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Abstract

Extreme weather induced migration is a growing concern for low and middle income countries due to the increased variability in the weather and the increase in the number of extreme weather disasters associated with climate change. The objective of this paper is to examine the inter-linkages between weather, disasters, and migration, in India. To examine the bidirectional flow of migrants across Indian states, we estimate gravity models with Poisson Pseudo Maximum Likelihood (PPML), in line with previous studies' methodology. We find that agriculture-dependent states and states with low level of human development are more likely to face out-migration driven by weather variations and disasters. Internal migration is seasonal, temporary and often short-distance in nature. We find statistical evidence that repeated exposure of vulnerable populations to extreme weather and disasters may ultimately lead to more permanent migration. This raises urgent questions concerning the efficacy of disaster risk management and climate change adaptation policies at the sub-national level.

JEL-Codes: O150, Q540.

Keywords: climate, disasters, bilateral migration, NELM, gravity model.

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Extreme weather and inter-state migration in India

1. Introduction

We examine the inter-linkages between extreme weather and migration, specifically focusing on internal migration in India. There is a burgeoning literature asking whether and how climate change and disasters influence population movements (for example, Beine and Jeseutte, 2021; Beine et al., 2021; Ferris, 2020; Hoffmann et al., 2020). Some predictions, such as in the World Migration Report (McAuliffe and Triandafyllidou, 2021), suggest that by 2050 the number of people displaced globally due to environmental factors could be anywhere between 25 million to 1 billion (admittedly a very wide range). The figure most frequently cited is 200 million environmental migrants, from an earlier report from the same source (McAuliffe and Khadaria, 2019), and there are similar predictions from the Institute for Environment and Human Security of the United Nations University (IEHS-UNU), the Norwegian Refugee Council (NRC), and the Internal Displacement Monitoring Centre (IDMC). This number could be an underestimate because the frequency and severity of extreme events including the risk of droughts and desertification, prolonged heat waves and cold conditions, have been increasing more quickly than previously anticipated.[1] For India specifically, the Climate Action Network South Asia estimates that approximately 45 million people would be forced to migrate due to extreme weather events by 2050 (Garg et al., 2021).

Generally, it is well documented that economic, geographic, cultural, and demographic factors determine the volume and direction of migration (McAuliffe and Triandafyllidou, 2021). One plausible factor affecting migration is the occurrence of extreme shocks to incomes and livelihoods, and one possible cause of such shock is an extreme weather event. There are disparities across countries in terms of exposure, vulnerability, impacts, and policy responses to extreme weather events, and more generally between high-, middle-, and low-income countries. These disparities therefore require the study of migration flows separately in these different contexts (Hoffmann et al., 2020).

India, a large and a geographically very diverse country, faces various extreme weather hazards including floods, droughts, hailstorm, cyclones, wildfires, heat waves, and extreme cold events. The impacts of these extreme weather events vary substantially across states, and this can lead

[1] Global Report on Internal Displacement May 2016 (Bennett et al., 2016). Available at: https://www.internal-displacement.org/sites/default/files/publications/documents/2016-global-report-internal-displacement-IDMC.pdf

to internal migration flows as a plausible adaptation or accommodation strategy to escape a changing climate and increasing extreme weather risks (Mallick, 2023; NDMA, 2019; Gemenne and Blocher, 2017). India has the largest emigrant population in the world at 18 million. Recently, in 2020 for example, disasters have triggered large-scale internal displacement of nearly 3.8 million (IDMC, 2021). These disparities and diversities make India a very informative case study with which one may examine the factors that shape migration driven by weather risks. The existing literature indicates that future climatic changes may trigger cross-border immigration from India and to India from neighbouring countries like Bangladesh and Nepal (Ferris, 2020; Panda, 2017). This present study, however, focuses on internal (domestic) migration only. A few studies, and especially Dallmann and Millock (2017), explored the relationship between climate-induced disasters and population movement at the sub-national level, sometimes with a specific focus on India. The results from these studies are inconclusive because the circumstantial differences across countries are large, and the interactions between different impacts are seemingly complex (Helbling et al., 2023; Black et al., 2011).

This study uses data from three Census rounds from India: 1991, 2001 and 2011. The Census of India provides data on the measurement of migration, its composition, reasons of migration, employment status of migrants (employed or unemployed), destination, and period of stay. Data is available at the state and district levels. This Census data is then matched with daily weather data collected from the Indian Meteorological Department (IMD). We use these data from 1980 to 2010 to span the years that are relevant for the Census data we have. Information on disasters is sourced from the Central Water Commission (CWC, 2020) for the same period. The study considers the data on flood disaster considering the data availability. Other variables used in our empirical specifications are collected from the Reserve Bank of India's Handbook of Statistics on Indian States, the Global Data Lab (GDL) available from the United Nations Development Program (UNDP), and Indian states' Statistical Handbooks.

