urban migration (Marchiori et al., 2012).

ing countries, including 36 Sub-Saharan African countries from 1901 to 1998, and find that a one-percent fall in normalized precipitation induces urbanization to rise by 0.45 percent and attribute the cause to the destruction of homes and livelihoods. This effect is observed exclusively in Sub-Saharan Africa and does not extend to other regions within the developing world. The authors argue that this viewpoint is tenable because climate change affects established migration patterns adapted to adverse conditions. Thus, incremental climate changes impose minimal additional pressure compared to catastrophic shifts. But, monitoring urbanization rates circumvents the conflation of analysis with other time-variant and location-specific idiosyncrasies.

Marchiori et al., 2012 use a theoretical framework to show that rainfall and temperature anomalies increase rural-to-urban migration, subsequently influencing urban-to-international migration in equilibrium. By decreasing rural wages (w^a) and increasing urban labor share (L_t), the rural-urban migration is captured as $\frac{dL}{dc}$[8] $= \frac{w_c^a(w_L^u + w_{1-N}^u) - g_c w_N^u}{w_L^u w_{1-L}^a + w_{1-N}^u(w_L^a + w_{1-L}^u)} > 0$. Simultaneously, the influx into urban areas reduces urban wages (w^u), prompting international migration: $\frac{dN}{dc} = \frac{g_c}{w_N^u + w_{1-N}^u} - \frac{w_L^u}{w_N^u + w_{1-N}^u}\frac{dL}{dc} < 0$. Empirical tests further reveal that, on average, 0.3 per thousand individuals in Sub-Saharan Africa were displaced annually during the latter half of the 20th century due to weather anomalies with 53% displacements accruing to rainfall variations, especially in agriculturally dependent countries.

Mueller et al., 2014 conducted a 21-year longitudinal study (1991-2012) in rural Pakistan to investigate the impact of flooding on long-term human migration. They find that, despite significant relief efforts, floods had a modest to insignificant migration impact. The study linked individual-level panels of migration and non-migrating household members to satellite-derived climate measures and used multivariate analysis to control potential confounders. Yet, this study skips to address intra-household dependencies and interactions, which are critical for ac-

[8] The weather is measured by the author through a random variable z, with support $z \in [0, \infty)$. On average, it is expected that $c = E(z)$, while a year with a worse outcome would imply $c > E(z)$. $N_t \in [0, 1]$ here refers to internationally mobile workers that only work in the urban sector but are mobile across countries.

curately assessing migration drivers and outcomes. In this essay, I provide insights by analyzing the migration response at the household level and account for these inter-dependencies.

In their study, Chen et al., 2017 examine household-level migration responses to flooding in Bangladesh using satellite-based flood measures. They employ a linear probability model to estimate the impact of flooding at time $t-1$ on the probability of a household having at least one migrant at time t. They find that extreme flooding decreases the likelihood of household migration by 0.4 to 1.8 percentage points, suggesting that individuals are more likely to be trapped rather than displaced by floods. This phenomenon could be attributed to credit constraints, as identified by Bryan et al., 2014 as a barrier to rural-urban migration in Bangladesh through a randomized controlled trial (RCT). Banerjee, 2010 posit an alternative explanation that the benefits of extreme flooding, such as improved soil quality and subsequent crop yields, may outweigh the short-term costs, thus increasing the opportunity cost of a family member's absence. Chen et al., 2017 concludes that extreme flooding generally reduces migration, potentially due to present bias about the short-term benefits of flooding improving agricultural productivity, or because individuals lack the resources to relocate.

On the contrary, (Giannelli & Canessa, 2022) utilize a difference-in-difference model with fixed effects to study the impact of the 2014 floods on migration in Bangladesh and find internal migration increasing by 7% for low-wealth households. They employ georeferenced data from NASA satellites to capture floods as a share of the inundated areas for each sample village. These insights highlight the complexity of migration dynamics in response to environmental shocks and underscore the importance of using detailed, objective measures in such analysis.

The papers discussed above have utilized several traditional flood measures to study its impact on migration such as the number of people affected, precipitation data, self-reported exposure, flood frequency, and flood severity index[9], and flood magnitude (calculated as the

[9] The Dartmouth Flood Observatory developed the Flood Severity Index, which integrates easily obtainable physical parameters within a short timeframe. This index considers factors such as flood frequency (comparing the current flood to historical events), magnitude, land cover, slope, and, where available, pre-event simulated flood depth.

logarithm of the product of frequency and duration), besides the conventional measure of mean annual rainfall. (Attri and Tyagi, 2010, Guiteras et al., 2015a, Ghimire and Ferreira, 2016, Barrios et al., 2006). These measures have faced criticism for being weak proxies for flood exposure (particularly mean exposure to floods), with concerns of capturing only the physical aspect of flood and that measurement errors may be correlated with key determinants of socio-economic outcomes (Guiteras et al., 2015b, Dallmann and Millock, 2017). Chen et al., 2017 also acknowledges the variability in estimates depending on the measure of flooding, with satellite-based measures capturing more localized effects than rainfall proxies. However, they may not fully represent the socio-economic impacts on affected populations, and resultant underestimate the potential impact on migration.

In Indian states, precipitation data alone do not encompass all categories of flood events. Therefore, I use a flood damage measure as a proxy for flood exposure instrumented with rainfall intensity since focus regions witness flash floods. I will discuss it in detail in Section 4. Furthermore, I identify three channels through which the effects would be stronger: flood damages' interaction with the population affected, human lives lost, and cattle lives lost in the particular states. The mechanism of influence on migration through climate effects on crop yields is already embedded in my flood measure in terms of 'total damage'. Existing studies have also explored channels of social networks and crop yields (Bohra-Mishra et al., 2017).

Overall, I make four contributions to the previous studies on micro-level migration flows. First, I utilize a repeated cross-sectional survey dataset to observe the migration patterns of hypothetically similar households from 1980 to 2007 to study the impact and its heterogeneity across various socio-economic groups. Second, I introduce flood damage measures as a relevant indicator of flood exposure, instrumented with annual rainfall intensity. Third, I identify and test mechanisms through which flood variability escalates livelihood risks and empirically investigate which one induces migration strongly. Toward the end, I predict migration trends from 2007 to 2017 and provide a few actionable policy recommendations.

3 Theoretical Model

The neoclassical microeconomic theory posits that individuals are central to the decision-making process regarding migration (Todaro, 1976, Massey, 1999). In contrast, the New Economics of Labour Migration (NELM) literature views migration as a household decision, emphasizing a household's collective strategy to mitigate risks and improve its livelihood (Stark and Bloom, 1985). I integrate these perspectives[10] to focus on the role of flood shocks as a precipitating determinant of a risk-averse household's propensity to migrate.

