Weathering changes – livelihood adaptation to weather shocks in rural India by disadvantaged social groups

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Abstract

In this paper, we examine how households from disadvantaged social groups in India adapt through migration to climate-related shocks. We examine the relative importance of factors like social networks and public intervention in enabling adaptation to slow-onset climate change. We use household and village level data from two consecutive waves of the Indian Human Development Survey and gridded weather data from the CRU, the University of East Anglia, for our analysis. Our results indicate that in India, major changes in dryness do significantly increase migration. However, disadvantaged social groups are less likely to participate. Social networks do not play any significant role in the migration behavior of disadvantaged groups facing these changes. Efficient implementation of NREGS through poverty alleviation can improve the probability of migration among disadvantaged social groups.

Introduction

Climate change is no longer a distant event. Its effect can be seen all over the world as extreme weather events have become more frequent and severe (Christensen et al., 2007; Masson-Delmotte et al. 2018). This has important consequences in developing countries where the population is often dependent on agriculture and other climate-sensitive natural resources for their livelihood and they also lack sufficient financial and technical capacity to mitigate such risks (Dell, Jones, and Olken 2014; Harrington et al. 2016; Millock 2015; Skoufias, Rabassa, and Olivieri 2011). This has led to considerable interest in understanding the ability of these societies to adapt to climate change. However, such adaptation is often difficult for disadvantaged groups in these countries, as they are more likely to be exposed to such conditions, having limited resources to mitigate those conditions. In addition, they are more likely to be further impoverished as a result of climate hazards, which reduces their ability to cope and recover from its consequences (Field and Barros, 2014; Islam and Winkel 2017).

In this paper, we focus on the adaptation to climate change among disadvantaged social groups in India. A recent study (A. Mohanty 2020) documents that India experienced an exponential increase in extreme events during the period 1970-2019, with the last two decades showing significant acceleration. In 2018, India was ranked the fifth most climate-vulnerable country in the world (Eckstein et al. 2019). While agriculture and allied sectors contribute 15% of GDP, nearly 75% of Indian families rely on rural income. The agricultural sector remains a major livelihood support to more than 70% of the rural workforce. This is especially relevant as approximately 70% of poor households are concentrated in rural areas (World Bank, 2012).

India has several social groups that were either historically excluded from its development process or for whom the development process remained distant because of their remote location. The Scheduled Castes are those who have been historically segregated primarily by occupational opportunities. They suffer diverse types of exclusion, but their occupational segregation affects their economic conditions the most. The Scheduled Tribes are those who mainly live off natural resources whose livelihood is often threatened by encroachment from the rest of the society. The Indian constitution recognizes 1108 different castes and 754 different tribes. These groups are quite heterogeneous in their composition but are very similar in their disadvantages. The Scheduled groups have the highest incidence of poverty in India along with a low measure of health and human capital. Several affirmative action policies have reduced discrimination substantially (e.g., in access to public education or employment), but they are hardly enough to counter centuries of exclusion. Membership of such groups is considered one of the primary risk factors for being poor in rural India. According to the 2011 Census, SCs and STs comprised 16.2 and 8.2 percent of the population respectively yet accounted for 40.6 percent of the poor in the 2004/2005 household expenditure survey.

Several studies in India have highlighted the effect of climate change on health and mortality. Burgess et al. (2017) using district-level daily weather and annual mortality data from 1957 to 2000, found that hot days lead to substantial increases in mortality in rural but not urban India. Others note how it also results in misallocation of resources like lower investment in human capital. For example, Garg, Jagnani, and Taraz (2020) observed that hot days during the growing season reduce agricultural yields and test score performance with comparatively modest effects of hot days in the non-growing season. Carleton (2017) even observed that fluctuations in temperature significantly influence suicide rates during India's agricultural growing season, when heat also lowers crop yields.

The results corroborate studies in other contexts that show how climate-related shocks can force vulnerable households to make use of unsustainable coping strategies by an inefficient allocation of their resources (Johnson and Krishnamurthy

2010; Warner and Afifi 2014; Warner and Van der Geest 2013; Sabates-Wheeler and Waite 2003; Jacoby and Skoufias 1997; Barnett and Webber 2009). Under such conditions, the inability to diversify livelihoods spatially or in sectors that are not sensitive, possibly through migration, is a cause of concern (Adger and Adams, 2013; Warner, 2010; Renaud et al. 2007; Black et al. 2011). Historically, migration has played the role of a natural adaptive strategy for adverse environmental conditions (Hugo, 1996; Cattaneo et al., 2019; McLeman and Smit 2006). For disadvantaged social groups In India, migration takes special importance as other avenues like switching crops, investment in irrigation, etc. are not pertinent for they are often landless or with very little landholding (Government of India 2015; B.B. Mohanty 2001).

Migration is generally low in India compared to countries at similar stages of development (Keshri and Bhagat, 2010; Munshi and Rosenzweig, 2016; Topalova 2010). Although there has been some increase between decennial censuses, the pattern of migration has generally remained the same in the last few decades. The bulk of the movement is within the same district followed by those within the states, with around a tenth of the migration being interstate (Bell et al. 2015). Interstate migration (among those who moved in the last five years) is a fifth of that in China, which has restrictions on such movement. However, temporary or circular migration for work has increased over the years (Deshingkar 2008). The majority of these migrations involves a few members leaving the household for work while the household remains in the state of origin.

But the poor have other obstacles. Poverty makes households risk-averse to such enterprises. Moreover, their low human capital makes it less likely for them to be employed in the more productive sectors of the economy. For poorer groups, migration may also increase vulnerability and reinforce poverty. For example, when such migration is debt-financed or when their only employment possibilities are in the precarious urban unskilled labor market. As a result, they often decide on profitable opportunities (Kanbur, 1979; A.V. Banerjee and Newman 1991).

