Hedging against climate risks: long-term vs circular migration in rural India

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Abstract

A growing body of research on climate change and migration focuses on district- or state-level analysis, neglecting household-level experiences. This paper addresses this gap by using longitudinal household-level data from the Indian Human Development Survey (2011-12 and 2022-24) to examine how climate shocks influence rural male migration decisions and how the demographic patterns of long-term migration differ from those of short-term circular migration. The results of the logistic regression indicate that while extreme heat increases the likelihood of long-term migration by 2 percentage points, dry rainfall anomalies decrease the likelihood of long-term migration by 1.4 percentage points. This is further moderated for farm households with access to irrigation facilities. In contrast, short-term circular migration patterns are more driven by drought and tend to be a dominant coping strategy among landless households. These findings underscore the crucial role of both climate variability and rural livelihood structures in shaping migration decisions, highlighting the need for targeted policies that improve resilience to climate change.

Keywords: Internal migration, Climate variability, Climate anomalies, Rural India

JEL Classification: J61, O15, Q54

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1 Introduction

Climate change is becoming an increasingly significant driver of migration, particularly in countries like India, where agriculture forms the backbone of rural livelihoods. With around 44 percent of the Indian population reliant on agriculture for income and sustenance in 2023 (ILO Modelled Estimates database), erratic weather patterns pose severe challenges to household stability. Climate anomalies such as unpredictable rainfall and rising temperatures have already begun to reshape migration patterns, forcing many agricultural households to seek alternative livelihoods. According to recent estimates, India saw over 450 million internal migrants in 2020 (Economic survey, 2017-18), a number that continues to rise as environmental pressures intensify. These migrations are not uniform; they are often triggered by climate-induced agricultural failures, particularly in rain-fed regions that lack access to reliable water sources.

The relationship between climate shocks and migration is multifaceted (Mueller et al. 2014; Mishra et al. 2014; Mastrorillo et al. 2016; Missirrian & Schlenker 2017). On the one hand, households experiencing severe climate stress may view migration as a survival strategy, an immediate response to crop failure or income loss. On the other hand, migration can also reflect longer-term decisions aimed at diversifying income sources and reducing dependence on increasingly volatile agricultural production. However, migration is not the only adaptive response available to households. The ability to cope with and adapt to climate shocks often hinges on access to local resources and infrastructure, such as irrigation. The question, therefore, is not just whether households will migrate in response to climate change, but how local adaptation mechanisms, particularly irrigation, can moderate this decision.

In 2011, approximately 53.8 percent of India's total internal migration was rural-to-rural, largely driven by agricultural livelihoods (Singh & Biradar 2022). However, climate change has begun to alter this pattern, with more households migrating from rural to urban areas in search of stable income sources as agricultural productivity declines. Data from the Indian Human Development Survey (IHDS) show that migration is not only increasing in frequency but also changing in nature, with a significant portion of migrants being younger, working-age individuals, which could lead to demographic shifts in rural communities. These trends underline the importance of local adaptation measures, like irrigation, which can stabilize agricultural production and reduce the need for outmigration.

India's agriculture is heavily dependent on the monsoon, with about 55 percent of farmland lacking irrigation facilities, leaving a large portion of the rural population vulnerable to rainfall variability

(Kumar et al. 2004; Deshpande 2022). Irrigation infrastructure can significantly buffer the impact of climate shocks by ensuring a steady water supply during periods of drought or erratic rainfall.

The existing literature has extensively examined the relationship between climate change or weather and migration across various dimensions [1]. For example, studies by Dillon et al. 2011; Gray & Mueller 2012a, 2012b, and Thiede & Gray 2017 identify heterogeneous effects based on gender, while research by Beine & Parsons 2014; Gray & Mueller 2012b; Groschl & Steinwachs 2017, and Mastrorillo et al. 2016 highlight varying effects linked to different wealth levels. Similarly, Baez et al. 2017 and Mastrorillo et al. 2016 demonstrate differing migration patterns across age groups. Additionally, some literature suggests that migration may not always serve as a successful coping mechanism. Policymakers have proposed alternative strategies, such as shifting from farm to non-farm livelihoods, to enhance adaptive capacities and reduce the need for migration (Sreekumar et al. 2024; Nandy et al. 2017; Imai et al. 2017; Guang & Zheng 2005). Despite these studies, there remains a limited understanding of how persistent climate change impacts migration among Indian households and how irrigation influences climate-induced migration. This study seeks to bridge this gap and contributes to the literature in several key ways.

First, much of the existing research has focused on aggregated district- or state-level analyses, often neglecting the diversity in household experiences. By leveraging household-level data from the most recent wave of the IHDS-3 (2022-24) alongside IHDS-2 (2011-12), this study offers a more granular perspective on the relationship between climate change and rural male migration. This approach allows us to capture how climate change impacts migration decisions at the household level, where factors such as resource access, livelihood structure, education, and family composition play critical roles.

Second, our climate variables are drawn from highly disaggregated data provided by the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), which allows us to examine the effect of variability in climate patterns on migration decisions. Our analysis captures not only the occurrence of positive or negative climate shocks but also the varying intensities of these shocks. For example, in the case of droughts, we differentiate between moderately dry and extremely dry conditions, recognizing that the empirical and intuitive impacts on migration of these variations can be vastly different.

Furthermore, as India continues to grapple with the twin challenges of climate change and migration, this research provides valuable insights for policymakers. We provide empirical evidence on

[1] Table A1 in the appendix summarizes the findings of existing related literature.

how the type of households (farm/business/landless-agricultural wage/non-agricultural wage laborer), along with the spending on irrigation, can play an effective and moderating role in mitigating migration, specifically. This focus is crucial for policymakers aiming to enhance resilience, as it highlights the need for targeted investments that benefit landowning households more effectively. For instance, investments in irrigation infrastructure, particularly in vulnerable regions, could play a critical role in reducing forced migration and stabilizing agricultural incomes.

The logistic regression results reveal that wet rainfall anomalies significantly reduce the likelihood of long-term migration by 3.4 percentage points, likely due to improved agricultural productivity as compared to normal rainfall conditions. In contrast, very hot conditions lead to an increase in probability of long- term migration by 2.2 percentage points, suggesting extreme heat as a key driver of outmigration. Additionally, irrigation access plays a crucial role in mitigating migration, with households owning irrigation assets less likely to migrate. Socioeconomic factors like wealth, education, caste, and the type of household also significantly shape migration decisions, highlighting the complex interactions between climate stressors and household characteristics.

The next section outlines the main channels (models) through which climate change can lead to migration and the hypotheses of this study. Following that, we discuss the data variables, sources, and construction of key variables, and present descriptive statistics in Section 3. Section 4 details the empirical methodology employed in the study, after which we present the results, followed by a discussion.

2 Migration models and key hypotheses

Early models of migration, such as the neo-classical economic models relied on rural-urban wage differential as the key driver for migration (Todaro, 1969; Harris and Todaro 1970). The New Economics of Labor Migration (NELM), on the other hand, considered the household as the decision unit, with the decision to migrate collectively taken by members of the household as insurance against rural risk, with an effort to maximize expected earnings and reduce food insecurity (Lucas and Stark, 1985; Stark & Bloom, 1985). The proponents of NELM argued that rural areas in developing countries continue to heavily depend on agriculture and allied activities for their livelihoods, and are largely subject to market failures such as inadequate access to formal credit, capital, or insurance markets, etc. To mitigate against such risk, one or more household members migrate to urban areas as a livelihood diversification strategy (Taylor & López-Feldman 2010).