Our focus is on characterising the impacts of extreme weather and disasters on migration, motivated by the overwhelming evidence connecting climate change and extreme events (McAuliffe and Triandafyllidou, 2021; IPCC, 2022 and 2018) and suggesting that the frequency and intensity of these extreme events are both increasing. We estimate the determinants of migration using a gravity model estimated using the Poisson Pseudo Maximum Likelihood (PPML) method, as is common in migration studies (e.g., Beine et al., 2021, Beine et al., 2016). The New Economics of Labour Migration (NELM) theorises that migration is an outcome of multiple factors and is based on household-level decisions instead of individual preferences (Stark and Bloom, 1985). This literature identifies both push and pull factors for migration. Migration push factors are associated with environmental shocks, social tensions, family pressures, and safety concerns, while economic and environmental prospects in the destination are examples of pull factors (Urbański, 2022). Our study looks at the relationship between weather-induced disasters and migration. Previous research has shown that out-migration is more evident in states where agriculture dominates over other sectors (Abel et al., 2019; Klepp, 2017; Cai et al., 2016; Viswanathan and Kumar, 2015). In India, the earnings in agriculture-dependent states are strongly correlated with rainfall during the monsoon months as variations in monsoon rainfall affect farm income (Jha et al., 2017). Rainfall variation may thus be statistically related to out-migration (Berlemann and Steinhardt, 2017; Afifi et al., 2016). Floods and droughts similarly affect sowing and harvesting of crops, thereby decreasing the income of those who depend on agriculture for livelihood, further leading to forced migration (Aryal et al., 2018; Black and Collyer, 2014). Ultimately, our investigation is aimed to inform policymaking for sustainable social security programmes, identification of climate-smart livelihood strategies, labour market policies, public goods procurement, mitigation and adaptation decisions, and skilling programmes. All of these have the potential for limiting the distressed migration we identify.

The next section provides a brief review of relevant literature, the third section presents the methodology, followed by a detailed discussion of the results in the fourth section. The final section summarises the key insights from the study.

2. Review of Literature

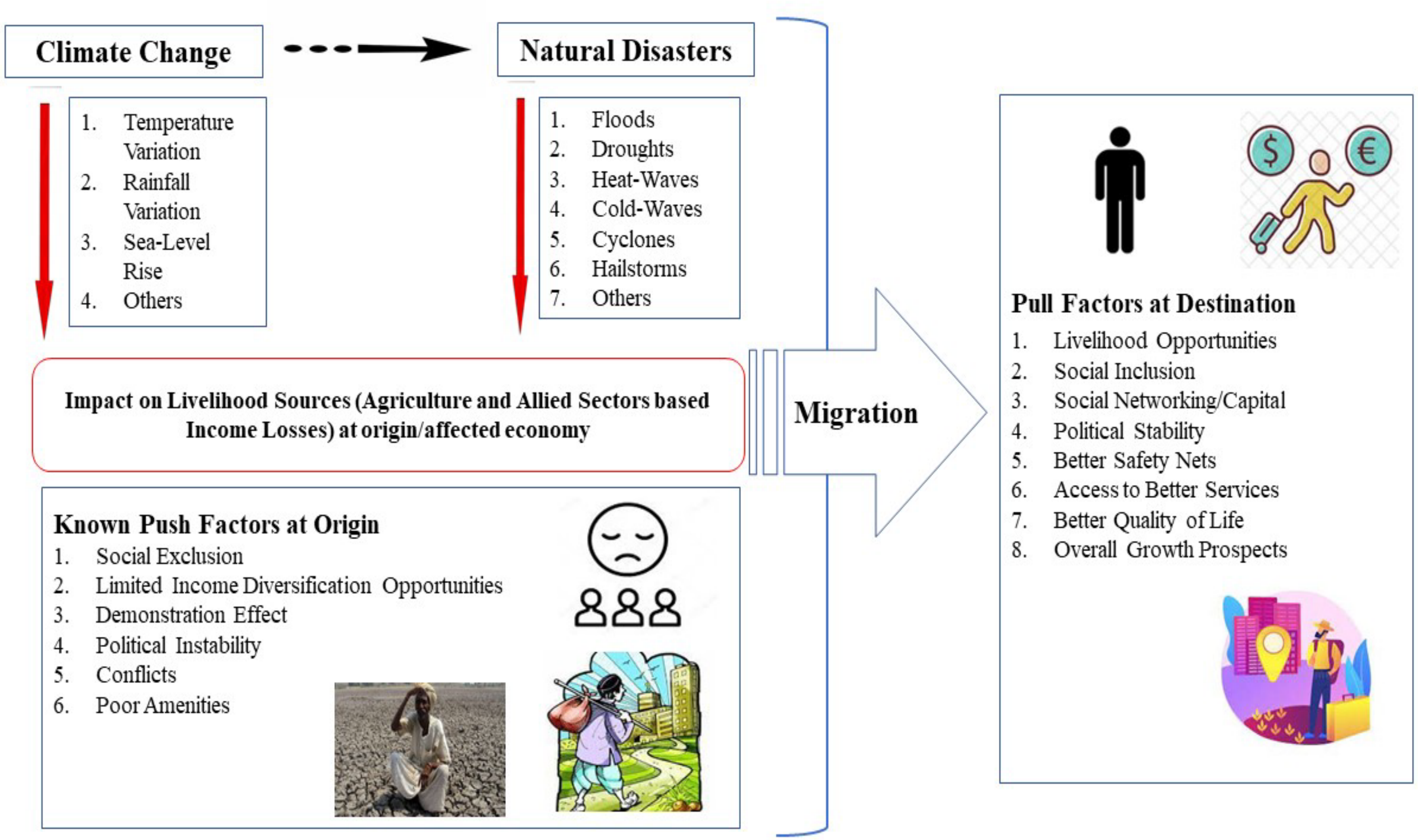
2.1 Theoretical considerations

Migration is a widely discussed topic in the Development Economics literature since the 1950s (Ruiz and Vargas-Silva, 2013). This literature has conceptualized the migration-decision based on a broad set of push and pull factors (e.g., Lewis, 1954; Fei and Ranis, 1961; Harris and Todaro, 1970). Our focus here is on the NELM theory, which emphasizes that a decision to migrate could depend not only on the individual migrant's decisions, but also on other members of their household, and on their wider social networks (Stark and Bloom, 1985). Further, the NELM incorporates the role of exogenous factors in triggering migration – in our case, weather extremes. Other factors documented in the NELM literature as shaping migration decisions are other types of disasters, social tensions, and local conflicts (Berlemann and Tran, 2020).