In India, migrants are less likely to be members of Scheduled groups (Hnatkovska and Lahiri, 2015; Bhattacharya, 2002; Deshingkar and Start, 2003; Mosse 2010). This is not only because of the higher incidence of poverty among them but also the discrimination faced by migrants and those belonging to disadvantaged groups. Iversen et al. (2014) show SCs do better in villages than they are in majority. In addition to the barriers to migration highlighted earlier, the scheduled groups may face additional barriers due to affirmative action programs which reserve jobs and educational opportunities for disadvantaged groups due to their state of original residence.

There are numerous studies on the increase in migration probability due to extreme heat or lack of precipitation (Feng, Krueger, and Oppenheimer, 2010; Gray and Mueller, 2012a, 2012b; Gray and Bilsborrow 2013; Jessoe, Manning, and Taylor 2018). Yet others note that climate shocks can also decrease migration due to the adverse effect they have on the resources required to finance migration journeys (Cattaneo et al. 2019). It is often the case that those who are most vulnerable to climate change are most constrained to move and smooth consumption over time (Black et al. 2013). Several studies have also examined the relationship between the effects of climate change and migration in the Indian context using different datasets. Viswanathan and Kumar (2015) examined the three-way linkage between weather, agricultural performance, and internal migration. They also note that weather-induced drop in agricultural productivity increases interstate migration. Dallmann and Millock (2017) show that drought frequency in the origin state increases interstate migration in India. This effect is stronger in agricultural states. Sedova and Kalkuhl (2020)using household survey data show that adverse weather shocks decrease rural-rural and international migration and push people into cities. However, none of the studies on India specifically look at the impact of climate change on the migration patterns of disadvantaged groups, even though their lives are more likely threatened by slow-onset climate change.

Research questions

One important aspect of slow-onset climate change compared to extreme weather events like flood or weather anomalies from long-term trends (e.g, heat waves) is the inertia associated with reacting to it. Fussell, Hunter, and Gray (2014) review highlighted that migratory responses to slow-onset climate change differ from rapid onset ones as in the former labor migration is more likely to be a livelihood diversification strategy. Earlier research on India does indicate that there is an association for people to migrate based on weather anomalies, but it is not clear whether agricultural or groundwater drought would lead to similar movements. This is especially because of the ability of slow-onset climate change to deplete resources or to force the inefficient use of resources. Dallmann and Millock (2017) do address drought, but their measure based on precipitation does not account for the impact of changing temperature and other environmental parameters. So, our first research question examines whether does slow-onset climate change lead to migration in rural India?

We are also interested in the heterogeneity of this migration pattern. So, we also examine whether disadvantaged social groups also take part in such migration?

While migration is a common way to diversify risk in developing countries, it is not necessarily the only way. A usual substitute is informal insurance provided by others within their social network (Rosenzweig and Stark, 1989; Townsend, 1994; Munshi and Rosenzweig 2016). Such social networks can be built proactively by being members of different groups or through kinship and reciprocal arrangements, and it may reduce the need to migrate. Several studies note that such investment in social networks can play an important role in mitigating the negative impacts of climate shocks (Adger, 2010; Wolf 2011). So next we examine whether access to social networks may explain the variation in migration probability among disadvantaged groups?

Finally, we examine the role of a poverty alleviation program that was implemented in India on the pattern of migration. In 2005, the Indian government introduced the National Rural Employment Guarantee Scheme (NREGS) which essentially guaranteed manual employment for 100 days for a member of a household for those who are willing to work (Khera 2011). By incorporating work requirements as a screening device, it is supposed to ensure proper targeting (Drèze and Khera 2011). The program did achieve some success like increasing consumption expenditure (Imbert and Papp, 2015; Ravi and Engler, 2015; Deininger and Liu 2013). However, its impact varied by state, and the poorer states lagged in their capacity to implement the scheme (Dutta et al., 2014; Stahlberg, 2012; Liu and Barrett 2013). Although some studies note a decline in distress migration during agricultural lean seasons following the introduction of the scheme (Deshingar et al., 2010; Imbert and Papp, 2015; Liu and Barrett 2013), others observe mixed results (Khan and Saluja 2007; Datar 2007; Das 2015; Novotný, Kubelková, and Joseph 2013; Solinski 2012). Some of it is due to the fact that studies were conducted at different stages of the implementation, while some are possibly due to state-level differences in the efficiency of the program implementation. While several studies have examined the effect of the program on migration, their focus was specifically on its implications on lean season migration. None of these studies specifically explored its effect on scheduled groups in areas facing adverse climate change. Finally, we examine whether poverty alleviation programs affect migration among disadvantaged groups facing the effects of climate change?

Data

Several studies in India have examined the impact of climate change on agriculture output and jointly its effect on irrigation (Guiteras, 2008; Taraz, 2018). While such an approach acknowledges the effect of changes in weather conditions on plant stress or groundwater access, the variables used to identify the same, like meteorological drought (usually measured by deviation in temperature or precipitation from a long-term average) are limited in capturing the effect of climate-crop relations. Alternatives like the Standardized Precipitation Index (SPI), although widely used, do not account for the impact of rising temperatures and several other factors. Such relations are better captured by measures of agricultural drought, or hydrological drought which identifies when plants are stressed and when groundwater is scarce.

Agricultural drought is usually referred to cases where there is plant water stress, reduced biomass, and yield due to soil moisture deficits. Hydrological drought refers to a significant decrease in water availability resulting in reduced streamflow, inflow to reservoirs, and groundwater levels (Wilhite and Glantz 1985). Here we identify these characteristics using the Standardized Precipitation-Evapotranspiration Index (SPEI) (Vicente-Serrano, Beguería, and López-Moreno 2010). Instead of temperature, precipitation, etc., SPEI uses time-series data on “water balance” which is the difference between precipitation and potential evapotranspiration. Potential evapotranspiration is the amount of evaporation and transpiration that would occur as a result of temperature, vapor pressure, cloud cover, and wind-field values if a sufficient water source were available.