The utility function of a risk-averse household in this model[11] is represented by a concave utility function $u(w)$ where w denotes safety, such that $u(w) = \log(w)$ or $u(w) = \frac{w^{1-\theta}}{1-\theta}$ for $\theta > 0$, where θ is the coefficient of relative risk aversion.

The household decides to migrate if the expected utility of migrating eu_m is greater than the expected utility of staying eu_s:

$$eu_m = p \cdot u(w - c + x) + (1 - p) \cdot u(w - c)$$

$$eu_s = q \cdot u(w + y) + (1 - q) \cdot u(w)$$

Here c represents the cost of out-migration and x, y represents the benefits from out-migrating. A credit-constrained household might not be able to afford c due to a lack of access to credit or savings. The decision to stay might not be voluntary but rather a constraint. In this case, the agent will migrate if their expected level of safety and well-being exceeds the cost of migration and the expected utility from migrating is higher than staying back if $w \geq c$: $eu_m > eu_s$.

[10] Following the neoclassical theory, the household will maximize the expected utility after assessing the expected benefit of migrating against its cost. Further, I utilize the nuanced understanding offered by NELM which intertwines migrants' perception of staying in rural areas with risks of potentially not being secure, however here with uncertainty about climate-induced disasters even in urban regions.

[11] The model makes several key assumptions. Households are risk-averse and seek to maximize their expected utility. Migration decisions are influenced by climate-induced risks, socio-economic characteristics, and access to knowledge and technology (Thalheimer and Webersik, 2020) (Banerjee et al., 2017; Beine and Parsons, 2015; Jha and Gupta, 2021; Marchiori et al., 2012). Households have imperfect access to credit markets, leading to potential credit constraints (Bryan et al., 2014). Households consider the utility of future generations(Hänsel et al., 2020), incorporating intergenerational altruism. The model accounts for both the direct and indirect costs of migration, including financial, social, and psychological costs.

To incorporate livelihood risks faced by households Adger et al., 2015; Warner and Afifi, 2014, let us introduce a parameter r which represents the threat to socio-economic stability due to climate events. The expected utility equations would then adjust for this risk:

$$eu_m = p \cdot u(w - c + x - r) + (1 - p) \cdot u(w - c)$$
$$eu_s = q \cdot u(w + y - r) + (1 - q) \cdot u(w)$$

Further, I incorporate intergenerational altruism, considering regions with a history of recurring flood shocks. Therefore, a household that cares about the risks and disruptions their descendants would face may prefer to migrate permanently. We introduce a parameter δ which represents the weight given to the utility of future generations. Let $u_t(w)$ be the utility of the current generation and $u_{t+1}(w)$ be the utility of the next generation. The intergenerational utility function can be written as: $u(w) = u_t(w) + \delta \cdot u_{t+1}(w)$. With intergenerational altruism, the expected utility equations modify to:

$$eu_m = p \cdot (u_t(w - c + x - r) + \delta \cdot u_{t+1}(w - c + x - r)) + (1 - p) \cdot (u_t(w - c) + \delta \cdot u_{t+1}(w - c))$$

$$eu_s = q \cdot (u_t(w + y - r) + \delta \cdot u_{t+1}(w + y - r)) + (1 - q) \cdot (u_t(w) + \delta \cdot u_{t+1}(w))$$

A household will migrate if the expected utility of migrating eu_m is greater than the expected utility of staying eu_s, taking into account both current and future utilities:

$$\text{Migrate} = \begin{cases} 1 & \text{if } w \geq c \text{ and } eu_m > eu_s \\ \\ 0 & \text{if } w < c \text{ or } eu_m \leq eu_s \end{cases}$$

A simplified functional representation of migration influenced by climate change, specifically by flood shocks, credit constraints, livelihood risk aversion, and intergenerational altruism, is:

$$m_{\text{climate}} = \beta_0 + \beta_1 f + \beta_2 i + \beta_3 c + \beta_4 r + \epsilon$$

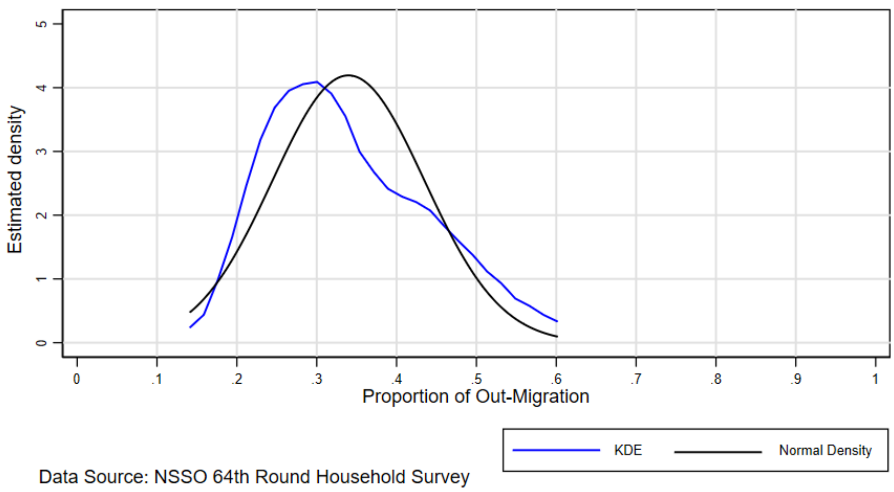
Where β_0 and β_1 quantify the base migration level and the sensitivity to flood shocks, respectively, β_2 quantifies the sensitivity to intergenerational altruism, β_3 represents the effect of credit constraints, β_4 represents risk aversion to livelihood risks, and ϵ accounts for other unmodeled factors.

4 Datasets and Methodology

I obtained the household-level migration dataset from the 2008 NSSO's[12] 64th round of the nationally-representative household-level survey. Table I (see Appendix B) stores descriptive statistics for the socio-economic characteristics of the sample households. This dataset is unique as it captures how many years ago the household migrated and the nature of the movement. I utilize this detail to longitudinalize the dataset and observe households 350-500 households on average migrating from 1980- 2007. Figure II plots the distribution of yearly proportions of households sampled that out-migrated from 1980 to 2007 using a Kernel Density Estimate. The plot peaks at 0.35, suggesting that the proportion centers around 35%, with a significant concentration of proportions between 20% and 50%.

Figure II

Kernel Density Estimate of Yearly Proportion of Out-Migrating Households



Data Source: NSSO 64th Round Household Survey

Note: The plot shows the estimated density of the yearly proportion of households that out-migrated due to floods from 1980 to 2007.