A state-level gravity model supports the fundamental hypothesis underlying the current study, that migration may take place due to differences across states (e.g., economic, social, and environmental differences - Trinh et al., 2021). It describes a context where migrants (mostly labourers) move from place A to place B (Anderson, 2010; Karemera et al., 2000; Mátyás, 1998). The model, formulated similarly to the gravity model for trade, assumes that there exists a direct relationship between the cross products of income at site A and B with the volume of migration between A and B (Saldarriaga and Hua, 2019; Lewer and Van den Berg, 2008). Similarly to trade flows, the distance between two places is hypothesized to constitute a hindrance to the movement of migrants, and thus adversely affects migration flows (Park et al., 2018; Backhaus et al., 2015). Overall, the gravity model of migration aims to clarify how different factors affect migration flows (Mátyás, 1998; Vanderkamp, 1977).

The factors that potentially affect migration and are the focus of our research are variations in the weather, and extreme weather disasters. Figure 1 is used to depict the association between climate change, disasters, and migration. Figure 1 focuses on highlighting how climate change and disasters may trigger mobility by affecting farm income at the origin. For example, the adverse impact on crop-productivity and reduction in farming income adversely affect living standards and prospects at the origin, when these are a consequence of disasters or extreme climatic variability (Mbaye, 2017; Do Yun and Waldorf, 2016). Other known push factors are social exclusion, poor amenities, political instability, and peer effects. On the other hand, the figure shows few important pull factors. These pull factors may also play a significant role in the migration-decisions of a household (Ebeke and Combes, 2013). One may argue that climate change and disasters might affect pull factors as well, but the evidence on this is limited.

Figure 1: Push and Pull Factors of Migration (with special reference to climate change induced or disasters related migration)



Source: Authors' own illustration

2.2 Empirical Evidence

Migration studies have focused mostly on international migration, with limited emphasis on intra-national (domestic) migration, largely because international migration data is more easily available. Internal migration, however, is a major challenge in low- and middle-income countries (IDMC, 2019; UNHCR, 2020). Previous studies considering environmental migration analysed mostly south-south migration where internal migration dominates, and international migration is mostly seen as a future threat (Beine et al., 2021). Few studies have also examined the limited voice of marginalised and trapped populations and consequently their inability to migrate, especially internationally (Nawrotzki and DeWaard, 2018; Noy, 2017). Few explored impact of sudden onset disaster shocks on migration (e.g., Suleri and Savage, 2007; Young et al., 2007), though the impact of gradual changes in the environment on migratory decisions has also been analysed (Oliveira and Pereda, 2020; Dallmann and Millock, 2017). Some of these studies have also emphasized the various difficulties in identifying the patterns of climate change-induced migration accurately in aggregate migration flow data (Muttarak, 2021; Cattaneo et al., 2019; Neumann and Hinderink, 2015; Kaczan and Meyer, 2020).

Previous studies exploring the linkages between climate variability and migration in the Indian context used three types of databases - the National Sample Survey Organization (NSSO, 2008 64th Round), the India Human Development Survey (IHDS), and the Census. The NSSO, 2008 and the IHDS collect data for a few representative samples specific to certain geographies. The present study is not limited to one specific geography and aims to consider the overall pattern of climate induced migration in India. Therefore, we use the Census. The Census provides information on the length, duration, reasons for migration and answers to other related questions. Viswanathan and Kumar (2015), for example, used the Census data, together with the identification of weather shocks on agriculture yields, to examine the impact on migration due to agricultural livelihood crises considering 15 Indian states. Similar observations were made by Dallmann and Millock (2017), a state level analysis using the Census and the Climatic Research Unit (CRU) data. A handful of other studies utilised survey data to understand the hot-spots of climate induced migration (for example, Bhagat, 2018). The inter-linkages between agricultural stress due to extreme events and migration, as a livelihood diversification strategy, has been analysed, mostly using primary surveys (Singh, 2019; Lohano, 2018; Neumann and Hilderink, 2015, Robalino et al., 2015; Kavi Kumar and Viswanathan, 2013).

Given this background, the current study aims to examine the relationship between climatic change, weather disasters and bilateral migration flows across Indian states. It is the first that uses disasters as an input in determining the linkages between climatic variations and inter-state migration in India. This substantially adds to the limited empirical literature that aims to measure climate and weather induced migration for low- and middle-income countries at the sub-national level.