We use TS4.04 data for monthly gridded precipitation and potential evapotranspiration for 1970-2010 from the Climate Research Unit of the University of East Anglia (Harris et al. 2020) to construct SPEI. Calculation of SPEI involves fitting the water balance data with a distribution with heavier tails, transforming the probability distribution into a standardized normal distribution, and then computing the inverse probability to obtain index. We use R library SPEI created by Santiago Beguería and Sergio M. Vicente-Serrano for its calculation. SPEI can be calculated for different time scales pertaining to water balance for 3, 6, to 48 months. Soil moisture conditions respond to water balance anomalies on a relatively short scale. Groundwater, streamflow, and reservoir storage reflect the longer-term water balance anomalies. In this paper, we use 6 months to reflect short-term agricultural drought and 18 months to reflect droughts that affect the hydrological cycle.

The SPEI values are used to classify wetness and dryness as follows.

SPEI	Moisture Category	SPEI	Moisture Category
2.00 and above	Extremely Wet	-1.00 — -1.49	Moderately Dry
1.50 — 1.99	Very Wet	-1.50 — -1.99	Severely Dry
1.00 — 1.49	Moderately Wet	-2.00 and below	Extremely Dry

Values between -0.99 and +0.99 are considered as normal water balance. Defrance, Delesalle, and Gubert (2020) also use SPEI in studying migration in Mali.

Figure 1 shows the distribution of SPEI6 values across the districts used in this study for each month between 2000 and 2010. Each line represents a box plot with the thicker part showing the intraquartile range. For several months between 2002 and 2003, the interquartile range dipped below -1 indicating the incidence of agricultural drought. Similar distribution can be seen between 2009 and the first half of 2010. Moreover, between 2006 and 2007 and during the second half of 2010, the intraquartile range crossed +1 indicating periods of excess wetness. The SPEI18 plot in Figure 2 by construct shows a smoother pattern and a slightly longer duration of excessive dryness or wetness months.

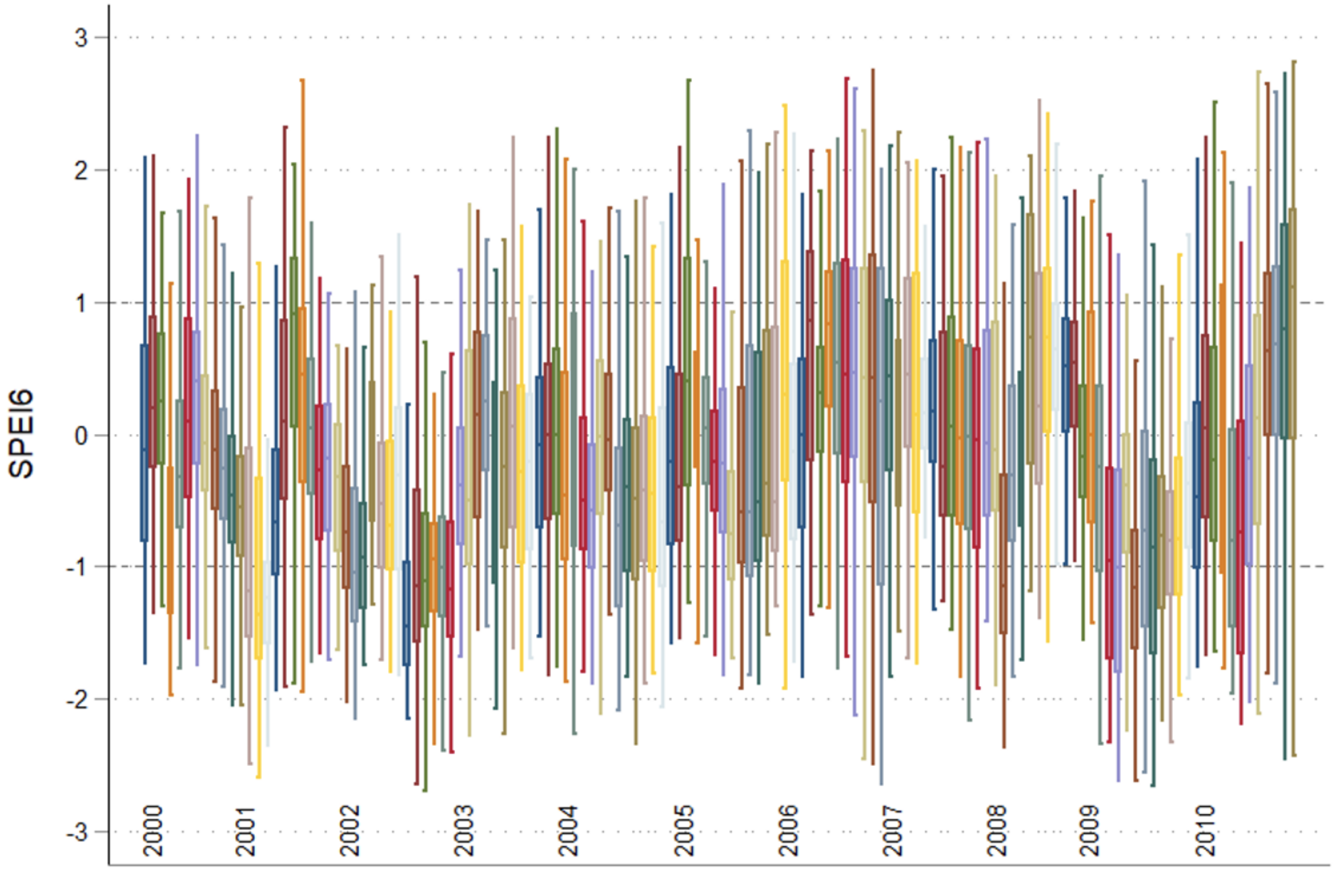

Figure 1. SPEI6 for IHDS (rural) districts (2000-2010)