Several studies have also explored migration linked to climate-induced factors, rainfall and temperature shocks, and how these adversely affect rural livelihoods that continue to be dominated by agricultural or resource-based livelihoods (Eakin 2005, Hunter 2018). In the absence of insurance markets, rural households may allocate some or part of their labor supply towards migration into urban areas in response to environmental stress, as part of their household risk diversification strategies, consistent with the NELM model (Dillon et al. 2011, Joarder and Miller (2013)).

Research on climate-induced internal migration in India is scant and is restricted to a handful of states (Morten, 2013; Pradhan & Narayanan, 2022). To the best of our knowledge, ours is the first study to use a nationally representative sample to examine climate risks and migration likelihood as a household diversification strategy. More specifically, we test the following **key hypotheses**:

1. *Hypothesis H1*: Climate shocks are likely to lead to migration among Indian households and varying intensities of climate shocks can affect migration decisions differently. Heat and rainfall shocks influence migration decisions in distinct ways.

2. *Hypothesis H2*: Poorer, less educated, and resource-constrained (for example, landless) households are more likely to resort to short-term circular migration as a survival strategy in response to climate risks, migrating during periods of climate stress, and returning to rural markets when climate stress eases.

3. *Hypothesis H3*: Long-term migration is more likely to be a strategy of upward mobility for educated households, who may move to urban areas that provide access to jobs with higher returns to skilled labor.

4. *Hypothesis H4*: Access to irrigation infrastructure, having farms and business decreases the likelihood of long-term migration, as these facilities have the potential to improve climate-resilience and weather-proof agricultural productivity.

3 Data, variables, and summary statistics

3.1 Migration data

We source our migration data from the two waves of the India Human Development Survey (IHDS), conducted in 2011-12 and 2022-24. IHDS-2 interviewed a nationally representative sample of 42,152 households[2] , including 204,569 individuals. For IHDS-3, the re-contact rate is 94% of the original households surveyed in 2011-12, along with households that had split from the originals but remained within the same locality. The re-contact rate is higher at 98% in rural areas. The sample covers 34 states and union territories, and includes households from 972 urban blocks and 1503 villages across 406 districts in India[3]. The IHDS is jointly conducted by the University of Maryland and the National Council of Applied Economic Research in New Delhi. The IHDS dataset offers a rich source of migration data compared to other sources like the Census of India or NSSO surveys, which primarily provide basic statistics such as migrant counts and broad reasons for migration. In contrast, IHDS offers detailed, household-level information on socio-economic factors, agricultural practices, employment, and household composition, all of which are critical for understanding migration decisions. In particular, IHDS-3 enhances the migration data with a dedicated migrant questionnaire, collecting specific reasons for short-term circular migration along with individual and household characteristics such as education and income levels. The survey also tracks migrants longitudinally, following changes in their location,employment, and socio-economic status over time. This comprehensive dataset allows for deeper analysis of how climate shocks, economic stressors, and access to resources like irrigation influence migration, making IHDS an ideal source for examining the multi-dimensional drivers of migration, especially in the context of climate change.

3.2 Climate data

We utilize district-level monthly weather data obtained from the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), which includes key variables such as rainfall, minimum and maximum temperatures at the monthly level[4]. The data set spans the period from January 1, 1958, to December 31, 2023, and covers 602 districts. It is derived from highly granular spatial datasets developed by the Climatology Laboratory, commonly known as TerraClimate.[5] We integrate this weather data for rainfall and mean temperature[6] with the India Human Development Survey (IHDS)

[2]Re-interviewed approximately 83% of the original households that were initially surveyed in the first wave of the IHDS, that is IHDS-1

[3]We exclude all observations related to households (and individuals) that were not part of IHDS-2. Additionally, we drop households (and individuals) where information is incomplete due to unfinished interviews for any reason.

[4]Additionally, it also has data on actual evapotranspiration, potential evapotranspiration, and other relevant indicators

[5]http://www.climatologylab.org/terraclimate.html

[6]We construct district-specific monthly mean temperatures by taking the simple average of the corresponding monthly minimum and maximum temperatures.

dataset, focusing on 405 districts.[7] To ensure consistency, we manually verified and reconciled the district names to account for administrative boundary changes and variations in nomenclature over time.

Figure 1 and Figure 2 illustrate the trends in annual rainfall (mm)and mean temperature (°C)[8] for approximately four decades, from 1982 to 2023. The rainfall pattern exhibits significant year-to-year variability, reflecting its erratic nature, with the fitted trend line indicating a slight increase over time. Similarly, in the early part of the dataset (1980s), temperatures fluctuate around 25°C, but in later years, particularly after 2000, there are more extreme temperature peaks, with values occasionally exceeding 25°C. Despite these annual fluctuations, the fitted line suggests a long-term warming trend in temperature.

Figure 1: Trends in annual rainfall (mm), 1982-2023

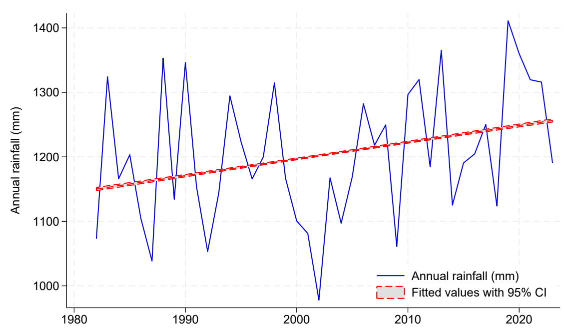
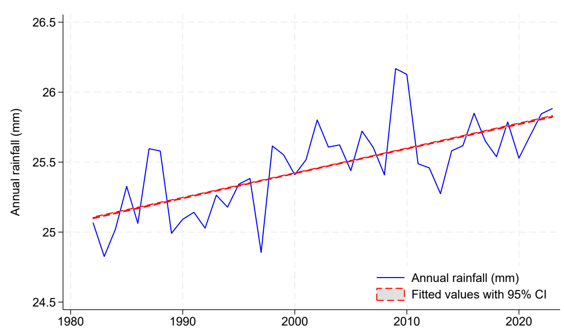


Figure 2: Trends in annual mean temperature (°C), 1982-2023



[7]Districts from Jammu & Kashmir, Sikkim, and Union Territories are excluded from our analysis due to the unavailability of corresponding climate data.

[8]We calculate district-specific annual rainfall and temperature as the sum of monthly rainfall values and the average of monthly mean temperatures, respectively, for each district over the year.

3.3 Key measures of migration, climate change and summary statistics

3.3.1 Migration variables

We use two measures of migration: (a) long-term migration and (b) short-term return or circular migration.

(a) The dependent variable, long-term migration, was measured using a tracking instrument that monitored the location of each household member from the 2011-12 survey during the 2022-24 interview period. For each individual from round 2, we gathered information on their current whereabouts during the IHDS round 3 interview. For migrants, proxy information about their current location was obtained from household members still residing at the original location or from neighbors.

(b) For individuals still living in the household, respondents were asked, "Have you or any member of your household left to find seasonal/short-term work in the last five years and return to live here?", forming the basis for measuring return or short-term circular migration.

By combining these two sets of questions with pre-migration information from IHDS round 2, we construct a more complete picture of migration patterns from rural India. However, circular (or return) migration is slightly underestimated since it is based on a five-year reference period, unlike long-term migration, which spans nearly seven years.

We measure migration among rural male individuals aged 15 and older[9]. Migration from urban areas, including migration across different urban centers is often driven by a different set of factors, such as economic opportunities, infrastructure development, and social mobility, which can dilute the specific role of climate change as a driver. Therefore, in this analysis, we focus on rural migration that can provide clearer insights into the direct impact of climate change on vulnerable populations.