The outcome variable of interest is binary: whether Household i migrates out of a rural region or an urban region. The dataset provides information solely on the type of the last usual

[12]The survey was administered by the National Sample Survey Office (NSSO) under the Ministry of Statistics and Program Implementation (MoSPI) of the Government of India (GoI). The 64th round of the NSSO's Employment and Unemployment and Migration household survey provides the most recent and comprehensive dataset on migration from government sources in India. This dataset encompasses the entire Indian Union, excluding Leh (Ladakh) and Kargil districts in Jammu and Kashmir, interior villages of Nagaland beyond 5km of the bus route, and villages in the Andaman and Nicobar Islands that are inaccessible throughout the year. The primary sampling unit is household i within district d. The survey collected responses from 125,578 households, of which 9,331 households are pertinent to this study. The reference period of the survey was from July 1st, 1999 to June 30st, 2000 (NSSO, 2001).

place of residence of the migrating household, not the location type to which they migrated. Consequently, the empirical analysis in this essay examines rural-total[13] migration comprehensively. This approach may implicitly capture the effects of subsequent intra-urban migrations, whose impact will be discussed in Section 6.

This survey dataset is merged with state-level flood damage records (in Rupee Crores) collected from the Central Water Commission (CWC)[14] of India whose summary statistics are stored in Table II. The considerable standard deviations throughout these periods suggest that the extent of flood damage experienced significant variability, highlighting the unpredictability and changing impact of floods over time.

TABLE II
SUMMARY STATISTICS OF FLOOD DAMAGE BY FIVE YEAR INTERVALS (1980- 2017)

	(1) Affected Population (in millions)		(2) Human Lives Lost (in millions)		(3) Cattle Lives Lost (in millions)		(4) Total Damage (in Rupee Crores)	
Years	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
1980-1984	44.93	13.40	44.90	13.36	27.09	12.84	41.12	24.46
1985-1989	48.29	10.41	29.57	19.55	30.47	24.03	27.11	18.18
1990-1994	49.89	18.45	32.86	15.67	27.71	18.84	42.51	18.28
1995-1999	34.66	25.33	31.79	23.37	25.69	2.00	17.87	20.32
2000-2004	34.93	22.40	40.15	24.58	28.08	19.51	27.88	19.51
2005-2009	20.97	16.01	22.63	20.38	17.21	18.75	13.61	12.21
2010-2017	26.81	22.64	29.80	22.49	35.00	24.08	17.06	17.50

Note: Total damage captures monetary valuation of crops, houses, and public utilities (in Rs. Crores)
Source: Central Water Commission, India.

Endogenity concerns: IPCC Sixth Assessment Report (AR6)[16] finds that structural and non-structural measures like early warning systems, climate services, and social safety nets, etc cushion losses in case of inland flooding (medium-high confidence). Other factors include the region's development level encompassing physical infrastructure and human capital, flood management response, the efficacy of these responses amidst the increased frequency of shocks, improved political coordination, civil society pressure, informational advantages, etc. There is

[13]Total here includes both urban and rural regions.
[14]CWC publishes the yearly annual damage in Indian states concerning total damage in money valuation[15] (in Rs. Crores) of crops, land, and public utilities. Housing and crop damage accounts for nearly 80% of the total damage accruing due to flash floods. It also published information related to land area affected, and human and cattle lives lost.
[16]IPCC AR6 Synthesis Report, Climate Change 2023

little evidence that better governance reduces fatalities and damages during flood events in 75 countries including India once the within-country correlation of standard errors is taken into account (Ferreira et al., 2013, Bahinipati and Patnaik, 2015). They still find an indirect non-monotonic effect of income on flood magnitude and frequency, with net reductions in fatalities occurring only in lower-income countries.

Das et al., 2022 exploit Principal Component Analysis[17] and Power Law Distribution[18] to provide evidence that Gross State Domestic Product (GSDP) stands a poor indicator of the flood damage records that I am utilizing for this study. Further investigation on the same flood damage records of India reveals that increasing mitigation efforts since 1948 have not produced a monotonically decreasing long-term trend in flood damage (Mohanty et al., 2020, Gupta et al., 2003).

I use annual flood intensity[19] as an IV to address the potential endogeneity arising in the state-level flood damage records. The instrument measures the deviations of annual rainfall from the historical average. While the instrument does not significantly impact our binary outcome of interest (Appendix A Figure 4.), I acknowledge that this in itself does not establish the instrument's exogeneity. Nonetheless, the variation in rainfall intensity is relevant for explaining the extent of flood damage. Instrument's relevance is also supported by a weak instrument variable test, an under-identification test (Kleibergen-Paap LM statistic), a weak identification test (Cragg-Donald Wald F statistic), and an over-identification test (Hansen J test) (Appendix Figure 4). Using this valid instrument, the impact of flood shocks on out-migration is estimated by fitting a Logit IV regression model taking the form:

$$\ln\left(\frac{P_i}{1-P_i}\right) = \alpha + \beta_1 \ln(\text{Total } \widehat{\text{Flood Damage}}_d) + \epsilon_i \tag{1}$$

$$\ln\left(\frac{P_i}{1-P_i}\right) = \alpha + \beta_1 \ln(\text{Total } \widehat{\text{Flood Damage}}_d) + \beta_3 \mathrm{X}_i + \beta_4 \mathrm{I}_i + \epsilon_i \tag{2}$$

[17] https://royalsocietypublishing.org/doi/10.1098/rsta.2015.0202
[18] https://dash.harvard.edu/bitstream/handle/1/34651705/68262294.pdf
[19] This instrument is constructed from the distribution of annual rainfall data extracted from the Indian Meteorological Department (Appendix A Figure 3.).

I address potential omitted variable bias by controlling for the household-level characteristics. X_i, t in Eq(1) is a vector of household characteristics in period t when they migrated, such as household size, whether former member(s) of the household have migrated, religion, social groups, landholdings (in hectares), occupation of the head of the household, and in which expenditure tertile they belong. H_i in Eq(1) contains Household head characteristics such as age, sex, marital status, level of general education, and usual principal economic activity.

The sample is restricted to households that reported all the aforementioned characteristics and the rest are dropped to retaining 9,331 households from which 2,691 migrated at one point from 1980 to 2007. Incidentally, all the households retained after restricting the dataset have a track of at least one former member of the household migrating. This hints at informational bias whose impact on estimated outcomes is discussed in Section 6. To account for district and year-specific unobserved heterogeneity, district and year dummies are introduced in Eq. 3, and standard errors are clustered at the state level.

$$\ln\left(\frac{P_i}{1-P_i}\right) = \alpha + \beta_1 \ln(\text{Total } \widehat{\text{Flood D}}\text{amage}_d) + \beta_3 \mathrm{X}_i + \beta_4 \mathrm{I}_i + \delta_d + \gamma_t + \epsilon_i \tag{3}$$

$$\frac{P_i}{1-P_i} = \exp\left(\alpha + \beta_1 \ln(\text{Total } \widehat{\text{Flood D}}\text{amage}_d) + \beta_3 \mathrm{X}_i + \beta_4 \mathrm{I}_i + \delta_d + \gamma_t + \epsilon_i\right) \tag{4}$$

The model is further transformed to equation (4) where $\exp(\beta_1)$ represents the multiplicative change in the likelihood of out-migration for a one-percent increase in flood damage. All the coefficients are estimated and analyzed in terms of odds ratio which if greater than one indicates a positive relationship between the variables, converse otherwise.