3. Data and Methodology

3.1 Data

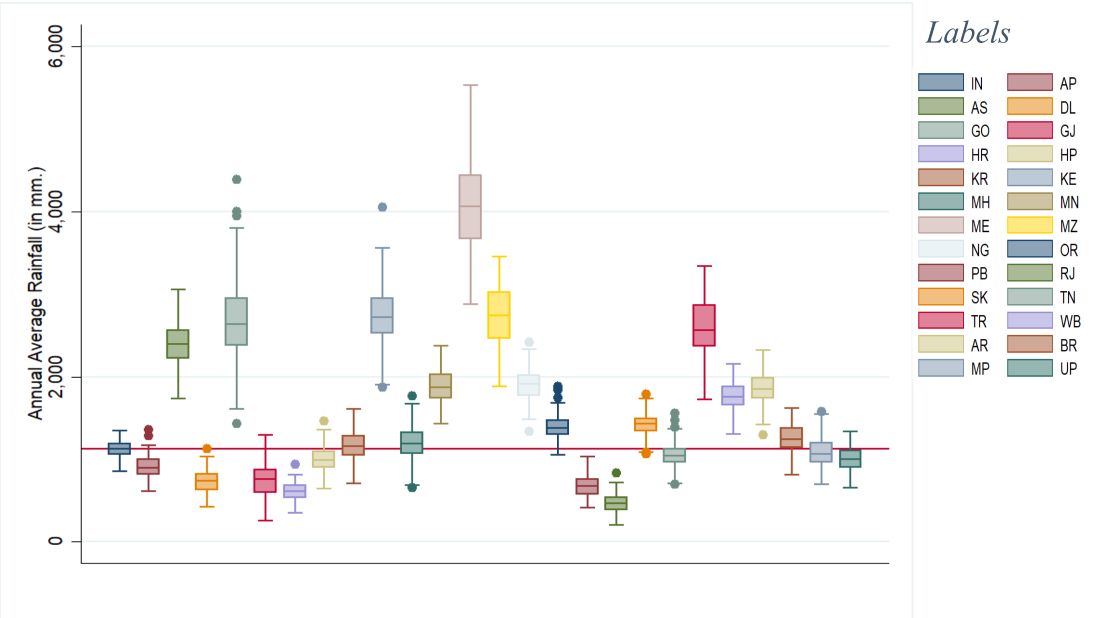
The study considers 25 Indian states (24 states and one union territory). Data for the states of Jharkhand, Uttarakhand and Chhattisgarh are merged with Bihar, Uttar Pradesh, and Madhya Pradesh, respectively, because prior to 2001 they were parts of these states. These states except Jammu and Kashmir (for which data is not available) constitute approximately 90 percent of the population of India. The Union Territory (UT) of Delhi is also included as it is an important centre of both internal in- and out-migration (Senapati, 2022; Keshri and Bhagat, 2012). Other UTs lacks data for some of the variables used here. Therefore, the final sample of the study includes 24 Indian states out of 25 states that existed in 1991 and one UT out of seven.

Our dependent variable is bilateral migration, collected from the Census of India. Bilateral data is useful to analyse important macroeconomic variables such as trade, migration, flow of financial assets, etc. (Beyer et al., 2022; Beine et al., 2016). Bilateral migration is defined as the flow of migration from origin to destination (Nejad and Young, 2014). The bilateral data has been compiled using the Indian Census of 1991, 2001 and 2011 for 25 by 25 pairs over three time periods. The final sample size is thus 1875 (there are no missing data for the migration flows). The bilateral migration data includes the total number of migrants originating from a state and living in another state: For less than one year, one to five years and five to ten years. Additional categories considered while compilation are: Rural to rural migration, rural to urban, and urban to urban.[2]

[2] The Census of India provides migration (both in migration and out migration) data based on four characteristics namely, place of birth, place of last residence, reason for migration and duration of stay since migration. A movement is considered as 'migration' if it involves change of residence from one village /town to another village / town). A detailed description of how the migration numbers were arrived at in the Census 2011 is available at: https://censusindia.gov.in/nada/index.php/catalog/42597/download/46244/Census%20of%20India%202011-Migration.pdf.

The explanatory (independent) variables included are based on a review of literature. These variables measure economic and social circumstances, are related to weather and disaster events and to the geography of each state. The economic and social variables include the difference in state product from agriculture, and manufacturing, between each bilateral pair, as well as differences in the Human Development Index, and the states' urbanization rates. Past studies have shown that migration due to climate variability takes place to nearby locations, so that the main geographic variable we include is a binary variable denoting whether there is a shared border between each bilateral pair (e.g., Mallik, 2023; Muttarak, 2021; Oliveira and Pereda, 2020). Coefficient of variations of temperature and rainfall are included as proxy measures of climate variability over each decade. Decadal variability is used to match it with the dependent variable of decadal bilateral migration flows.