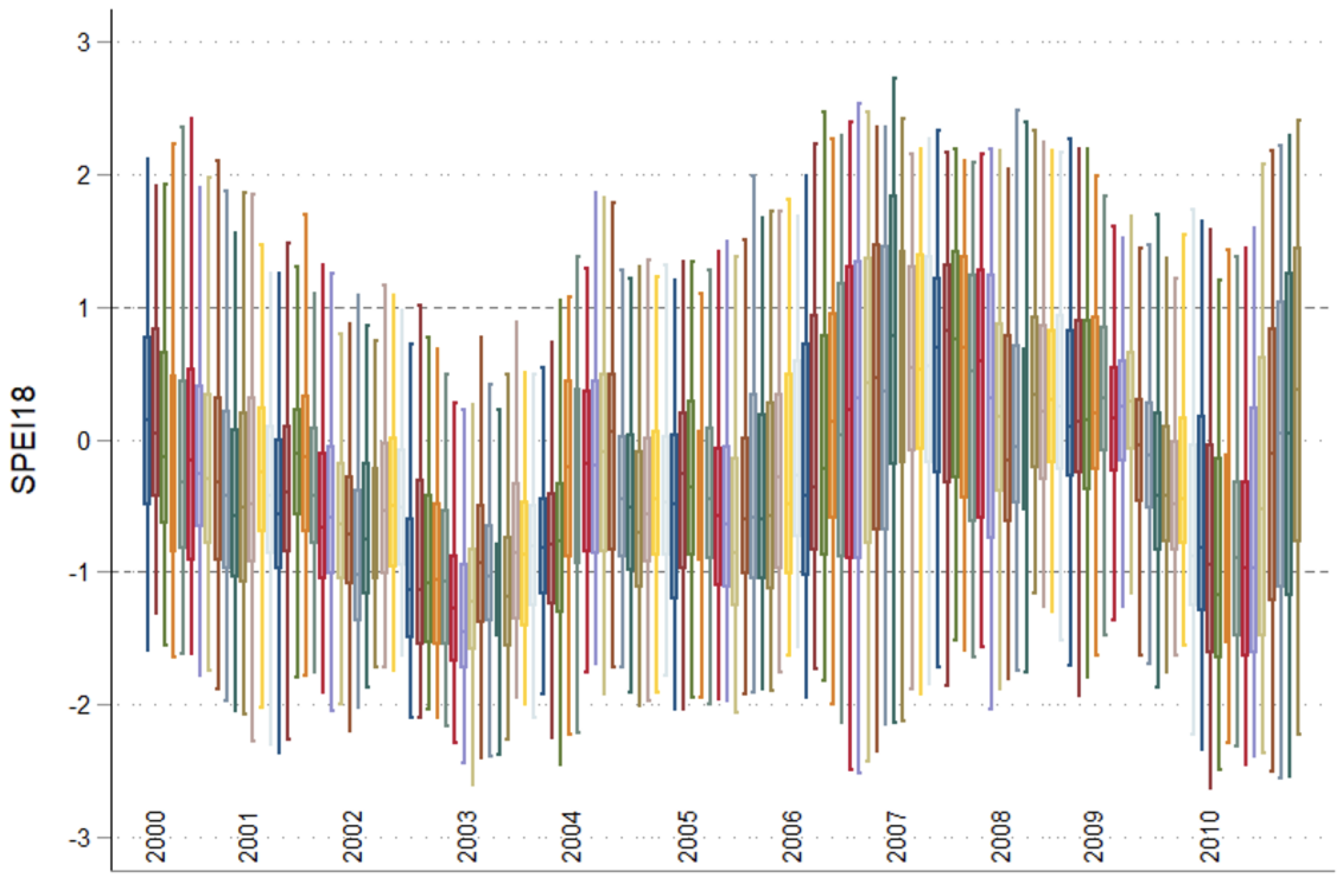

Figure 2. SPEI18 for IHDS (rural) districts (2000-2010)

Our main climate variables are based on the 60 months preceding the household surveys. Excess dryness or wetness is measured by the number of months when SPEI is less than -1 or greater than +1, respectively, in those 60 months. Alternative measures like the intensity of wetness and dryness are also calculated by summing over SPEI values when they are greater than +1 or the sum of absolute values when they are less than -1. Figure 3 - Figure 6 shows different choropleth plots. Figure 6 shows the main identifying factor for this study, the change in the number of dry days between the waves. It shows a decline in the number of dry days in the western Indian states of Maharashtra and Karnataka while an increase in the number of dry days in the northern states of Uttar Pradesh and Bihar.