Finally, $(\exp(\beta_1) - 1) \times 100\%$ in Eq-(4) specification is interpreted as the percentage change in the likelihood of households out-migrating from a rural region with a percent increase in the flood damage, holding other factors and time and district-specific unobserved variations constant.

5 Results

TABLE III
ODDS RATIO ESTIMATED EFFECT OF FLOOD SHOCKS ON RURAL OUT-MIGRATION

	(1) Logit IV Total Migration	(2) Logit Rural- total	(3) Logit Rural- total	(4) Logit IV Rural- total
Log (Total flood damage)	0.867***	1.162***	1.227***	1.821***
	(0.044)	(0.002)	(0.005)	(0.191)
Household Characteristics				
Household size	0.954	0.873	0.921	0.925
	(0.144)	(0.180)	(0.190)	(0.192)
Household type	1.136***	0.895***	0.877***	0.876***
	(0.0401)	(0.00479)	(0.0150)	(0.0130)
Religion	0.665**	0.701***	0.709***	0.710***
	(0.124)	(0.0143)	(0.00514)	(0.00352)
Social group	0.954***	0.814***	0.827***	0.834***
	(0.00438)	(0.00637)	(0.0237)	(0.0306)
Land holdings	0.899***	1.149**	1.136*	1.129*
	(0.0237)	(0.0770)	(0.0778)	(0.0713)
Expenditure tertile	1.372***	0.801**	0.823*	0.835*
	(0.0788)	(0.0883)	(0.0843)	(0.0801)
Household Head Characteristics				
Sex	85.85***	4.250***	4.484***	4.430***
	(27.28)	(0.0855)	(0.335)	(0.368)
Age	1.006**	0.999	0.999	1.000
	(0.00283)	(0.00250)	(0.00477)	(0.00475)
Marital Status	1.080	0.770*	0.764	0.780
	(0.171)	(0.119)	(0.128)	(0.124)
General education	1.064***	0.906***	0.902***	0.903***
	(0.0238)	(0.0306)	(0.0290)	(0.0284)
Usual principal activity	1.015	0.993**	0.995	0.994
	(0.0160)	(0.00297)	(0.00538)	(0.00611)
	(0.0213)	(2.133)	(0.954)	(0.540)
Constant	0.001***	3.247	2.660	0.780
	(0.000)	(4.654)	(6.799)	(2.170)
Year dummy	Yes	Yes	Yes	Yes
District dummy	Yes	No	Yes	Yes
Observations	9,304	2,679	2,610	2,610
Log Likelihood	-2809	-1075	-996.3	-996.8

*Robust standard error eform, clustered at the state level in parentheses *** p<0.01, ** p<0.05, * p<0.1*
Note: Total damage captures the monetary valuation of crops, houses, and public utilities (in Rupees Crores). Columns (2) and (3) also include dummies for 70-(1) districts of Uttar Pradesh (UP) and Bihar; and 26-year dummies from 1981- 2007.

Table III stores the estimation results for Eq (3) specification. Column (1) delineates the migration pattern for the entire sample of 9304 households, while columns (2), (3), and (4) focus on the subset of households that migrated. Our primary interest lies in these latter columns, as they elucidate the nuances of migration directionality. Column (3) introduces the district dummy controls and Column (4) implements the logistic model with IV. Column (4) suggests that in ceteris paribus, a percent increase in flood damage leads to an 82.1% increase in the likelihood of a household out-migrating from a rural region, at a 1% significance level. Moreover, various household characteristics, economic variables, and attributes of the household head significantly influence migration decisions, corroborated by high confidence levels. This is consistent with findings from Kurosaki, 2015, Taylor et al., 2003 of rural out-migration in response to flood shocks to enhance life safety and sustainability.

5.1 Migration Mechanisms

Thomas and Benjamin, 2021 attribute prolonged displacement of the region's population to the destruction of communities. Widespread deaths due to EWEs in the Pacific regions have forced many people to relocate (Deschenes and Moretti, 2009, Singh et al., 2020). To investigate what mechanisms have a stronger effect on households' decision to out-migrate in the context of UP and Bihar, I interact equation (3) with the logarithm[20] of the count (in millions) of the population affected, human lives lost, and cattle lives lost. The regression specification now takes the form:

$$\ln\left(\frac{P_i}{1-P_i}\right) = \alpha + \beta_1 \ln(\text{Total Flood Damage}_d) + \beta_2 \left(\ln(\text{Total Flood Damage}_d) \times \ln(\text{Mechanism}_t)\right) + \beta_3 \mathrm{X}_i + \beta_4 \mathrm{I}_i + \delta_d + \gamma_t + \epsilon_i \quad (5)$$

The survey also distinguishes between permanent and temporary household movements. A duration of absence exceeding one year from the usual place of residence is classified as permanent movement; otherwise, it is considered temporary. This distinction is utilized to explore the dimension of intergenerational altruism by examining whether a household migrated permanently or temporarily. Risk aversion generally leads to a conservative approach, paradoxically,

[20] Since the effect of the logarithm of total flood damage interacts multiplicatively with other variables (e.g., a percentage increase in population affected), I employ the logarithm of these counts. Their lower-order main effects are excluded from the regression because the extent of flood damage directly affects them (bad controls). Throughout this essay, all regression specifications treat the baseline interaction effects as separate entities rather than absorbing their effects in the constant term.

when faced with the possibility of a sure loss, households may engage in riskier behavior which here is permanent migration even at a high cost that they would normally not consider.

$$
\begin{aligned}
\ln\left(\frac{P_i}{1-P_i}\right) = \alpha + \beta_1 \ln(\text{Total Flood Damage}_d) \\
&+ \beta_2 \left(\ln(\text{Total Flood Damage}_d) \times \ln(\text{Mechanism}_t)\right) \\
&+ \beta_3 \left(\ln(\text{Total Flood Damage}_d) \times \ln(\text{Mechanism}_t) \times \text{Nature of Movement}_i\right) \\
&+ \beta_4 \text{X}_i + \beta_5 \text{I}_i + \delta_d + \gamma_t + \epsilon_i
\end{aligned}
\tag{6}
$$

Table IV results reinforce this idea and suggest that affected population density due to flooding exerts the most substantial influence on migration decisions. The likelihood of a household out-migrating increases by 19.3% for each percentage increase in the affected population density in the surrounding area, with this result being statistically significant at the 1% level. Moreover, cattle lives lost predominantly affect permanent migration decisions. These results underscore the multifaceted nature of migration drivers in response to flood shocks.