Figure 2: Intra-state Rainfall Variability over 1901-2020

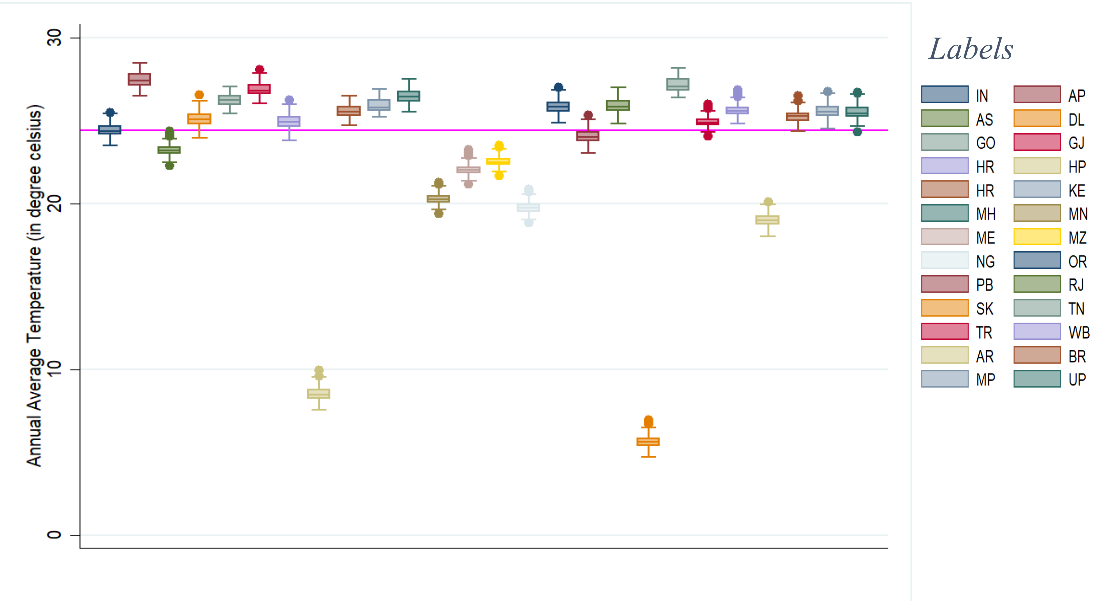


Source: Authors' own calculation using IMD GRID database. The state name label are: IN- India; AS-Assam; AP- Andhra Pradesh; DL- NCT Delhi; GO- Goa; GJ- Gujarat; HR- Haryana; HP- Himachal Pradesh; KR-Karnataka; KE- Kerala; MH- Maharashtra; MN- Manipur; ME- Meghalaya; MZ- Mizoram; NG- Nagaland; OR-Orissa; PB- Punjab; RJ- Rajasthan; SK-Sikkim; TN- Tamil Nadu; TR- Tripura; WB- West Bengal; AR- Arunachal Pradesh; BR- Bihar; MP- Madhya Pradesh; UP- Uttar Pradesh.

Figures 2 and 3 show intra-state rainfall and temperature variability. The coefficient of variation is calculated for both temperature and rainfall using data collected from the Indian Meteorological Department. The original daily observations correspond to high resolution $(0.25)^2$ degree grid cells. These have been collated to compute average annual temperature and rainfall across Indian states. The Coefficient of Variation of rainfall and temperature is then computed for each decade from the annual data. For example, coefficient of variation for rainfall for the period 1991 is the variation captured over the period 1981-1990. The decadal variation in temperature and rainfall captures the annual climatic variations that is hypothesized to have a more direct link with migration outcome, following Mallick (2023) and Hoffmann et al. (2020).

Figures 2 and 3 show that there is significant temperature and rainfall annual variation across states. Further, such variations could impact adaptation strategies at the sub-national level, as states are heterogeneous due to their exposure and vulnerability to disasters and extreme events (for example, Mbaye, 2017; Beine and Parsons, 2015; Black and Collyer, 2014 consider various combinations of actual anomalies and deviations of climatic indicators). Some studies find that climatic variability has a non-linear impact on mobility (Dallmann and Millock, 2017; Cai et al., 2016; Black et al., 2011). To capture this possible non-linearity of the climatic indicators, we also add square terms in our analysis. We also referred literature pertaining to non-linear estimators in gravity model such as Mnasri and Nechi (2021).

Figure 3: Intra-state Temperature Variability over 1901-2020



Source: Authors' own calculation using IMD GRID database

Data for extreme events are collected from India's Central Water Commission. A combination of both measures of climate variability and disasters has been utilised by Beine and Parson (2015) in their study on climate variability and international (global) migration over 1960-2010. To the best of our knowledge, both climatic changes and disasters together have not been used in any state-level analysis on migration (using correlation matrix in Table 3). The value of the correlation coefficients between them is always less than 0.50 (Table 3) ameliorating any concern about multi-collinearity. The development indicators included in the analysis are HDI and the state-level urbanization rate (Oliveira and Pereda, 2020; Dallmann and Millock, 2017). Table 1 lists the independent variables and Table 2 presents the summary statistics of these data.

Table 1 Description of Variables

Category of Variables	Variables	Symbol	Units	Description
Economic	Cross-State Difference of Gross Product from agriculture (AGSDP)	$logY_{ijt}^{A}$	Rs Million	Sum of value of products produced by the agricultural and allied sector plus any net product taxes (less subsidies) not added over a financial year. GSDP difference from agriculture between origin and destination. *Source: RBI Statistical Handbook*
	Cross-State Difference of Gross Product from industry (IGSDP)	$logY_{ijt}^{I}$	Rs Million	Sum of value of products produced by the industrial sector plus any net product taxes (less subsidies) not added in one financial year. The difference of GSDP of industry between origin and destination. *Source: RBI Statistical Handbook*
Demographic and Development	Cross-state Difference of Human Development Index	ΔHDI_{ijt}	Ratio	An index capturing of human development in a specified territory (state in this study). Difference of HDI between origin and destination is used. *Source: Global Data Lab*
	Cross-state Urbanisation differential	ΔU_{ijt}	%	Measures population living in an urban agglomeration in a state. The difference of level of urbanisation between origin and destination is used here. *Source: Census of India (1991-2011)*
Climatic	Coefficient of variation of temperature	T_{it}	%	Measure of high temperature, expressed in degrees Celsius. *Source : IMD (Pai et al., 2014), India*
	Coefficient of variation of rainfall	R_{it}	%	Measure of rainfall and expressed in centimetres *Source: IMD (Pai et al., 2014), India*
Disaster and Dummy Variables	10 Year Average Crop Damages at origin	$logCE_{it}^{C}$	Rs Million	Loss of crops due to climate-induced extreme events such as floods or drought; 10 years average. *Source: CWC (2020)*
	10 Year Average House Damages at origin	$logCE_{it}^{H}$	Rs Million	The value of houses damaged including both kutcha and pucca houses due to climate-induced extreme events; 10 years average. *Source: CWC (2020)*
	10 Year Average Loss of Lives at origin	$logCE_{it}^{L}$	Million	Mortality due to disaster; 10 years average. *Source: CWC (2020)*
	Common Border	BD_{ijt}	Binary	If origin shares borders with destination then value is 1, Otherwise 0