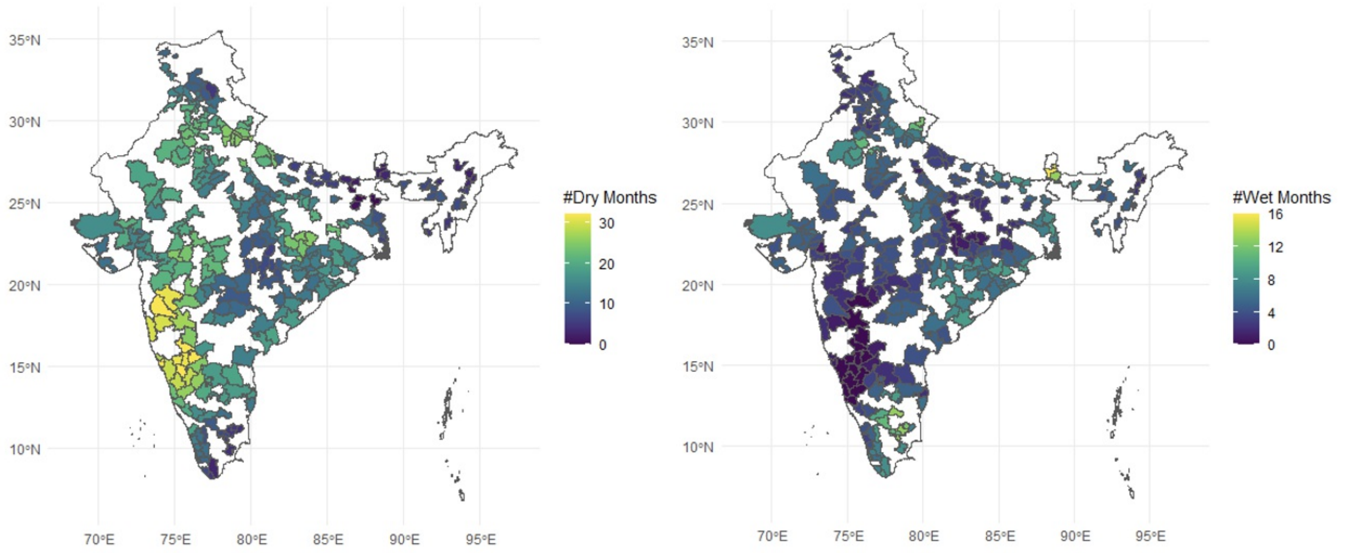

Figure 3. Number of dry and wet months by district based on SPEI6 (Wave I)

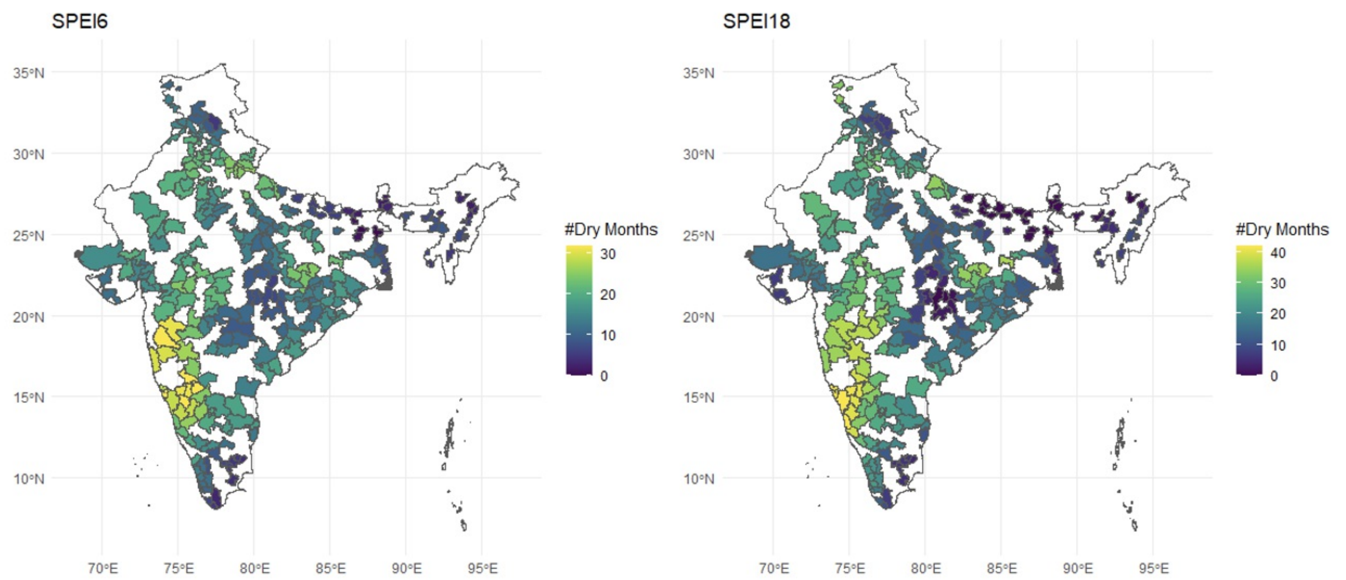

Figure 4. Number of dry and wet months by district based on SPEI6 and SPEI18 (Wave I)

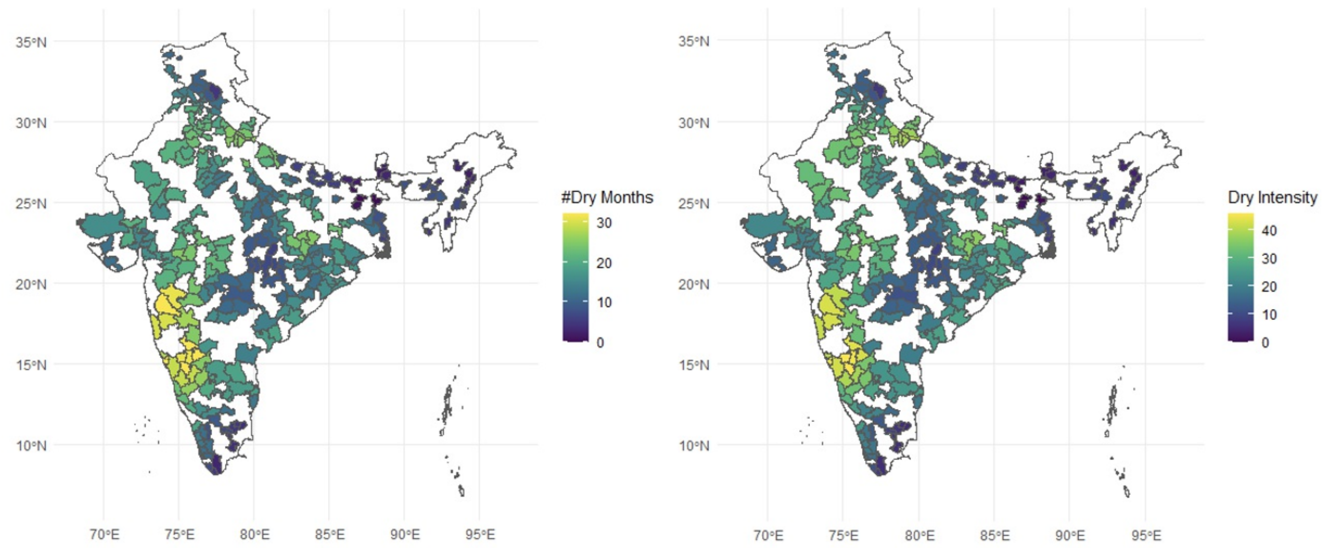

Figure 5. Number of dry months and intensity of dryness by district based on SPEI6 (Wave I)