3.3.2 Control variables

We control for an array of individual and household characteristics using 2011-12 data from IHDS-2. By using characteristics from the earlier round (IHDS-2), we capture the pre-existing conditions before migration decisions were made. Migration decisions are influenced by the household's and individual's situation before the migration occurs. This helps establish a clearer timeline of cause and effect, ensuring that characteristics we are controlling for precede the migration event, reducing the risk of reverse causality.

[9]This is because this age group is typically more mobile and plays a crucial role in labor markets, socioeconomic dynamics, and household decision-making

Our control variables include (a) individual-level characteristics, such as male age in years and years of completed education, (b) household-level indicators, such as various socio-economic factors such as caste and religious groups, household wealth measured by number of durable assets held, land size, livelihood structure (whether the household is engaged in farming or business or whether members are engaged as landless agricultural wage laborers or non-agricultural wage laborers[10]), and (c) village-level indicator such as distance to the nearest town. For farm households, we also create a binary variable based on the availability of irrigation inputs, including ownership of tube wells, electric pumps, diesel pumps, drip irrigation, and sprinkler systems.

3.3.3 Descriptive Statistics

Table 1 highlights significant variations in migration patterns among rural males based on education, social groups, assets, land ownership, and proximity to infrastructure, respectively. Education plays a significant role in migration patterns. The data show that the proportion of long-term migrants increases with education peaking at the "Class 12 & some college" level, where 19.85% are long-term migrants, although there is a very small dip for those with a college degree. Quite intuitively, higher levels of educational attainment are correlated with low circular migration.

Migration patterns vary across caste and religion. Forward castes and OBCs tend to have higher proportions of long-term migrants (13.37% and 12.49%, respectively), while Dalits and Muslims have higher share of circular migrants (7.40% and 10.65%, respectively). This could indicate that migration for Dalits and Muslims may be a more temporary coping mechanism, acting as insurance against variability in rural income, and they return to rural areas. Among religious groups, Christians, Sikhs, and Jains show a higher proportion of long-term migrants (11.36%) and the lowest share of circular migrants (1.06%).

The data indicate that migration rates decrease as household asset ownership increases. Households with more assets are more likely to remain non-migrant. For example, the richest asset quintile has the highest proportion of non-migrants (85.49%), while the poorest quintile has the highest share of return migrants (9.85%), highlighting the economic pressures faced by asset-poor households, which may lead to temporary migration.

Land ownership provides a stable livelihood in rural areas, reducing the need for migration, while landless households are more vulnerable and may resort to migration. Proximity to towns and trans-

[10]We consider non-labor income as the omitted category.

portation facilities impacts migration. Households located closer to towns (less than 5 km) have slightly lower proportions of non-migrants (81.75%), while those further away (21- 30 km) see an increase in circular migration (7.38%).

Farm households have a higher proportion of non-migrants (85.27%) compared to non-farm households (80.89%), reflecting the stability of agricultural livelihoods for some. Business households also exhibit a high proportion of non-migrants (84.34%). However, landless households have a higher share of circular migrants (9.13%), indicating that in the absence of land, households may resort to temporary migration as a diversification strategy to insure their sources of income.

Table 1: 2011-12 Status of Household Members Interviewed for IHDS-III (2022-23) - Rural Males

Characteristics	**Non-migrant**	**Long-term migrant**	**Circular migrant**	**Total**
Level of education completed				
No education	87.91	5.96	6.12	100
1-4 std	85.36	8.74	5.91	100
5-9 std	80.55	12.88	6.57	100
10-11 std	79.75	16.02	4.23	100
Class 12 & some college	76.49	19.85	3.66	100
College graduate & above	78.55	19.15	2.31	100
Social groups: Caste and religion				
Forward caste	84.06	13.37	2.58	100
OBC	82.80	12.49	4.71	100
Dalit	80.82	11.78	7.40	100
Adivasi	81.92	11.39	6.69	100
Muslim	77.51	11.84	10.65	100
Christian/Sikh/Jain	87.58	11.36	1.06	100
Assets quintiles				
Poorest	77.59	12.57	9.85	100
2nd quintile	78.11	12.88	9.01	100
Middle quintile	82.35	12.08	5.57	100
4th quintile	85.45	11.20	3.35	100
Richest	85.89	13.73	1.38	100
Distance to nearest town (in km)				
Less than 5 km	81.75	13.04	5.21	100
6-10 km	82.92	12.01	5.08	100
11-20 km	82.56	11.87	5.57	100

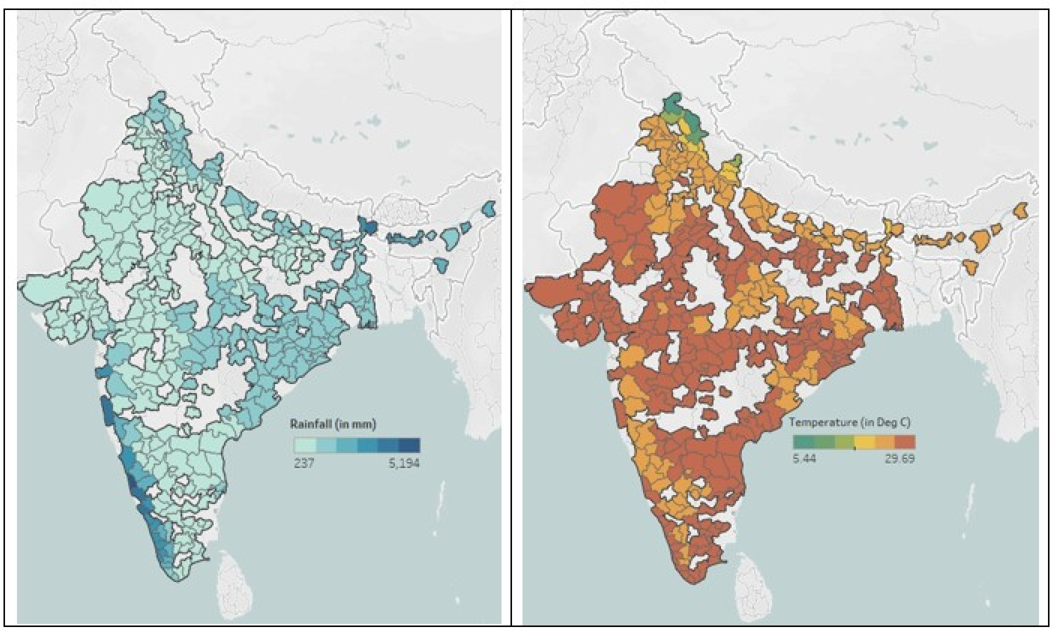
Characteristics	Non-migrant	Long-term migrant	Return migrant	Total
21-30 km	79.34	13.27	7.38	100
More than 30 km	82.18	12.18	5.64	100
Farm, business, landless households				
Farm households	85.27	10.35	4.38	100
Non-farm household	80.89	13.09	6.02	100
Business households	84.34	11.61	4.06	100
Non-business households	81.92	12.37	5.70	100
Landless households	77.01	13.86	9.13	100
Land owning households	82.30	12.26	5.45	100
Irrigation assets				
Farm households owning irrigation assets	83.92	10.60	5.48	100
Farm households not owning any irrigation assets	79.51	12.47	8.02	100
All India	82.15	12.30	5.55	100
Sample size	35,752	5,353	2,414	43,519

3.3.4 Climate anomalies

Mendelsohn (2009, 2014) has used actual precipitation and temperature values or their averages. On the other hand, several other studies (Taraz 2018, Costa et al. 2022) capture climate change by parameterizing climate variables. They often represent temperature through cumulative heat exposure or categorize it into bins based on cooling degree days, growing degree days (GDDs), and killing degree days (KDDs).[11]

In contrast, we capture climate change using anomalies (Sedova and Kalkuhl 2020, Zaveri et al. 2020) rather than actual values. This offers the advantage of understanding long-term climate trends and facilitates meaningful comparisons across regions and periods. Anomalies indicate deviations from long-term averages, known as 'climate normal'. Following the methodology of the Indian Meteorological Department (IMD), we calculate rainfall and temperature anomalies as the deviation from district-specific long-period averages (LPA), which are based on the first thirty years (1982–2012) of our climate data spanning 1982-2023. These anomalies are then standardized by dividing the absolute deviations by the district- specific standard deviations for the same period.