Table 2: Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
(Mig_{ijt})	56491.95	189288.06	0	2854297
R_{it}	14.582	5.274	0.739	32.422
T_{it}	1.522	1.235	0.515	7.355
R_{it}^2	240.428	181.508	0.546	1051.185
T_{it}^2	2.953	7.205	0.265	54.096
$logCE_{it}^L$	75.02	92.859	0	414
$logCE_{it}^H$	62281.293	100313.79	0	612813.06
$logCE_{it}^C$	3923.142	6300.54	0	32154
$logY_{ijt}^A$	-0.003	5.139	-17.054	17.054
$logY_{ijt}^I$	0.001	6.912	-30.235	30.235
ΔU_{ijt}	0	0.245	-0.875	0.875
ΔHDI_{ijt}	0	0.082	-0.229	0.229
BD_{ijt}	0.053	0.224	0	1

Source: 1875 observations for all variables. Authors' own computation.

3.2 Method of Estimation: A Gravity Approach using Poisson Pseudo Maximum Likelihood

The bilateral flows data are estimated using a gravity model. The traditional approach to estimate gravity equations is using a log-linearised specification estimated with Ordinary Least Square (OLS) (Silva and Tenreyaro, 2006). However, there are multiple zero observations in the migration bilateral flows, and potential heteroskedasticity, so OLS estimates may be inconsistent. Alternatives to OLS include PPML and Common Correlated Effects (CCE) (Beyer et al., 2022; Vavrek, 2018). The assumptions of CCE are too restrictive, as highlighted by Bertoli and Moroga (2013). As proposed by Silva and Tenreyaro (2006), the PPML is simpler and thus more commonly used in the recent literature.

The PPML model does not assume that the data have need to be characterised with a Poisson distribution (Beine et al., 2016). PPML has several advantages over OLS. First, the use of PPML removes the sample selection bias that is introduced when zero-value observations are dropped (Anderson, 2010). Second, it is consistent with fixed effects that permit the control of multilateral resistance occurring in the model. Multilateral resistance implies the effect of one pair on others apart from the independent variables (Beine et al., 2016; Bertoli and Moraga, 2013). The dependent variable is a linear term in the PPML but independent variables can be used in logarithmic form and therefore the PPML coefficients can be interpreted as semi-elasticity (Beine and Parsons, 2015).

Table 3 presents the correlation matrix of dependent and independent variables. There are no high correlation coefficients among the independent variables (except for the obvious correlation between the climatic variables and their respective quadratic terms). Descriptive statistics in Table 4 show that the bilateral migration outcome lies between 0 and 2.85 million. While looking at other factors such as urbanization and HDI, the statistics highlight that there is a large disparity, especially between Southern and Northern states (NITI, 2022). Similarly, disaster losses are also distributed disproportionately across states. In Bihar, Assam, Odisha, West Bengal, and Andhra Pradesh, such losses from disasters are very high as compared to states such as Punjab, Haryana, Karnataka – this is largely an East and West division.

Table 3: Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) Mig_{ijt}	1.000												
(2) R_{it}	0.055	1.000											
(3) T_{it}	0.064	0.002	1.000										
(4) $(R_{it})^2$	0.036	0.972	-0.030	1.000									
(5) $(T_{it})^2$	0.061	0.025	0.954	-0.048	1.000								
(6) $logCE_{it}^{C}$	0.078	-0.044	-0.119	-0.067	-0.098	1.000							
(7) $logCE_{it}^{H}$	0.134	-0.182	-0.184	-0.191	-0.143	0.502	1.000						
(8)$logCE_{it}^{L}$	0.288	-0.114	-0.227	-0.119	-0.171	0.397	0.613	1.000					
(9) $logY_{ijt}^{A}$	0.037	-0.197	0.204	-0.176	0.150	-0.024	-0.129	-0.214	1.000				
(10) $logY_{ijt}^{I}$	-0.075	-0.163	0.201	-0.135	0.166	-0.144	-0.307	-0.405	0.802	1.000			
(11) ΔU_{ijt}	0.145	-0.206	0.128	-0.235	0.119	0.093	0.116	0.101	0.139	-0.064	1.000		
(12) ΔHDI_{ijt}	0.129	-0.047	-0.077	-0.080	-0.066	0.124	0.283	0.243	-0.243	-0.484	0.600	1.000	
(13) BD_{ijt}	0.241	0.019	-0.049	0.025	-0.046	0.044	0.020	0.016	0.059	0.060	0.037	0.019	1.000

Source: Authors' own computation.