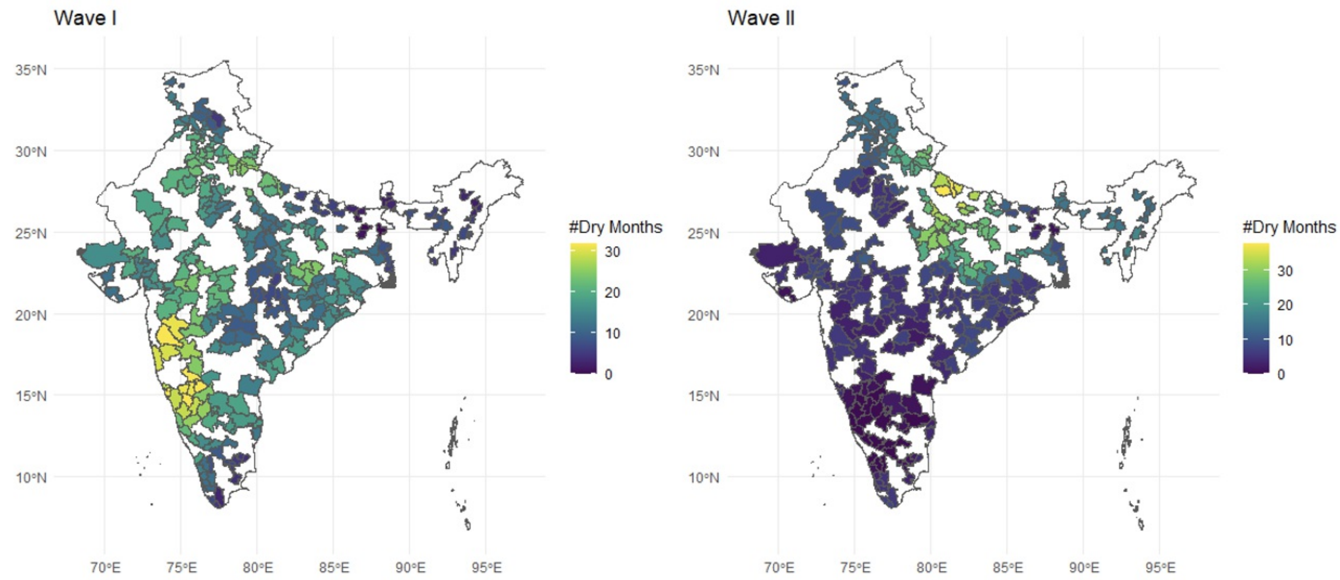

Figure 6. Number of dry months by district based on SPEI6 (Waves I & II)

As most of the migration in India is circular, it is useful to analyze migration in the 'New Economics of Labor Migration' framework, pioneered by (Stark and Bloom 1985). Here, the interest is not in whether the entire household migrates, but whether the household diversifies livelihood by sending a few members as a household-level income diversification strategy. While the decennial censuss captures migration between waves, they are not useful to capture short-term or temporary migration where only a few members of the household leave for migration. Other sources like National Sample Survey do capture household-level data (e.g., 55th round, 64th round), but they do not track the same household over the waves. This is the main reason for using India's Human Development Survey data. The IHDS survey is a nationally representative multitopic panel survey in India and is conducted jointly by the University of Maryland and National Council of Applied Economic Research (NCAER), New Delhi (Desai, Vanneman, and National Council of Applied Economic Research 2018, 2019). We restrict our analytical sample to households residing in rural areas in wave I of the survey. The attrition rate for the rural subsample is low (around 9%).

Migrants within a household can be identified in different ways in the IHDS surveys. The first is the "tracking sheet" for the survey in the second wave which reports if anyone missing in the household is missing as they have migrated for economic or other reasons. While this is the only place where a migrant is directly identified, it does not clearly state the economic attachment through remittances or transfers. This, however, can be found in the non-resident files in both waves where it is possible to identify the spouse of any household member or the parent of any children who reside outside and regularly transfers money to this household. Such individuals meet our conceptualization of livelihood diversification at the household level and are identified as a migrant for this analysis.

While the survey identifies several groups, here we identify the social groups in three broad categories — Backward Class (OBC), Scheduled groups, and others not classified either as OBC or Scheduled groups. We introduce the OBCs who face similar economic disadvantages like the scheduled group, but unlike the latter, they do not face social barriers like untouchability (Thorat and Joshi 2020) and they have been more successful in altering their conditions through political and social organizations in recent years.

Table 1 shows the distribution of migrant households among different social groups. The overall percent of the migrant household has increased between the waves. The tabulation shows that the OBCs are more mobile in Wave I, but "Others" are more mobile in Wave II of the survey. Table 2 shows the distribution of different characteristics of the households where the number of migrants increased between the waves and where they did not. The households which saw an increase in the number of migrants are more likely to have a larger number of members and lower dependency ratios. They are more likely to be literate and less likely to be poor. Change in the number of migrants is lowest among households whose main source of income is agricultural labor and higher among professionals ("Others"). An increase in the number of migrants is more among the OBC or others and less among the Scheduled group households.