TABLE IV
IMPACT OF TOTAL FLOOD DAMAGE ON RURAL OUT-MIGRATION (PERMANENT vs. TEMPORARY) THROUGH IDENTIFIED MECHANISMS: AFFECTED POPULATION, HUMAN LIVES LOST, AND CATTLE LIVES LOST

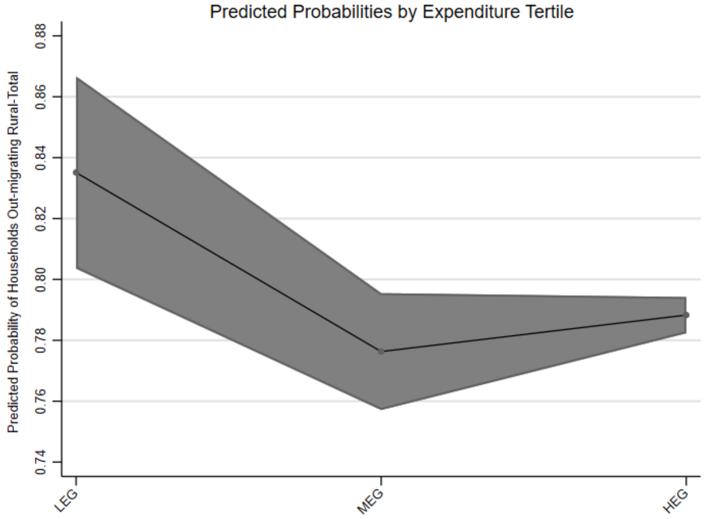
	(1)	(2)	(3)	(4)	(5)	(6)
ln (TFD) * ln (Affected population)	1.072***	0.934***				
	(0.00135)	(0.00493)				
ln (TFD) * ln (Affected population) * Permanent migration		1.193***				
		(0.0110)				
ln (TFD) * ln (Human lives lost)			1.039***	0.902***		
			(0.00196)	(4.70e-05)		
ln (TFD) * ln (Human lives lost) * Permanent migration				1.176***		
				(0.000474)		
ln (TFD) * ln (Cattle lives lost)					1.036***	0.878***
					(0.00198)	(0.00589)
ln (TFD) * ln (Human lives lost) * Permanent migration						1.207***
						(0.0104)
Household level characteristics						
Household size	0.930	0.929	0.925	0.920	0.925	0.905
	(0.187)	(0.211)	(0.186)	(0.219)	(0.187)	(0.227)
Household type	0.876***	0.876***	0.876***	0.869***	0.876***	0.868***
	(0.0132)	(0.0106)	(0.0135)	(0.0152)	(0.0133)	(0.0133)
Religion	0.725***	0.704***	0.708***	0.691***	0.714***	0.701***
	(0.0199)	(4.76e-05)	(0.00209)	(0.0255)	(0.00815)	(0.0267)
Social group	0.830***	0.794***	0.831***	0.814***	0.830***	0.809***
	(0.0274)	(0.0352)	(0.0291)	(0.0309)	(0.0278)	(0.0317)
Land possessed	1.126*	1.109**	1.136*	1.119*	1.135*	1.119*
	(0.0683)	(0.0546)	(0.0769)	(0.0659)	(0.0759)	(0.0655)
Expenditure tertile	0.833**	0.853	0.826*	0.833	0.828**	0.833
	(0.0776)	(0.0873)	(0.0813)	(0.0927)	(0.0797)	(0.0983)
Household head characteristics						
Sex	4.399***	3.568***	4.477***	3.775***	4.479***	3.811***
	(0.407)	(0.528)	(0.333)	(0.543)	(0.334)	(0.624)
Age	0.999	0.999	0.999	0.998	0.999	0.998
	(0.00526)	(0.00770)	(0.00489)	(0.00648)	(0.00497)	(0.00682)
Marital status	0.800*	0.773***	0.771	0.742*	0.775*	0.753*
	(0.104)	(0.0761)	(0.125)	(0.118)	(0.120)	(0.110)
General education	0.903***	0.899***	0.903***	0.903***	0.903***	0.903***
	(0.0284)	(0.0315)	(0.0279)	(0.0328)	(0.0279)	(0.0325)
Usual principal activity	0.992	0.982**	0.994	0.990	0.994	0.991
	(0.00747)	(0.00827)	(0.00608)	(0.00879)	(0.00558)	(0.00662)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
State dummy	Yes	Yes	Yes	Yes	Yes	Yes
Constant	2.302	3.755	3.685	7.501	4.291	8.065
	(5.495)	(9.439)	(9.203)	(20.52)	(10.60)	(22.36)
Observations	2,610	2,607	2,610	2,607	2,610	2,607

*Standard error presented in eform, clustered at the state level in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$*

Note: TFD stands for Total Flood Damage. Regression specification for all the columns implements Logit IV instrumenting TFD with the rainfall intensity measure.

I now test the hypothesis that economic status substantially mediates the migration response to flood shocks by examining expenditure tertile. Figure 5. shows that the predicted probability of households out-migrating is highest in the low-expenditure tertile, around 0.84, however in the reverse direction. This stands in contrast to the findings of Giannelli and Canessa, 2022 in Bangladesh that individuals from lower economic groups are more likely to migrate due to their higher vulnerability and fewer resources to withstand the impacts of floods. The wider confidence interval for the low-expenditure group indicates greater variability or uncertainty in their migration response, in contrast to the more consistent migration behavior observed in the other two groups.

Figure 5.
Predicted Probabilities by Expenditure Tertile



These findings support the hypothesis that economic status significantly affects the likelihood of rural out-migration in response to flood shocks. To test the robustness of this finding, I also study the interaction effects with the amount of land possessed by the household- another indicator of their economic foothold. Table V (see Appendix B) suggests that the likelihood of households out-migrating increases from an odds ratio of 1.828 for those who own up to 1 hectare of land to 2.265 for households possessing more than 4 hectares of land. This illustrates a stronger migration response as landholding size increases. A similar effect is observed for permanent migration, emphasizing intergenerational altruism. Households with larger landholdings migrate to ensure immediate safety and secure future stability for subsequent generations.

Migration Behavior in Response to Household Head Gender Dynamics: The gender of the household head emerges as a critical determinant in migration decisions, especially in the context of Indian settings Sarkar et al., 2022. In this study, female-headed households display a more pronounced response to flood damage, particularly concerning permanent migration (see Table VI). This is consistent with Lu, 2012, who argues that men may exhibit heightened stress levels compared to women because, in many developing societies, they often bear greater responsibilities to support their families, and that would impact their propensity to migrate. In contrast, women might better utilize social support systems, as seeking help aligns more with traditional feminine roles.