3.3 Empirical Specification

Following Beine and Parsons (2015) we estimate the equation,

$$Mig_{ijt} = \beta_0 + \beta_1 R_{it} + \beta_2 T_{it} + \beta_3 R_{it}^2 + \beta_4 T_{it}^2 + \beta_5 logCE_{it}^C + \beta_6 logCE_{it}^H + \beta_7 logCE_{it}^L + \beta_8 logY_{ijt}^A + \beta_9 logY_{ijt}^I + \beta_{10}\Delta U_{ijt} + \beta_{11}\Delta HDI_{ijt} + \beta_{12} BD_{ijt} + \alpha_{ij} + \gamma_t + \epsilon_{ijt} \quad \ldots\ldots (1)$$

The dependent variable is bilateral migration (Mig_{ij}). Mig_{ijt} is the migration inflows in the previous decade from state i to state j as measured in year t. Logarithmic transformations are not used because there are no flows between a few bilateral pairs. An alternative to overcome this issue is to add one to each observation.

The independent variables (except for ratios and percentages) are in natural logarithm (Beine and Parsons, 2015). Few variables are expressed as ratios and their logarithm is not considered because such transformation would lead to inclusion of imaginary numbers in the econometric specification (Ramos and Suriñach, 2016; Greene, 2011).

R_{it} is the coefficient of variation of rainfall estimated for a period of 10 years to capture the inter-annual weather variations. Similarly T_{it} is the coefficient of variation of temperature over a decade to include the inter-annual temperature fluctuations. R_{it}^2 and T_{it}^2 are included to capture the non-linear impacts of climatic variations. Disaster damages are included, referring to data on disaster induced losses in terms of lives lost, house damages, and crop damages.

Given the focus on environmental factors (climatic variability and disasters), the study uses a parsimonious specification for observable controls as discussed in the data section. Y_{ijt}^A is the difference in GSDP from agriculture sector between each pair of states. Y_{ijt}^I measures the same for the industrial sector, as these two sectors are the most sensitive to climatic variations. Variable ΔU_{ijt} is the urbanization rate difference. ΔHDI_{ijt} is the difference between origin and destination level of human development. BD_{ijt} captures whether the origin and destination states are contiguous. The contiguity measure can capture both distance and language-cultural differences across origin and destination and provides a better control than the geographical distance measure (Backhaus et al., 2015; Nejad and Young, 2014). α_{ij} captures the state-pair characteristics while γ_t captures the temporal external shocks to states; ϵ_{ijt} is the error-term in the model.

4. Results and Discussion

Our variables of interest are climate variability and extreme weather disasters. We hypothesize that both may act as push factors for migration. The estimation results are presented in table 4 in columns 1-4. Model 1 is estimated using PPML with only the climate variability variables. Results show that both temperature (T_i) and rainfall (R_i) variability are statistically significant in explaining the bilateral migration flows between Indian states. Maybe unsurprisingly, in both cases the quadratic term is negative. This suggests a non-linear convex relationship in which at some point, additional increases in temperature and rainfall variability will no longer increase migration flows.

In Model 2, we introduce the three variables measuring the impacts of disaster events (losses). The results for disaster variables (crop losses, homestead losses, and human-lives lost) are shown to have significant and positive push impact on bilateral migration flows. In model 3 and 4, we add more controls to the estimated specifications to reduce the possibility of missing variable biases – model 3 is estimated with economic variables, while model 4 also added the social and geographic indicators. Most importantly, the inclusion of these additional controls does not change the estimated results for the climate variability and the disaster impact measures.

The agriculture production measure shows a significant and positive result with migration flows from origin to destination, whereas the industry GSDP shows a significant negative relationship with migration flows. This implies that each state's structure of production between the primary and secondary sectors is important in determining out-migration. In particular, high dependence on agriculture leads to more emigration, and the opposite is true for manufacturing.[3] Model 4 reveals that higher urbanisation in the destination state attracts migration (e.g., Combes et al., 2020; Tumbe, 2018; Dutta, 2016; Keshri and Bhagat, 2012). The HDI is negatively related to migration flows, implying that states with lower human development are more likely to have people choosing to migrate to where human development is higher. As expected, the coefficient for the contiguous border indicator variable is positive and significant (Chowdhury et al., 2022; and Chen and Mueller, 2018). For both model 3 and

[3] Possible explanations include the reliance on rain-dependent agriculture coupled with low capacity to irrigate when rainfall is scarce may lead to failure of crops that often force people to migrate (Cattaneo et al., 2019; Barve et al., 2019; Berlemann and Steinhardt, 2017).

4, the Ramsey reset (1969) specification test does not reject the null hypothesis of a correctly specified model.

Table 4: Results of PPML Models (1-4)