Analytical strategy

In this paper, we establish the causality of climate change on household migration behavior using the first-difference regression to account for unobserved time-invariant household level factors.

$$\begin{aligned} \Delta Migration = \; & \beta_{0j} + \beta_1 \Delta Wetness_j^d + \beta_2 \Delta Dryness_j^d + \beta_3 SocGroup_i \\ & + \beta_4 SocNet_i + \beta_5 NREGSadv_i + \beta_6 Z_{ij} + \epsilon_{ij} \\ \beta_{0j} = \; & \gamma_{00} + u_{0j} \end{aligned} \tag{1}$$

As our climate variable is at the district level and we are primarily interested in measuring cross-level interactions, for estimation purposes, we use multilevel modeling using a random intercept at the district level (Aguinis, Gottfredson, and Culpepper 2013; Gelman and Hill 2006; Mathieu et al. 2012). $\Delta Migration$is calculated as a binary variable indicating whether the household shows an increase in the number of migrants over the survey. Since wetness and dryness can potentially have different effects, they are accounted for separately. $\Delta Wetness$ and $\Delta Dryness$ refer to a change in the count of SPEI values in the 60 months before the surveys in the respective districts. It is the nature of the slow-onset climate change that the magnitudes of effects are low, even if they are significant and robust. So, in addition, we further exploit the spatial variation in changes in wetness and dryness to examine the effect of climate change. In one, we identify districts with lower or above median (for the specific wave) count of wetness or dryness. Then we created a categorical variable indicating whether the district remained in less than the median count, changed from higher to lower than the median count, or from lower to higher than the median count, or remained higher than the median count district over the two waves. In addition, we also create a binary variable indicating whether the district shows a movement from lower to higher than the median count or not.

SocGroup refers to the social group of the household head and is classified as mentioned earlier.

SocNet here indicates the presence of a social network. Here we use two alternative definitions based on IHDS instruments. In one, a binary variable is created based on whether the household has anyone among their acquaintances and relatives, and professionals associated with medical care, education, or government services who also belong to the same caste group. This will capture the quality of the household's social network (*SocNetQ*). We also create an alternative variable to indicate whether anyone in the household belongs to a religious or social group or a festival society or a caste association. This is expected to capture the household's interest in group membership (*SocNetM*). We use the binary variable *NREGSadv* which indicates whether, at the village level, NREGS wages are at least as high as the prevailing female unskilled worker wages.

The regression control for several other variables like the number of household members and a quadratic term, the dependency ratio (based on the number of persons less than 15 vs those above - as in developing countries it is often the case that people work till, they are fully incapacitated). Other controls include occupation, which is the main source of income for the household, categorized as cultivation, agricultural labor, non-agricultural labor, and others; whether anyone in the household is literate, whether the household is poor based on per capita consumption expenditure. At the village level, the regression controls for distance from the nearest town (as a measure of remoteness), whether villagers leave this village for a seasonal job (as a measure of migrant network), and the proportion of villagers belonging to the same social group as the household head. The specification also controls for a quarter of the survey in either wave.

As is common in a similar analysis, we do not control for crop yields, wages, income, etc, even though they are important in determining migration changes. It has been argued that such controls may lead to overcontrolling as they are affected by climate (Beine and Jeusette, 2019; Cattaneo et al. 2019).

Subsequently, to examine the heterogeneous pattern of the effect of drought on social groups, we consider the following specification.

$$\Delta Migration = \beta_{0j} + \beta_1 \Delta Wetness_i^d + \beta_2 \Delta Dryness_i^d + \beta_3 SocGroup_i + \beta_4 \Delta Wetness_i^d \times SocGroup_i + \beta_5 \Delta Dryness_i^d \times SocGroup_i + \beta_6 SocNet_i + \beta_7 NREGSadv_i + \beta_8 Z_{ij} + \epsilon_{ij} \quad (2)$$
$$\beta_{0j} = \gamma_{00} + u_{0j}$$

Here we use a binary variable to indicate districts with major changes in wetness and dryness as an indicator of change in wetness and dryness.

Finally, we consider the above specification among households with or without social networks and with or without NREGS advantage. A difference-in-difference-in-difference model is also used to examine whether those belonging to scheduled groups with a social network from a district with adverse dryness conditions show significantly different migration patterns compared to the base social group category ("others").

$$\Delta Migration = \beta_{0j} + \beta_1 \Delta Wetness_i^d + \beta_2 \Delta Dryness_i^d + \beta_3 SocGroup_i + \beta_4 SocNet_i + \beta_5 \Delta Wetness_i^d \times SocGroup_i + \beta_6 \Delta Dryness_i^d \times SocGroup_i + \beta_7 \Delta Wetness_i^d \times SocNet_i + \beta_8 \Delta Dryness_i^d \times SocNet_i + \beta_9 \Delta Wetness_i^d \times SocGroup_i \times SocNet_i + \beta_{10} \Delta Dryness_i^d \times SocGroup_i \times SocNet_i + \beta_{11} NREGSadv_i + \beta_{12} Z_{ij} + \epsilon_{ij} \quad (3)$$
$$\beta_{0j} = \gamma_{00} + u_{0j}$$

A similar exercise were repeated for those not from or from NREGS advantage villages.

In all regressions, we use a linear probability model to estimate the regression mainly for simplicity of interpretation (Horace and Oaxaca 2006).

Regression results

Table 3 shows the results of the primary regression. Here we observe that while one extra month of agricultural dryness (measured using SPEI6) significantly increases the probability of an increase in the number of migrants in the household, one extra month of hydrological dryness (measured using SPEI18) does not have any significant effect. In the latter case, an additional month of wetness is significantly associated with a decrease in migration. Similar results of the consequence of excess precipitation are also observed by Gray and Mueller (2012b) following floods in Bangladesh. It is possible that it increases agricultural productivity and reduces the need to migrate (L. Banerjee 2010). In either specification, we note that those belonging to scheduled groups significantly decrease the probability of migration compared to the base category. The effect for the OBC households, however, is not significant.