TABLE VI
ODDS RATIOS FOR FLOOD-INDUCED MIGRATION: IMPACT VARIABILITY ACROSS HOUSEHOLDS BY GENDER OF THE HEAD

	(1) Logit IV Interaction Effect	(2) Logit IV Permanent migration effect
ln (TFD) * Female HoH	1.937*** (0.218)	
ln (TFD) * Male HoH	1.607*** (0.125)	
ln (TFD) * Female HoH * Temporary		1.081 (0.0517)
ln (TFD) * Female HoH * Permanent		2.128*** (0.390)
ln (TFD) * Male HoH * Temporary		0.959 (0.256)
ln (TFD) * Male HoH * Temporary		1.709*** (0.323)
Constant	12.50 (32.70)	19.53 (57.92)
Year dummy	Yes	Yes
District dummy	Yes	Yes
Observations	2,610	2,607

*Robust standard error eform in parentheses *** p<0.01, ** p<0.05, * p<0.1*
Note: Here TFD stands for the predicted value of the total flood damage after it is instrumented with the rainfall intensity. HoH stands for the Head of Household. Each column specification contains the year and district dummy as controls.

5.2 Heterogeneous Impact Across Other Household Level Characteristics

Concerning household size, I find that the percentage increase in the likelihood of permanent out-migration from a rural region is significantly higher among smaller households with fewer than five members (see Table VII). According to Hoang, 2011 migration decisions are invariably made within a specific context, where individuals' agency is either facilitated or constrained by various socio-cultural structures. I investigate this with social group identification[21] of the sample

[21] Social groups are considered here as people identifying themselves in the category of Scheduled Caste (SC), Other Backward Classes (OBC), Scheduled Tribes (ST), and Others

households. Table VIII indicates that the migration response of Scheduled Tribes in these states is the most sensitive to flood damage. Results are consistent with studies exploring the relation between drought and migration in India (Panda, 2017a, Jülich, 2011 Panda, 2017b, Sahu, 2017, Sundari, 2005, Debnath and Nayak, 2022). This analysis reveals a gradient of vulnerability across social groups, underscoring the importance of considering social stratification in policy-making and planning for disaster management and mitigation.

5.3 Forecasting Migration Coefficients for Flood Damage

To understand the potential impacts of flood damage on migration trends for the period 2007-2017, I employ a predictive logistic regression structure for 2007- 2017:

$$\ln\left(\frac{P_i}{1-P_i}\right) = \hat{\alpha} + \hat{\beta}_1 \ln(\text{Total }\widehat{\text{Flood D}}\text{amage}_{d,\text{new}}) + \hat{\beta}_3 \text{X}_{i,\text{new}} + \hat{\beta}_4 \text{I}_{i,\text{new}} + \hat{\delta}_{d,\text{new}} + \hat{\gamma}_{t,\text{new}} + \hat{\epsilon}_{i,\text{new}} \quad (6)$$

Figure 6 (see Appendix B) suggests that the predicted migration effect displays a general trend of stability, staying within a range that slightly oscillates around 1.5 to 2.5 in terms of odds ratios. This suggests a moderate but consistent perception or risk of migration due to flood damage among the population. The actual log of flood damage, plotted as a line on the graph, shows a slight undulating pattern without significant peaks or troughs.

The stability in both the predicted migration effect and the actual logarithm of flood damage suggests that, historically, the conditions have not fluctuated widely enough to cause dramatic changes in migration patterns. There could be also a latent 'learning effect'- resilience or an adaptation of the population to the existing levels of flood risk, or effective management and mitigation of flood impacts in the affected areas. Furthermore, the closeness of the predicted migration effects within their confidence intervals indicates a reliable model with consistent outcomes over the years examined.

6 Discussion

From this essay, it is evident that in the context of Uttar Pradesh and Bihar, flood shocks impose significant constraints on the budget sets of vulnerable households, inhibiting their economic capacity and norms for private protection. The direction of the results are consistent with Mueller et al., 2014 and points that households do not feel trapped to relocate as Chen et al., 2017 observed in Bangladesh. Other findings underscore the necessity for targeted flood mitigation strategies in rural regions, particularly since female-headed households exhibit a pronounced propensity to relocate. Among the various factors driving migration, population density in affected regions emerges as a predominant determinant. Additionally, the significant loss of cattle lives is a major impetus for permanent migration and suggests the exercise of intergenerational altruism among migrant households.

The study reveals substantial heterogeneity in migration responses across different socio-economic strata. Households with larger landholdings demonstrate a stronger migration response compared to those with smaller landholdings. Additionally, smaller households (fewer than five members) and socially disadvantaged groups (e.g., Scheduled Tribes) exhibit heightened sensitivity to flood-induced migration pressures. These findings emphasize the need for targeted interventions that address the nuanced vulnerabilities of different social and economic groups in rural regions. Forecasted migration patterns from 2007 to 2017 indicate a consistent risk perception and migration trend in response to flood damage.

Addressing market failures by inviting equitable investments in robust flood control infrastructure, climate-resilient agricultural practices, comprehensive land-use planning, and effective social protection programs are imperative. Policies should also explicitly recognize and address climate-induced displacement, incorporating provisions for environmental refugees. This is crucial in a country like India, where the Inter-State Migrant Workmen Act of 1979[22] that

[22] Chief Labour Commissioner, Government of India

regulates migration, lacks explicit provisions to address individuals displaced due to climate change.

6.1 Limitations and Future Research Course

Due to data limitations, ascertaining the subsequent destinations of migrating households remains challenging, which hinders a comprehensive understanding of their ongoing livelihood risks. The 2007-2008 migration records utilized in this study represent the most recent available dataset, rendering the formulation of optimal migration policies presently indeterminate. Re-estimating model parameters will be necessary as new data becomes available and underlying patterns evolve.

The findings of this study are not directly transferable to other states due to the diverse nature of flood shocks experienced across different regions of India and the unique socio-economic contexts of each state, thereby limiting external validity. Additionally, the impact may be overestimated due to potential site selection bias, as Uttar Pradesh and Bihar were chosen due to their high susceptibility to flash floods. Other limitations include possible underestimation and overestimation of current estimates. Underestimation may occur due to the census nature of the data and the exclusion of households that have relocated multiple times or returned home[23]. Conversely, overestimation is possible since all households included have at least one former member who has migrated in the past, which might relax the uncertainty parameter in their expected payoff function.

While this study projects migration patterns up to 2017 using a logistic regression model, future research should employ more sophisticated models, such as Agent-Based Modeling (Entwisle et al., 2020), to enhance our understanding of migration dynamics and the constraints households face. Theoretical and macroeconomic research could further elucidate the dynamic effects of infrastructure investment in rural regions and migration incentives.

[23] https://assets.publishing.service.gov.uk/media/57a08ac0ed915d622c0008b5/Assessing$_{c}limate_{i}nduced_{m}igration_{i}n_{I}ndia-Data_{S}ources_{s}cenarios.pdf$

It will be interesting to conduct quasi-experimental studies in such settings and survey households that either migrate or stay back in response to climate change. This would provide insights into the factors influencing their well-being. A distinctive aspect of this research is the application of "flood damage" as a novel metric for flood exposure, enabling its comprehensive impact assessment on migration decisions. It offers a more precise gauge of household vulnerability to flood shocks than traditional measures such as precipitation data or flood frequency. Yet, quasi-experiments as ideated would also facilitate accounting for non-economic loss and damage, enabling a more comprehensive calculation of the costs required to restore affected households to their pre-shock state.