Figure 3: Normal rainfall (mm) and temperature (°C), 1982-2012



Note: These are the district-specific mean of average rainfall and temperature over time 1982-2012. Here, we include districts on which we have migration data from IHDS.

[11] GDDs and KDDs measure the cumulative heat exposure that crops experience during the growing season. They represent the sum of all daily average temperatures above a certain threshold throughout that season (PennState Extension).

Given India's vast agro-climatic diversity, there are significant variations in long-period averages across districts in our dataset. For instance, as shown in Figure 3 (left panel), the long-period average annual rainfall ranges from 275 mm in Bikaner, Rajasthan, to over 5000 mm in Udupi, Karnataka. Similarly, the long-period average annual temperature varies from 5.4°C in Kullu, Himachal Pradesh, to 29.69°C in Thoothukkudi, Tamil Nadu, as illustrated in the right panel of Figure 3.

3.3.5 Climate anomalies

If Ω_{it} is the rainfall in district i and time period t, $\bar{\Omega}_i$ and σ_{Ω_i}. are the 30-year averages and standard deviations of rainfall for district i, then rainfall anomaly (R_{it}) is defined as:

$$R_{it} = \frac{\Omega_{it} - \bar{\Omega}_i}{\sigma_{\Omega_i}}$$

Similarly, if ϕ_{it} is the temperature in district i and time period t, $\bar{\phi}_i$ and σ_{ϕ_i} are the 30-year averages and standard deviations of temperature for district i, then temperature anomaly (T_{it}) is defined as:

$$T_{it} = \frac{\phi_{it} - \bar{\phi}_i}{\sigma_{\phi_i}}$$

To analyze the impact of climate change on long-term and circular migration between 2011–12 and 2022, we adopt the following approach to measure climate variations over time:

Migration decisions are often influenced by persistent climate trends rather than short-term fluctuations. To capture this, we compute the district-level average rainfall and temperature anomalies over ten years (2013–2023). This method smooths out yearly variations and reflects sustained climatic deviations that may push households to migrate, therefore, here, we calculate the average rainfall (RA_i) and temperature anomalies (TA_i) for each district i as follows:

$$RA_i = \frac{1}{10} \sum_{t=2013}^{2023} \frac{\Omega_{it} - \bar{\Omega}_i}{\sigma_{\Omega_i}}$$

$$TA_i = \frac{1}{10} \sum_{t=2013}^{2023} \frac{\phi_{it} - \bar{\phi}_i}{\sigma_{\phi_i}}$$

Furthermore, to capture varying intensities of shocks, we classify rainfall (temperature) anomalies into different categories based on the percentile distribution[12] of the absolute (average) standardized

[12] Very dry (Very cold): Below the 5th percentile; Dry (Cold): Between the 5th and 25th percentiles; Normal rainfall

anomalies as follows (Figure 4 and Figure 5):

Figure 4: Distribution of rainfall anomalies

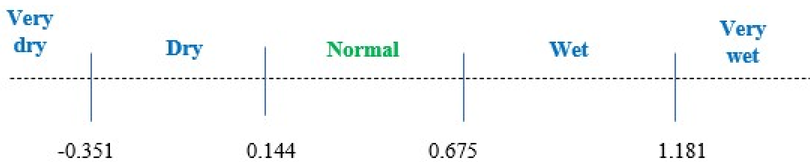
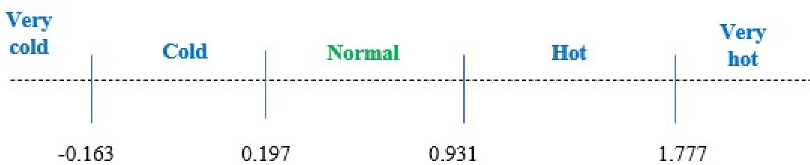


Figure 5: Distribution of temperature anomalies



Capturing varying intensities of shocks matters because household responses are diverse when climate shocks vary in degree. Borrowing or dipping into savings are temporary coping strategies for minor shocks, while migration is a more drastic measure for severe shocks. Recognizing these variations help us understand whether households are negatively impacted by weather shocks, and how the shock's severity shapes their adaptive strategies, thus enabling a more precise and perceptive analysis.

4 Empirical methodology

The following logit model is estimated to measure the impact of rainfall and temperature change on migration:

$$Y_{ihd} = \beta_0 + \beta_1 \sum_{k=1}^{4} R_d + \alpha_0 \delta_h + \alpha_0 \pi_i + \varepsilon_i \tag{1}$$

$$Y_{ihd} = \beta_0 + \beta_2 \sum_{m=1}^{4} T_d + \alpha_0 \delta_h + \alpha_0 \pi_i + \varepsilon_i \tag{2}$$

where, (Y_{ihd}) is the binary dependent variable indicating whether individual i in household h from district d migrated or not. In model 1, (R_d) represents rainfall anomalies in district d, with index k

(temperature): Between the 25th and 75th percentiles; Wet (Hot): Between the 75th and 95th percentiles; Very wet (Very hot): Above the 95th percentile.

ranging from 1 to 4, corresponding to different categories of rainfall anomalies (that are, very dry, dry, wet, very wet). Similarly, (T_d) represents temperature anomalies in district d, and index m goes from 1 to 4, representing different categories of temperature anomalies (very cold, cold, hot, very hot) in model 2, as discussed in the previous section. δ_h includes a vector of household characteristics such as household income, size, education, and other socioeconomic factors, while π_i represents individual characteristics such as age, education, or employment status, ε_i is the error term.

We analyze models (1) and (2) separately for long-term migrants and circular migrants in rural areas.

5 Results

Table 2 and Table 3 provide the population-averaged marginal effects (from logistic regression models) that estimate the impact of rainfall and temperature anomalies on two types of migration outcomes: long-term migration and circular migration, as specified in models (1) and (2).

5.1 Impact of rainfall anomalies

The effect of rainfall anomalies indicates varying effects on long-term and return migration.

a. Long-term migration

In comparison to periods of normal rainfall, exposure to very dry conditions significantly reduces the likelihood of long-term migration by 4.5 percentage points. Similarly, dry conditions (less extreme) are associated with a 1.4 percentage point decline, and wet conditions reduce long-term migration by 1.3 percentage points. Periods of extreme wetness (very wet) lead to the largest drop: 3.4 percentage points in the probability of long-term migration. These results underscore that both droughts and floods tend to deter sustained migration. Additionally, social identity plays a critical role: individuals from marginalized groups such as OBCs, Dalits, Adivasis, and Muslims are all significantly less likely to engage in long-term migration compared to forward castes, with declines ranging from 1.3 to 3.2 percentage points. Asset ownership and livelihoods also influence long-term migration: households in the poorest asset quintile are 2.6 percentage points more likely to migrate, while those in the fourth quintile are 1.1 percentage points less likely. Farm and business-owning households are also less likely to engage in long-term migration, by 3.2 and 2.2 percentage points, respectively. Educational attainment shows a strong positive association: those with more years of schooling are increasingly likely to migrate, with college-educated individuals showing a 9.2 percentage point higher probability. Age, in contrast, is negatively associated: each additional year of age reduces the likelihood of long-term migration by 0.5 percentage points. Lastly, distance to towns has a mixed effect; only those residing 21–30 km from a town shows a significant increase (1 percentage point) in long-term migration likelihood.