Independent variable	*Model 1*	*Model 2*	*Model 3*	*Model 4*
$\boldsymbol{R_i}$	0.268** (0.119)	0.287** (0.115)	0.259** (0.132)	0.266** (0.117)
$\boldsymbol{T_i}$	2.682*** (0.935)	2.701*** (0.963)	2.712*** (0.912)	2.521*** (0.942)
$(\boldsymbol{R_i})^2$	-0.003* (0.002)	-0.028* (0.002)	-0.004* (0.002)	-0.006* (0.003)
$(\boldsymbol{T_i})^2$	-0.791** (0.307)	-0.685** (0.375)	-0.826** (0.427)	-0.937*** (0.361)
$\boldsymbol{logCE_i^C}$		0.215** (0.097)	0.196** (0.089)	0.208** (0.087)
$\boldsymbol{logCE_i^H}$		0.096** (0.065)	0.094** (0.063)	0.102** (0.058)
$\boldsymbol{logCE_i^L}$		0.693*** (0.096)	0.721*** (0.098)	0.709*** (0.091)
$\boldsymbol{logY_{i,j}^A}$			0.05*** (0.038)	0.06*** (0.022)
$\boldsymbol{logY_{i,j}^I}$			-0.072*** (0.024)	-0.069*** (0.025)
$\boldsymbol{\Delta U_{i,j}}$				2.161*** (0.44)
$\boldsymbol{\Delta HDI_{i,j}}$				-3.138*** (1.174)
$\boldsymbol{BD_{i,j}}$				1.542*** (0.145)
Constant	-10.278*** (1.205)	-10.379*** (1.211)	-8.390*** (0.996)	-8.334*** (1.168)
Pseudo $\boldsymbol{R^2}$	0.1805	0.3482	0.3965	0.5752
Goodness of fit (χ^2)	182.539	202.292	310.520	327.390
Prob > (χ^2)	0.000	0.000	0.000	0.000
Akaike crit. (AIC)	3502.301	3105.102	3432.175	3339.407
Bayesian crit. (BIC)	3947.296	3502.821	3548.137	3414.251
Ramsey Reset (χ^2)	15.30	14.03	6.16	1.93
Prob > (χ^2)	0.0045	0.0125	0.0574	0.0625
N	1875	1875	1875	1875

Source: Authors' own calculation.
Note: All columns include state-pair and year fixed effects. *** *p<.01,* ** *p<.05,* * *p<.1*

Impact of Rainfall Variability on Migration

The rainfall variability (measured using the coefficient of variation) in the origin state is positively related to migration flows from origin to destination at five percent level of significance for all models, and the size of the coefficient is quite similar across specifications.

The results show that a variation in rainfall, which may affect (especially agricultural) livelihoods dependent on rainfall at the place of origin, is a robust determinant of migration (e.g., Bernzen et al., 2019; Chen and Mueller, 2018). The coefficients are expressed in semi-elasticities. For example, in model 4, one unit increase in rainfall variability causes 2.66 (0.266*100) percent increase in migration flows. The actual estimate on bilateral migration flows due to rainfall variability are 1502.68 for each pair. Correspondingly, for 25 states, it would be about 376 thousand people. The coefficient of square term of rainfall variability shows a negative significant relationship in the model, implying that as variability increases, its impact as a push factor for migration becomes less pronounced.

Impact of Temperature Variability on Migration

As was the case with rainfall, temperature variability also shows a consistently significant and positive association with migration flows across all the estimated models. Further, it has a larger impact than rainfall variability on migration flows in the specified models. The estimate for bilateral migration is 2.52*56491.95 equals to 142360 for each pair. The total estimates for 25 states are thus 2.559 million people. Past studies with similar observations in very different contexts include Oliveira and Pereda (2020), Dallmann and Millock (2017), and Beine and Parsons (2015). Again, the coefficient of the square of temperature variability is negative and significant in the models implying a non-linear relationship with migration. As with rainfall, this also highlights that high and low temperature variations lower migration. Extremely high climatic variations could affect the livelihood and wealth of the people at the origin and can disrupt the potential affordability to migrate (Berlemann and Tran, 2020; Luetz, 2018). It is tautological as to why low variations may not promote migration.

Impact of Disasters on Migration

Disasters (measured using flood induced damages) show a positive association with migration flows – more damages imply higher flows of out migration. Due to data availability constraints, three types of losses (crop-losses, homestead losses, and mortality) are considered. Floods are only one type of natural hazard that may lead to disasters, and thus to migration, but there is no available data on other hazards. The coefficients in our estimates can be interpreted as elasticities.

5. Conclusion

The study's focus is on three related findings. First, ceteris paribus, there is a significant relationship between climate variability (for rainfall and temperature) in the origin states and inter-state migration in India. Higher variability in the source state implies more out-migration. Second, losses due to disasters (in terms of lives and livelihood losses) are also associated with migration, implying the future increase in the frequency and/or intensity of disasters could potentially lead to more cross-state migration in India. Third, the problem of out-migration is more severe in states dependent on agriculture except Punjab and Haryana where irrigation infrastructure is better compared to other states, incomes are higher, and disaster frequency is limited. It is important to note that this study does not investigate the role of irrigation infrastructure and its implication for the agriculture sectors because of data constraints (Barve et al., 2019; Viswanathan and Kumar, 2015).

Increase in temperature and rainfall variability show a positive significant impact on migration flows. A one percent variation in average temperature over a decade causes 25.2 percent increase in bilateral migration flows. The findings are robust and corroborate existing literature that temperature variability is of a great concern and could lead to very significant impacts. One of the channels could be migration. Our analysis here shows that dependence on the primary sector and low level of human development results in more out migration from affected states.

This study, however, does not examine the underlying micro-processes that trigger the migration decision of individual households. These should be explored using micro-level data at household level, rather than using the state-level aggregate data as analysed here. Ultimately after all, migration decisions are undertaken at that household level.

Finally, we note that our analysis does not imply that this migration should be discouraged, or indeed that migration is necessarily harmful. Indeed, migration probably generates many benefits, and better micro-data may help identify in-depth arguments about the positive and negative consequences of disasters- and climate-induced migration. Ultimately, if migration were overwhelmingly positive, we would have seen it occurring similarly even without these climatic variations and extreme shocks. The fact that we do not, and that these events increase migration flows suggests that the current status quo is not optimal, and such research effort may be able to identify possible interventions, including climate mitigation and adaptation, that can improve Indian households' prosperity and wellbeing.

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