7 Appendix A

1. Average Annual Rainfall Pattern

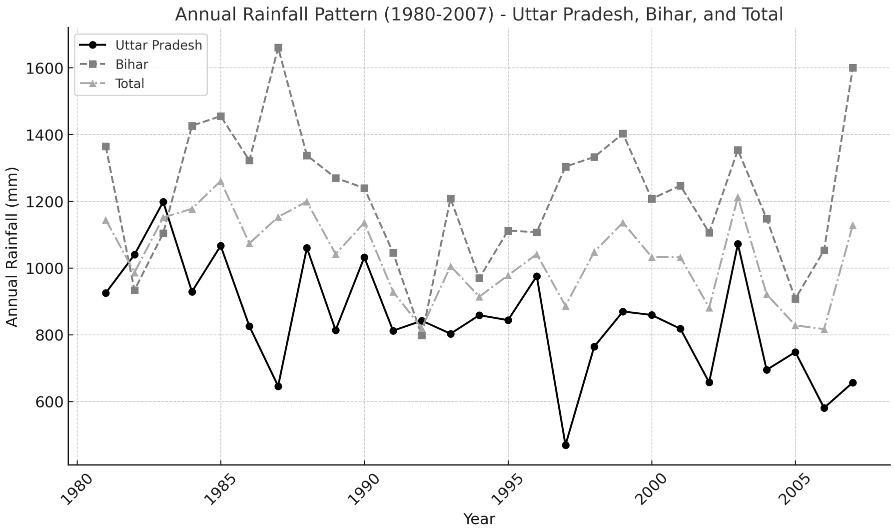


Figure 2: Source: Indian Meteorological Department

2. Weak Instrument Variable Test

```
IV (2SLS) estimation
--------------------

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity

                                                      Number of obs =      2690
                                                      F(  1,   2688) =    20.94
                                                      Prob > F       =   0.0000
Total (centered) SS     =  427.994052                 Centered R2    =  -0.0638
Total (uncentered) SS   =        2156                 Uncentered R2  =   0.7888
Residual SS             =  455.3149053                Root MSE       =    .4114

------------------------------------------------------------------------------
             |               Robust
location_l~r | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
total_damage |   .0055633   .0012154     4.58   0.000     .0031812    .0079454
       _cons |   .6815922    .028139    24.22   0.000     .6264409    .7367436
------------------------------------------------------------------------------
Underidentification test (Kleibergen-Paap rk LM statistic):            330.766
                                                   Chi-sq(1) P-val =    0.0000
------------------------------------------------------------------------------
Weak identification test (Cragg-Donald Wald F statistic):              319.833
                         (Kleibergen-Paap rk Wald F statistic):        308.274
Stock-Yogo weak ID test critical values: 10% maximal IV size             16.38
                                         15% maximal IV size              8.96
                                         20% maximal IV size              6.66
                                         25% maximal IV size              5.53
Source: Stock-Yogo (2005).  Reproduced by permission.
NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.
------------------------------------------------------------------------------
Hansen J statistic (overidentification test of all instruments):         0.000
                                                 (equation exactly identified)
------------------------------------------------------------------------------
Instrumented:         total_damage
Excluded instruments: flood_intensity
------------------------------------------------------------------------------
```

3. Summary Statistics: Households in repeated cross-sectional records also show similar characteristics on average in each year from 1980- 2007.

TABLE I
DESCRIPTIVE STATISTICS (2007- 2008) (in percentage)
CHARACTERISTICS OF SAMPLE HOUSEHOLD (UNWEIGHTED), NSSO 64th ROUND

	(1) All Households	(2) Migrant Households	(3) Rural-total Migrant Households
Household Level Characteristics			
Household size			
Greater than 5 members	0.40	0.57	0.57
	(0.491)	(0.496)	(0.496)
Less than 5 members	0.60	0.43	0.43
	(0.491)	(0.496)	(0.496)
Household type			
Self-employed in non-agriculture	0.09	0.05	0.05
	(0.285)	(0.214)	(0.212)
Agricultural labor	0.14	0.31	0.33
	(0.348)	(0.312)	(0.332)
Other labor	0.16	0.02	0.01
	(0.187)	(0.130)	(0.121)
Self-employed in agriculture	0.36	0.42	0.45
	(0.479)	(0.420)	(0.432)
Self-employed	0.11	0.08	0.07
	(0.311)	(0.273)	(0.251)
Regular wage-salary earning	0.06	0.08	0.05
	(0.231)	(0.271)	(0.220)
Causal labor	0.02	0.02	0.01
	(0.126)	(0.124)	(0.121)
Others	0.06	0.02	0.03
	(0.237)	(0.124)	(0.121)
Religion			
Majority religion	0.82	0.81	0.82
	(0.382)	(0.392)	(0.383)
Minority religion	0.17	0.18	0.17
	(0.377)	(0.385)	(0.378)
Social group			
Scheduled Caste (SC)	0.01	0.01	0.01
	(0.0946)	(0.0859)	(0.0935)
Scheduled Tribes (ST)	0.21	0.23	0.25
	(0.408)	(0.422)	(0.433)
Other Backward Classes (OBC)	0.54	0.50	0.53
	(0.498)	(0.500)	(0.499)
Others	0.24	0.26	0.21
	(0.425)	(0.438)	(0.410)
Land possessed			
Up to 1 hectare	0.86	0.93	0.93
	(0.344)	(0.251)	(0.249)
From 1.01 to 4 hectares	0.13	0.06	0.06
	(0.334)	(0.243)	(0.241)
More than 4 hectares	0.01	0.00	0.00
	(0.0912)	(0.0667)	(0.0645)
Expenditure Tertile			
Lower Economic Group	0.33	0.30	0.34
	(0.471)	(0.458)	(0.474)
Middle Economic Group	0.33	0.29	0.30
	(0.471)	(0.453)	(0.458)
Higher Economic Group	0.33	0.41	0.36