b. Circular Migration

Climatic conditions influence return migration differently. Exposure to very dry conditions increases the probability of return migration by 1.6 percentage points, and dry conditions by 1.8 percentage points. In contrast, wet conditions reduce the likelihood of return migration by 1.1 percentage points, while extreme wetness has no significant effect. Return migration is also significantly shaped by socio-economic and spatial contexts. Individuals in less developed villages are 2.1 percentage points more likely to engage in short-term seasonal or circular migration. Marginalized groups—including OBCs, Dalits, Adivasis, and Muslims—are consistently more likely to return, with increases ranging from 1.0 to 4.2 percentage points. Asset-poor households are especially vulnerable, with those in the lowest quintile being 6.4 percentage points more likely to return, and even the second and middle quintiles showing increases of 5.7 and 3.5 percentage points, respectively. Educational attainment has the opposite effect—those with higher education are significantly less likely to be involved in circular migration. College graduates, for instance, are 2.2 percentage points less likely to return. Age also plays a role, with each additional year reducing return migration likelihood by 0.2 percentage points. Distance from towns shows a non-linear effect: households located 21–30 km away are 2.3 percentage points more likely to be involved in circular migration, and those 11–20 km away show a 0.9 percentage point increase.

Table 2: Impact of rainfall anomalies

	Long-term migration	Circular migration
Climate variables(ref: Normal rainfall)		
Very dry	-0.045***	0.016*
	(0.007)	(0.008)
Dry	-0.014***	0.018***
	(0.005)	(0.006)
Wet	-0.013**	-0.011***
	(0.006)	(0.004)
Very wet	-0.034***	0.012
	(0.007)	(0.008)

Control variables

A. Household level characteristics		
Less developed village (ref: More developed village)	0.004	0.021***
	(0.004)	(0.004)
Social groups (ref: Forward caste)		
OBC	-0.013***	0.014***
	(0.004)	(0.004)
Dalit	-0.031***	0.028***
	(0.005)	(0.006)
Adivasi	-0.032***	0.010**
	(0.008)	(0.005)
Muslim	-0.024***	0.042***
	(0.008)	(0.008)
Christian/Sikh/Jain	-0.004	-0.005
	(0.017)	(0.014)
Assets quintile (ref: Richest)		
Poorest	0.026***	0.064***
	(0.009)	(0.004)
2nd quintile	0.014**	0.057***
	(0.006)	(0.004)
Middle quintile	0.001	0.035***
	(0.005)	(0.004)
4th quintile	-0.011*	0.018***
	(0.006)	(0.002)
Type of households		
Farm households	-0.032***	-0.003
	(0.003)	(0.002)
Business households	-0.022***	-0.007
	(0.006)	(0.006)
Landless households	0.009	0.008
	(0.011)	(0.005)
B. Individual level characteristics		
Level of education (ref: None)		
1-4 std	0.020***	-0.007***
	(0.003)	(0.003)
5-9 std	0.019***	-0.007**
	(0.003)	(0.003)
10-11 std	0.042***	-0.014***
	(0.005)	(0.005)
Class 12 or some college	0.063***	-0.018***
	(0.008)	(0.003)
College graduate and above	0.092***	-0.022***
	(0.011)	(0.006)
Age of individuals (in years)	-0.005***	-0.002***
	(0.000)	(0.000)

C. Village level characteristics

Distance to nearest town (Ref: Less than 5 km)		
6-10 km	-0.009	0.003
	(0.007)	(0.004)
11-20 km	-0.010	0.009**
	(0.007)	(0.003)
21-30 km	0.010*	0.023**
	(0.005)	(0.010)
More than 30 km	-0.004	0.007
	(0.006)	(0.008)
Clustering SE at PSU level	✓	✓
Observations	43,442	43,442

Note: The coefficients reflect population-averaged marginal effect (probability) from logistic regression for long-term and circular migration, respectively. Standard errors are in parentheses. ***indicates significance at 1%, ** at 5%, * at 10%.

5.2 Impact of temperature anomalies

a. Long-term migration

Relative to normal temperature conditions, exposure to very cold and very hot temperatures significantly increases the likelihood of long-term migration by 2.2 and 2.0 percentage points, respectively. Exposure to cold conditions also raises long-term migration by 0.7 percentage points, though to a lesser extent. Interestingly, hot temperatures (as distinct from very hot) slightly reduce long-term migration (–0.1 percentage points), indicating a non-linear effect of temperature anomalies on mobility decisions.

In terms of social identity, individuals from marginalized groups are consistently less likely to engage in long-term migration than forward castes. The likelihood is 1.4 percentage points lower for OBCs, 3.3–3.4 percentage points lower for Dalits and Adivasis, and 3.1 percentage points lower for Muslims, highlighting structural barriers to sustained mobility. The development level of the village, however, does not significantly influence long-term migration.

Economic status, proxied by asset ownership, shows a clear gradient: households in the poorest quintile are 2.7 percentage points more likely to long-term migrate compared to the richest. The second quintile also sees a significant increase of 1.4 percentage points, while effects for the middle quintile are not statistically significant. Interestingly, households in the fourth quintile are 1.0 percentage point less likely to migrate, suggesting a U-shaped pattern where the poorest migrate out of necessity, but relatively better-off households have options that reduce the need to migrate.

Occupation also plays a role: farm households and business-owning households are significantly less likely to long-term migrate (by 3.0 and 2.2 percentage points, respectively), whereas landless households show no significant association.

Educational attainment is strongly and positively associated with long-term migration. Compared to those with no education, individuals with 1–4 years and 5–9 years of schooling are 1.9 and 2.0 percentage points more likely to migrate, respectively. This effect grows with higher education: those with 10–11 years of schooling are 4.3 percentage points more likely, those with Class 12 or some college see a 6.3 percentage point increase, and college graduates or above experience the largest effect—9.2 percentage points more likely to migrate. Age has a negative effect, with each additional year reducing the probability of long-term migration by 0.6 percentage points, indicating higher mobility among the youth.

Finally, distance from the nearest town shows a non-linear influence. Compared to households located within 5 km of a town, only those 21–30 km away show a significantly higher likelihood (1.0 percentage point) of migrating long term. Other distance categories (6–10 km, 11–20 km, or beyond 30 km) show no statistically significant differences. This may reflect a "push effect" in moderately remote areas—where isolation limits local opportunities but proximity to urban hubs still makes migration feasible.

b. Circular migration In contrast to long-term migration, return migration responds differently to both temperature shocks and household, individual characteristics. Exposure to hot and very hot temperature anomalies significantly reduces the likelihood of return migration by 3.4 and 4.5 percentage points, respectively, potentially indicating that heat-related stress discourages or delays return. In contrast, cold conditions are associated with a 1.7 percentage point increase in return migration, suggesting that moderate cooling events may trigger reactive or short-lived migration episodes.

Social vulnerability plays a central role in shaping return migration. Individuals from less developed villages are 2.0 percentage points more likely to return migrate. Similarly, individuals from marginalized social groups exhibit significantly higher probabilities of returning. Compared to forward castes, Dalits are 2.9 percentage points more likely to return, Muslims by 4.3 percentage points, and OBCs by 1.2 percentage points. Adivasis also experience a 0.9 percentage point increase. These patterns suggest that structurally disadvantaged communities may not only face barriers to sustaining migration but also may lack adequate support at destination areas, compelling them to return home more often.