DESCRIPTIVE STATISTICS (2007- 2008) (in percentage)
CHARACTERISTICS OF SAMPLE HOUSEHOLD (UNWEIGHTED), NSSO 64th ROUND

	(1) All Households	(2) Migrant Households	(3) Rural-total Migrant Households
Household head characteristics			
Sex			
Male	0.74	0.22	0.15
	(0.438)	(0.418)	(0.361)
Female	0.26	0.78	0.85
	(0.438)	(0.418)	(0.361)
Age			
Up till 21	0.01	0.01	0.01
	(0.0928)	(0.0960)	(0.0885)
21- 50	0.51	0.69	0.72
	(0.500)	(0.464)	(0.450)
50- 70	0.39	0.25	0.22
	(0.489)	(0.432)	(0.417)
Above 70	0.09	0.06	0.05
	(0.283)	(0.232)	(0.215)
Marital Status			
Never married	0.02	0.00	0.00
	(0.123)	(0.0667)	(0.0569)
Currently married	0.85	0.77	0.77
	(0.353)	(0.420)	(0.424)
Widowed	0.13	0.22	0.23
	(0.335)	(0.416)	(0.421)
General Education			
Not literate	0.50	0.61	0.68
	(0.500)	(0.488)	(0.468)
Literate without any schooling	0.01	0.01	0.01
	(0.111)	(0.103)	(0.105)
Literate without formal schooling	0.06	0.05	0.05
	(0.239)	(0.219)	(0.224)
Primary	0.10	0.08	0.07
	(0.304)	(0.264)	(0.261)
Upper primary/ middle	0.11	0.08	0.07
	(0.312)	(0.272)	(0.259)
Secondary	0.08	0.06	0.04
	(0.270)	(0.233)	(0.201)
Higher Secondary	0.05	0.03	0.02
	(0.218)	(0.175)	(0.152)
Diploma/certificate course	0.01	0.01	0.00
	(0.0864)	(0.0859)	(0.0645)
Graduate	0.05	0.05	0.02
	(0.210)	(0.209)	(0.152)
Postgraduate and above	0.02	0.03	0.02
	(0.146)	(0.165)	(0.123)
N	9331	2689	2156

mean coefficients; standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

8 Appendix B

TABLE V
ODDS RATIO IMPACT VARIABILITY ACROSS HOUSEHOLDS WITH DIFFERENT LAND HOLDINGS

	(1) Interaction effect with land possessed	(2) Permanent migration effect
ln (TFD) * Land possessed		
(Up to 1 hectare)	1.828***	
	(0.186)	
(from 1.01 to 4 hectares)	2.017***	
	(0.328)	
(more than 4 hectares)	2.265***	
	(0.126)	
ln (TFD) * ln (Land possessed) * Permanent migration		
(Up to 1 hectare) * Permanent		1.986***
		(0.371)
(from 1.01 to 4 hectares) * Permanent		2.237***
		(0.578)
(more than 4 hectares) * Permanent		2.287***
		(0.0972)
Constant	0.901	2.481
	(2.475)	(7.686)
Observations	2,610	2,607

*Robust standard errors eform in parentheses *** p<0.01, ** p<0.05, * p<0.1*
Note: Both the specifications in Columns (1) and (2) control for Household level characteristics such as the household size, household type, religion, social group, landholdings, and expenditure tertile; and Household head characteristics such as age, sex, marital status, usual principal activity, and general education of the household head. Year and district dummies have been introduced as controls with standard errors clustered at the state level.

2. Differential Impact Across Household sizes

TABLE VII
ODDS- RATIO IMPACT VARIABILITY ACROSS DIFFERENT HOUSEHOLD SIZES

	(1) Logit IV	(2) Logit IV
Household size	14.20***	14.30***
	(0.677)	(4.484)
ln (TFD)* (< 5 members)	2.632***	
	(0.239)	
ln (TFD)* (>= 5 members)	1.053	
	(0.0983)	
ln (TFD)* (< 5 members) * Temporary		1.483***
		(0.171)
ln (TFD)* (< 5 members) * Permanent		2.901***
		(0.306)
ln (TFD)* (>= 5 members) * Temporary		0.649**
		(0.141)
ln (TFD)* (>= 5 members) * Permanent		1.141
		(0.281)
Constant	0.272	0.706
	(0.698)	(1.929)
Observations	2,610	2,607

Note: Both the specifications in Columns (1) and (2) control for Household level characteristics such as the household size, household type, religion, social group, landholdings, and expenditure tertile; and Household head characteristics such as age, sex, marital status, usual principal activity, and general education of the household head. Year and district dummies have been introduced as controls with standard errors clustered at the state level.
*Robust standard error eform in parentheses *** p<0.01, ** p<0.05, * p<0.1*

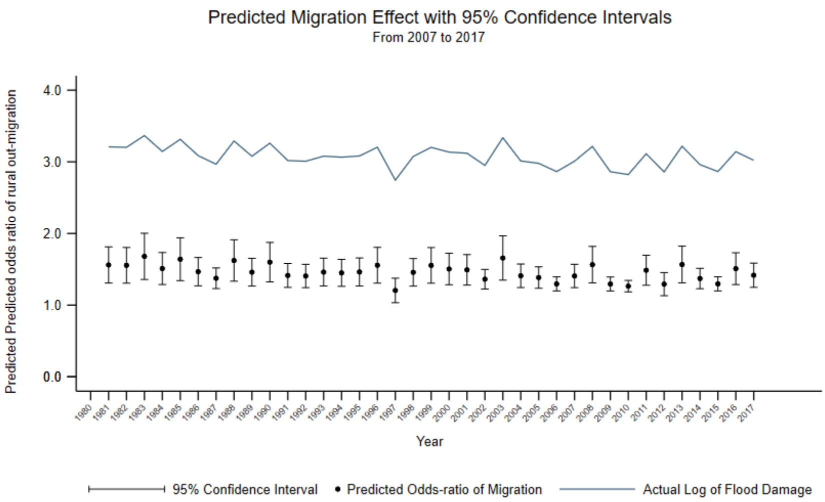
3. Differential Impact Across Social Groups(Caste Groups)

TABLE VIII
ESTIMATED ODDS-RATIO IMPACT ACROSS SOCIAL GROUPS: SCHEDULED CASTE(SC), SCHEDULED TRIBES (ST), OTHER BACKWARD CLASSES (OBC), OTHERS

	(1) Logit IV	(2) Logit IV
ln (TFD) * ST * Temporary		1.108*** (0.00395)
ln (TFD) * ST * Permanent		2.226*** (0.0118)
ln (TFD) * OBC * Temporary		0.995 (0.133)
ln (TFD) * OBC * Permanent		1.991*** (0.333)
ln (TFD) * Others * Temporary		1.059 (0.295)
ln (TFD) * Others * Permanent		1.621** (0.348)
ln (TFD) * SC	4.008** (2.206)	
ln (TFD) * ST	1.891*** (0.105)	
ln (TFD) * OBC	1.804*** (0.185)	
ln (TFD) * Others	1.523** (0.261)	
Constant	0.292 (0.473)	0.519 (1.067)
Observations	2,610	2,587

*Robust standard errors eform in parentheses *** p<0.01, ** p<0.05, * p<0.1*
Note: Both the specifications in Columns (1) and (2) control for Household level characteristics such as the household size, household type, religion, social group, landholdings, and expenditure tertile; and Household head characteristics such as age, sex, marital status, usual principal activity, and general education of the household head. Year and district dummies have been introduced as controls with standard errors clustered at the state level.

4. Linear Prediction of Migration Pattern



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