Economic vulnerability is even more strongly linked to return migration. Households in the poorest asset quintile are 5.2 percentage points more likely to return migrate, followed closely by those in the second quintile (4.8 percentage points), middle quintile (3.1 percentage points), and even the fourth quintile (1.8 percentage points)—all significantly higher than the richest households. These results suggest that although economically weaker households may be more likely to migrate, they often struggle to sustain their stay and are thus more prone to return. When viewed by household occupation, both farm households and business-owning households are less likely to return migrate, by 0.6 and 1.1 percentage points, respectively. Interestingly, even landless households, typically more vulnerable, show a 1.1 percentage point decrease in return migration, possibly reflecting stronger push factors that necessitate prolonged stays despite hardship.

Educational attainment shows a clear negative relationship with return migration. Compared to individuals with no schooling, those with 1–4 and 5–9 years of education are each 0.7 percentage points less likely to return. The likelihood declines further with higher education: 10–11 years (−1.5 percentage points), Class 12 or some college (−1.9 percentage points), and college graduates and above (−2.4 pp). This trend underscores that more educated individuals are better positioned to sustain migration, likely due to better job access or adaptability at destination locations. Age also plays a role—each additional year reduces the probability of return migration by 0.2 percentage points, reinforcing the idea that younger individuals are both more mobile and more resilient in maintaining long-term migration.

Finally, the distance from the nearest town also significantly shapes return migration behavior. Households located 11–20 km from a town are 0.9 percentage points more likely to return, and those 21–30 km away are 2.1 percentage points more likely, relative to those within 5 km. However, households located either closer (6–10 km) or farther (> 30 km) show no statistically significant differences. These findings indicate that intermediate rural distances are associated with higher circular migration, potentially due to limited access to stable opportunities at destination or greater dependency on home-based fallback options in these locations.

Table 3: Impact of temperature anomalies

	Long-term migration	Circular migration
Climate variables (ref: Normal temperature)		
Very cold	0.022**	0.002
	(0.009)	(0.009)
Cold	0.007*	0.017***
	(0.004)	(0.006)

Hot	-0.001**	-0.034***
	(0.005)	(0.004)
Very hot	0.020***	-0.045***
	(0.007)	(0.005)
Control variables		
A. Household level characteristics		
Less developed village (ref: More developed village)	0.002	0.020***
	(0.007)	(0.005)
Social groups (ref: Forward caste)		
OBC	-0.014***	0.012***
	(0.004)	(0.004)
Dalit	-0.033***	0.029***
	(0.005)	(0.006)
Adivasi	-0.034***	0.009**
	(0.007)	(0.005)
Muslim	-0.031***	0.043***
	(0.009)	(0.007)
Christian/Sikh/Jain	-0.011	0.006
	(0.016)	(0.018)
Assets quintile (ref: Richest)		
Poorest	0.027***	0.052***
	(0.008)	(0.004)
2nd quintile	0.014**	0.048***
	(0.006)	(0.003)
Middle quintile	0.002	0.031***
	(0.005)	(0.004)
4th quintile	-0.010*	0.018***
	(0.006)	(0.002)
Type of households		
Farm households	-0.030***	-0.006***
	(0.004)	(0.002)
Business households	-0.022***	-0.011*
	(0.006)	(0.006)
Landless households	0.008	0.005
	(0.011)	(0.004)
B. Individual level characteristics		
Level of education (ref: None)		
1-4 std	0.019***	-0.007***
	(0.003)	(0.003)
5-9 std	0.020***	-0.007**
	(0.004)	(0.002)
10-11 std	0.043***	-0.015***
	(0.005)	(0.005)
Class 12 or some college	0.063***	-0.019***
	(0.008)	(0.003)
College graduate and above	0.092***	-0.024***

	(0.009)	(0.006)
Age of individuals (in years)	-0.006***	-0.002***
	(0.000)	(0.000)
C. Village level characteristics		
Distance to nearest town (Ref: Less than 5 km)		
6-10 km	-0.008	0.001
	(0.007)	(0.004)
11-20 km	-0.009	0.009**
	(0.008)	(0.003)
21-30 km	0.010*	0.021**
	(0.006)	(0.009)
More than 30 km	-0.004	0.011
	(0.007)	(0.007)
Clustering SE at PSU level	✓	✓
Observations	43,442	43,442

Note: Standard errors are in parentheses. ***indicates significance at 1%, ** at 5%, * at 10%.

5.3 Role of irrigation

Table 4 reports the marginal effect of owning irrigation assets (for farm households) on long-term and circular migration under rainfall and temperature anomalies. Owning irrigation assets reduces the probability of long-term migration by 1.2% for farm households under rainfall anomalies. Similar to rainfall, having irrigation assets reduces the probability of long-term migration by 1.4% for farm households under temperature anomalies. This suggests that access to irrigation provides a sense of stability and economic security, which diminishes the need for individuals to seek opportunities elsewhere. Consequently, individuals in these households may feel more secure in their livelihoods, leading them to remain in their local communities rather than pursuing migration. This finding underscores the critical role of irrigation in stabilizing rural livelihoods. By improving resilience to climate anomalies, access to irrigation may effectively reduce the motivation for migration among farm households. In contrast, the coefficients for circular migration (both rainfall and temperature anomalies) are close to zero and not statistically significant, indicating that having assets related to irrigation does not significantly influence the decisions of individuals to opt for seasonal or circular migration.

Table 4: Marginal Effects of having irrigation assets by farm households

	Rainfall anomalies		Temperature anomalies	
	Long-term migration	Circular migration	Long-term migration	Circular migration
Farm households*irrigation assets	**-0.012***** (0.0025)	**0.002** (0.505)	**-0.014***** (0.011)	**-0.0003** (0.933)

Notes: Robust standard errors are reported in parentheses. *** denotes significance at the 1% level, ** at 5%, and * at 10%. Full results with interaction effects are reported in Appendix Tables A-II and A-III, showing the effects of rainfall and temperature anomalies on long-term and circular migration, respectively.

5.4 Robustness checks

To ensure the validity of our findings and the sensitivity of our results to alternative specifications, we perform several robustness checks.

First, we redefine the long-term period average (LPA) by using the first 20 years instead of the conventional 30 years, ensuring that the baseline reflects more recent climate patterns. Second, instead of relying solely on mean temperature to create temperature anomalies, we use both maximum and minimum temperatures, as extreme temperatures can have a more significant impact on livelihoods and migration decisions. Third, we account for climate variability by computing the coefficient of variation (CV) for temperature and rainfall, which captures fluctuations over time and helps assess the impact of unpredictable climate patterns on migration. Finally, we incorporate the frequency of extreme weather events; droughts, floods, heatwaves, and coldwaves, by identifying their occurrences based on the 10^{th} and 90^{th} percentiles of annual rainfall and temperature and aggregating them at the district level. This approach is particularly useful in understanding how sudden climatic shocks influence migration decisions. Together, these robustness checks provide a comprehensive and reliable assessment of climate variability and its implications.

Table 5 and Table 6 assess robustness and report the average marginal effects of logistic regression models estimating the impact of rainfall and temperature anomalies on long-term and circular migration, using various alternative definitions of climate change.

Using Table 5, panels A and B, we find that very wet conditions, relative to normal rainfall, reduce the likelihood of long-term migration but increase the probability of circular migration. In contrast, higher rainfall variability is associated with more long-term migration and less circular migration, although these effects in specification (2) remain statistically insignificant.

Table 6summarizes a series of robustness tests that build directly on our major findings. Alternative specifications, such as the 20-year long-period average, minimum and maximum temperature thresholds, temperature variation, and severe event measures, result in estimated effects that are consistent with those reported in the main specifications. Cold shocks, in particular, continue to boost long-term migration, whereas hot and very hot shocks have a negative effect on circular migration.

The stability of both the sign and statistical significance across these alternative measures demonstrates that our findings are not driven by a specific choice of anomaly definition. Rather, the results are robust to multiple specifications, reinforcing the central conclusion that cold shocks induce migration while heat stress, particularly extreme hot conditions, suppresses circular migration.

Table 5: Robustness Checks: Change in Rainfall

	(1)	(2)	(3)
Panel A: Long-term migration			
Very dry	-0.035***		
	(0.010)		
Dry	-0.002		
	(0.006)		
Wet	-0.009		
	(0.007)		
Very wet	-0.027***		
	(0.009)		
Variation in rainfall		0.022	
		(0.049)	
Drought wave			-0.001***
			(0.000)
Flood wave			-0.000*
			(0.000)
Panel B: Circular migration			
Very dry	-0.012		
	(0.010)		
Dry	0.025***		
	(0.006)		
Wet	0.004		
	(0.004)		
Very wet	0.025*		
	(0.014)		
Variation in rainfall		-0.040	
		(0.027)	
Drought wave			-0.000
			(0.000)
Flood wave			-0.000*
			(0.000)
Controls	✓	✓	✓
Clustering SE at PSU level	✓	✓	✓
Observations	43,277	43,276	43,276

Notes: Specification 1 considers the first 20 years as the long-period average (LPA). Specification 2 captures rainfall changes through variability, measured by the coefficient of variation in rainfall. Specification 3 accounts for rainfall fluctuations by considering the number of drought or flood years in each district. Panel A and Panel B report the effect on long-term and circular migration, respectively. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.10..

Table 6: Robustness Checks: Change in Temperature

	(1)	(2)	(3)	(4)	(5)
Panel A: Long-term migration					
Very cold	0.036***	0.019*	0.014		
	(0.012)	(0.011)	(0.014)		
Cold	0.016***	0.027***	0.007		
	(0.005)	(0.005)	(0.005)		
Hot	-0.002	0.003	-0.003		
	(0.006)	(0.004)	(0.006)		
Very hot	0.028***	0.037***	0.007		
	(0.008)	(0.008)	(0.007)		
Variation in temperature				-1.247***	
				(0.281)	
Heatwave					0.001**
					(0.000)
Coldwave					-0.001***
					(0.000)
Panel B: Circular migration					
Very cold	-0.002	-0.003	-0.011		
	(0.009)	(0.010)	(0.009)		
Cold	0.010**	0.010***	0.007***		
	(0.004)	(0.004)	(0.003)		
Hot	-0.036***	-0.037***	-0.036***		
	(0.003)	(0.004)	(0.004)		
Very hot	-0.051***	-0.052***	-0.046***		
	(0.003)	(0.003)	(0.004)		
Variation in temperature				0.047	
				(0.260)	
Heatwave					-0.001***
					(0.000)
Coldwave					-0.001***
					(0.000)
Controls	✓	✓	✓	✓	✓
Clustering SE at PSU level	✓	✓	✓	✓	✓
Observations	43,277	43,276	43,276	43,276	43,276

Notes: Specification (1) uses the first 20 years as the long-period average (LPA). Specifications (2) and (3) use minimum (night-time) and maximum (day-time) temperatures, respectively. Specification (4) captures temperature variability, measured by the coefficient of variation, while Specification (5) accounts for fluctuations by considering the number of hot or cold years in each district. Panel A reports effects on long-term migration and Panel B on circular migration. Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

6 Discussion and Conclusions

This study investigates the impact of climate anomalies, particularly rainfall and temperature deviations, on migration patterns in rural India. The logistic regression results reveal complex interlinkages between climatic stressors and socioeconomic factors influencing both long-term and circular migration decisions.

Rainfall (very dry, dry, wet, very wet) anomalies significantly reduce the likelihood of long-term migration. In contrast, extreme rainfall (very wet), does not significantly affect circular migration. Temperature anomalies present a contrasting pattern. Very hot conditions increase long-term migration likelihood, indicating that extreme heat prompts individuals to leave in search of better opportunities. Conversely, cold conditions reduce the likelihood of long-term migration, respectively, suggesting a preference for familiar environments or feasibility issues under cold stress. Extreme heat significantly reduces circular migration, illustrating that harsh conditions discourage circular due to ongoing heat stress.

Economic conditions are pivotal in migration decisions. Wealthier households are less likely to migrate, likely because they have better resources to mitigate climate anomalies. Education plays a crucial role, with higher levels linked to increased long-term migration likelihoods. This indicates that education equips individuals with skills and networks to view migration as a socio-economic opportunity. Vulnerable groups, such as OBC and Dalit communities, exhibit lower long-term migration likelihoods due to limited resources. Similarly, for circular migration, dry rainfall anomalies increase the likelihood, suggesting that migrants from drought-affected areas may perceive ongoing hardships at home, making short-term migration more appealing to livelihood distress in origin areas.

Access to irrigation emerges as a critical factor in reducing long-term migration. The negative relationship between irrigation access and migration likelihood underscores the importance of rural infrastructure for economic stability. Households with irrigation are less likely to migrate, as reliable water resources stabilize agricultural production, acting as a buffer against climate variability.

In conclusion, studying the impact of climate change on migration in reference to lower-middle income countries is essential due to heightened vulnerability to climate effects and limited adaptive capacity. Climate-induced migration can be triggered by humanitarian crises and economic challenges. The findings of this study have significant policy implications, particularly in the context of climate change. Investments in rural infrastructure, especially irrigation, alongside initiatives to improve educational access and economic opportunities, could alleviate migration pressures related to climate stress. This research is crucial for fostering social cohesion and ensuring the well-being of affected populations amidst ongoing climate change.

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Appendix

A-I: Key Existing Studies on Climate Change and Migration: Variables and Findings

Authors	**Area of Study**	**Data**	**Main Dependent Variable**	**Climate Change Measure(s)**	**Main Findings**
Barrios et al. (2006)	Sub-Saharan Africa	World Bank Panel Data	Migration	Drought frequency	Droughts reduce agricultural productivity and drive migration.
Afifi (2009)	Egypt	Household survey data	Rural-urban migration	Droughts, desertification	Droughts and desertification lead to rural migration.
Drabo and Mbaye (2011)	Developing Countries	World Bank Panel Data	International migration	Rainfall, temperature anomalies	Rainfall deficits and temperature anomalies spur international migration.
Drabo and Mbaye (2015)	Developing Countries	World Bank Panel Data, and Cred data	Emigration rate	Natural disaster	Natural disasters are positively associated with emigration rates.
Marchiori et al. (2012)	Africa	World Development Indicators	Migration flows	Rainfall variability	Rainfall variability linked to migration flows across Africa.
Gray and Mueller (2012)	Bangladesh	Household survey data	Temporary migration	Flooding, storm events	Flood events trigger temporary or permanent migration decisions.
Bohra-Mishra et al. (2014)	Nepal	Household survey data	Labor migration	Temperature and rainfall anomalies	Migration increases in response to climate anomalies.
Ghimire et al. (2015)	Nepal	National Living Standards Survey	Migration	Rainfall variation, crop loss due to floods	Crop loss strongly influences short-term migration patterns.
Millock (2015)	Global	Cross-country panel data	International migration	Temperature increase, droughts	Temperature rise and droughts drive international migration.
Beine and Parsons (2015)	International	Global Bilateral Migration Database	Migration	Climate anomalies, sea level rise	Climate anomalies and sea level rise increase migration between developing and developed countries.

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Authors	**Area of Study**	**Data**	**Main Dependent Variable**	**Climate Change Measure(s)**	**Main Findings**
Cattaneo and Peri (2016)	Global	World Bank and FAO Panel Data	Emigration	Temperature shocks, agricultural productivity loss	Agricultural shocks due to climate change increase emigration, especially to wealthier nations.
Thiede et al. (2016)	Bangladesh	Household survey and historical weather data	Outmigration	Flood and cyclone exposure, rainfall patterns	Flood/cyclone exposure drives rural outmigration.
Koubi et al. (2016)	Sub-Saharan Africa	Afrobarometer and climate data	Migration decisions	Perceptions of drought, temperature anomalies	Perceptions of drought strongly influence migration decisions.
Nawrotzki et al. (2017)	Mexico	Mexican Migration Project (MMP)	Migration	Temperature and precipitation variability	Migration to the U.S. increases during climate variability, especially with economic hardship.
Mueller et al. (2020)	Eastern Africa	LSMS–ISA	Outmigration	Rainfall shocks, temperature anomalies	Rainfall deficits and temperature anomalies increase internal migration; irrigation moderates impact.
Sedova & Kalkuhl (2020)	India	IHDS data	Migration	Lagged temperature anomalies, rainfall variability	Temperature anomalies have a strong effect on migration, especially with limited irrigation.
Hunter et al. (2021)	Global	Meta-analysis of climate-induced migration studies	Migration	Flooding, droughts, extreme heat, and sea level rise	A global synthesis shows that extreme weather events drive both internal and international migration.
Onuma et al. (2021)	Global	Disaster data from 1960	Economic growth, migration	Hydro-meteorological, geophysical disasters	Catastrophic disasters negatively impact economic growth, increasing migration.
Thiede et al. (2022)	Asia	Integrated Census and Survey Microdata	Interprovincial migration	Rainfall and temperature anomalies	Climate effects differ according to the distance and type of migration.

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Authors	**Area of Study**	**Data**	**Main Dependent Variable**	**Climate Change Measure(s)**	**Main Findings**
Vinke et al. (2023)	Global	World Bank and FAO Panel Data	Migration	Agricultural shocks, rainfall variability	Climate-driven agricultural shocks push migration globally, with developed regions handling shocks better.
Reiner et al. (2024)	Australia	Input-output model, tourism supply chains	Economic losses	Bushfires	Australian bushfires cause significant economic loss, pushing migration from impacted areas.
Abidoye et al. (2024)	Sub-Saharan Africa	World Bank and DHS datasets	Migration	Temperature, rainfall variability	Temperature increases reduce yields and drive migration, but financial access mitigates this effect.
Sreekumar et al. (2024)	India	IHDS data	Migration	Number of harmful degree days in the growing season (June-February), total number of rainy days	Presence of local non-farm activities and availability of local non-farm income further moderates the effect of climate change-induced yield loss on migration.

A-II: Effect of rainfall anomalies

	Long-term migration	Circular migration
Climate variables(ref: Normal rainfall)		
Very dry	-0.044***	0.015*
	(0.007)	(0.009)
Dry	-0.013***	0.018***
	(0.005)	(0.006)
Wet	-0.013**	-0.011***
	(0.006)	(0.004)
Very wet	-0.033***	0.011
	(0.007)	(0.008)
Control variables		
Less developed village (ref: More developed village)	0.005	0.021***
	(0.004)	(0.004)
Social groups (ref: Forward caste) OBC	-0.013***	0.014***
	(0.004)	(0.004)
Dalit	-0.032***	0.028***
	(0.005)	(0.006)
Adivasi	-0.032***	0.010**
	(0.008)	(0.005)
Muslim	-0.024***	0.042***
	(0.008)	(0.008)
Christian/Sikh/Jain	-0.002	-0.005
	(0.017)	(0.014)
Assets quintile (ref: Richest)		
Poorest	0.024***	0.065***
	(0.009)	(0.004)
2nd quintile	0.012**	0.057***
	(0.006)	(0.004)
Middle quintile	0.000	0.035***
	(0.005)	(0.004)
4th quintile	-0.012**	0.018***
	(0.006)	(0.002)
Type of households		
Farm households	-0.028***	-0.004**
	(0.004)	(0.002)
Business households	-0.022***	-0.007
	(0.006)	(0.006)
Landless households	0.008	0.008
	(0.011)	(0.005)
Irrigated households	-0.011***	0.009
	(0.003)	(0.006)
B. Individual level characteristics		
Level of education (ref: None)		

1-4 std	0.020***	-0.007***
	(0.003)	(0.003)
5-9 std	0.019***	-0.007**
	(0.003)	(0.003)
10-11 std	0.042***	-0.014***
	(0.005)	(0.005)
Class 12 or some college	0.063***	-0.018***
	(0.008)	(0.003)
College graduate and above	0.093***	-0.022***
	(0.008)	(0.006)
Age of individuals (in years)	-0.005***	-0.002***
	(0.000)	(0.000)
C. Village level characteristics		
Distance to nearest town (Ref: Less than 5 km)		
6-10 km	-0.009	0.003
	(0.007)	(0.004)
11-20 km	-0.010	0.009***
	(0.007)	(0.003)
21-30 km	0.009*	0.023**
	(0.005)	(0.010)
More than 30 km	-0.005	0.007
	(0.006)	(0.008)
Clustering SE at PSU level	✓	✓
Observations	43,442	43,442

Note: Standard errors are in parentheses. ***indicates significance at 1%, ** at 5%, * at 10%.

A-II: Effect of temperature anomalies

	Long-term migration	Circular migration
Climate variables(ref: Normal temperature)		
Very cold	0.022**	0.002
	(0.009)	(0.009)
Cold	0.007	0.017***
	(0.004)	(0.006)
Hot	-0.002	-0.034***
	(0.005)	(0.004)
Very hot	0.018**	-0.045***
	(0.007)	(0.005)
Control variables		
Less developed village (ref: More developed village)	0.002	0.020***
	(0.004)	(0.004)
Social groups (ref: Forward caste) OBC	-0.014***	0.012***
	(0.004)	(0.004)
Dalit	-0.034***	0.030***
	(0.005)	(0.006)
Adivasi	-0.035***	0.009*
	(0.007)	(0.005)
Muslim	-0.032***	0.043***
	(0.008)	(0.007)
Christian/Sikh/Jain	-0.009	0.006
	(0.017)	(0.017)
Assets quintile (ref: Richest)		
Poorest	0.025***	0.053***
	(0.008)	(0.004)
2nd quintile	0.012**	0.048***
	(0.006)	(0.003)
Middle quintile	0.001	0.031***
	(0.005)	(0.004)
4th quintile	-0.011*	0.018***
	(0.006)	(0.002)
Type of households		
Farm households	-0.026***	-0.007***
	(0.004)	(0.003)
Business households	-0.022***	-0.011*
	(0.006)	(0.006)
Landless households	0.007	0.006
	(0.011)	(0.004)
Irrigated households	-0.012***	0.008
	(0.003)	(0.006)
B. Individual level characteristics		

Level of education (ref: None)		
1-4 std	0.019***	-0.007***
	(0.003)	(0.003)
5-9 std	0.019***	-0.007***
	(0.004)	(0.002)
10-11 std	0.043***	-0.015***
	(0.005)	(0.005)
Class 12 or some college	0.064***	-0.019***
	(0.008)	(0.003)
College graduate and above	0.093***	-0.024***
	(0.009)	(0.006)
Age of individuals (in years)	-0.006***	-0.002***
	(0.000)	(0.000)
C. Village level characteristics		
Distance to nearest town (Ref: Less than 5 km)		
6-10 km	-0.008	0.001
	(0.007)	(0.004)
11-20 km	-0.009	0.009***
	(0.008)	(0.003)
21-30 km	0.010*	0.021**
	(0.006)	(0.009)
More than 30 km	-0.005	0.011
	(0.007)	(0.007)
Clustering SE at PSU level	✓	✓
Observations	43,442	43,442

Note: Standard errors are in parentheses. ***indicates significance at 1%, ** at 5%, * at 10%.