Table 4a shows the relations of a spatial heterogeneity of changes in the number of months of dryness measured using SPEI6. Here a 3 percent point a significant positive effect on migration can be seen only for households residing in a district which changes from less than the median dryness month to more than median. A numerically higher negative and significant effect can be seen here when either the district of residence changes from less than the median month of wetness to more than the median month of wetness or remains more than the median month of wetness in either wave of the survey. However, when a binary identifier is used for households from districts that moved from less than the median to more than median months of wetness, the effect is no longer significant. On the other hand, the results show a 3.2 percent point significant positive effect on migration for households in districts which changed from less than median to more than median dryness. The magnitude of these effects is higher in the case of SPEI18 although they follow a similar pattern (Table 4b). In the rest of the regressions, we will concentrate only on the binary indicator of change in wetness or dryness from less than the median to more than median months. This binary variable will be referred to as districts of major changes in the wetness of dryness for simplicity.

Our next set of results (Table 5) looks at the heterogeneous effect of these climate measures (both using SPEI6 and SPEI18) by social groups. In either case, we see a 3 percent point decline in migration among scheduled groups residing in districts with major change in dryness compared to other districts. In addition, we did not observe any significant decrease in the probability of migration due to scheduled group households residing in districts with major changes in wetness.

In Tables 6a and 6b, we examine how the heterogeneous effects of social groups discussed in Table 5 vary by households that have access to a social network or not. In Table 6a, we focus on social network quality. Scheduled group households without access to quality social networks residing in a district with major change in dryness show a significant negative effect on migration probability compared to the “Others” (Column 1). The decrease in probability, however, is not significant for those who have access to a quality social network (Column 2). However, a difference in difference in difference specification (Column 3) shows that social network quality has no significant effect on the probability of migration of the household of scheduled group households from districts with major change in dryness, compared to others. In Table 6b, the same specification is implemented with the alternative measure of a social network — participation in religious caste groups and activities. Here also we observe the same pattern — those with no social network are less likely to migrate compared to those with a social network. But the triple difference specification still shows no significant effect on influencing migration probability among scheduled groups in districts with major changes in dryness.

The results for villages having NREGS advantage, i.e., where the NREGS wage is higher than the prevailing wages for unskilled work among women, are different from those with or without access to social networks. While those from villages with no NREGS wage advantage, scheduled group households show a significantly lower probability of migration if the household is a resident because of districts of major change in dryness, it does not show a significant effect when there is an NREGS advantage. Furthermore, in the triple difference specification (Column 3), NREGS advantage shows a significant increase in migration probability among scheduled group households in districts with major changes in dryness.

Conclusion

The main purpose of this research was to examine how households belonging to disadvantaged groups adapt their livelihood strategies in the face of climate change in a developing country. Using data from two waves of IHDS, we find that migration as a livelihood diversification at the household level is sensitive to an increase in dryness as well as wetness. We find a significant positive effect for drought and a negative effect for excess wetness. Moreover, scheduled groups are more likely not to migrate even in the face of drought, while their behavior is no different in wet spells. Furthermore, we note that it is not because of their quality of the network but because of their disadvantages, most likely due to poverty that they do not migrate. This we can say like those from villages which benefited from higher wages through NREGS while being exposed to climate change, shows significantly positive behavior compared to those with none.

Our results agree with Taraz (2019) who notes that NREGS effectively transfers some of the risks of low rainfall shock away from households that are net sellers of agricultural labor towards households that are net buyers of agricultural labor. It may be alternatively suggested that efficient irrigation practices may be successful in reducing the effect of climate change on the rural economy. Taraz (2017) notes that adaptation by choosing different crops or investment in irrigation can recover only 14% of the profits lost due to harmful changes in India. She, however, attributes that to credit constraints and informational barriers. However, a recent paper by Fishman (2018) argues that sustainable use of irrigation water can mitigate less than a tenth of the climate change impact in India.

In the development literature (e.g., Gough (2004)) it is argued that developing countries often have poorly functioning labor and financial markets and the state often fails to compensate for the consequent inequitable outcomes of markets. In such cases, social relationships are often vital to mitigate income shocks. While they may be useful in the mitigation of idiosyncratic income shocks, slow-onset climate change poses different challenges for its potential to affect all those in the network (Carter and Maluccio 2003; Dercon 2005). This is because climate change in itself might deplete the ability of the household to invest in such a network by eroding social and cultural assets (De la Fuente 2007). Inability to contribute to such a network can reproduce preexisting disadvantages. The utility of social network-based risk sharing is highest when the income sources of these households are not similar. One way it can be achieved in the context of climate change, is through spatial diversification. However, distance often raises cost of maintaining such links. Fafchamps and Gubert (2007) argue that geographic proximity is a major determinant of interpersonal relationships, as it facilitates the development of such relationships and ensures monitoring and enforcement. Consequently, most networks are local and face similar risks. In the Indian context, Rosenzweig and Stark (1989) and Munshi and Rosenzweig (2016) observe that marriage migration often takes the form of risk diversification across geographical spaces.

Another way it can be achieved is through the building of networks across a social classes or through groups whose income sources are either negatively correlated to the base household's or uncorrelated with climate factors. However, social networks are rarely built across the communal or occupational divide. Thus, links may not be optimal as income or occupation does not play any significant role in link formation, which is often determined by social group identity. In most cases, households participating in such networks share similar livelihoods and living standards, leaving them unable to insure consumption fully (Carter and Maluccio 2003).

It is worth pointing out here is that the distress migration that the NREGS was supposed to reduce is quite different from the type of migration associated with slow-onset climate change. If the disadvantaged social groups cannot take advantage of migration opportunities for their risk aversion, such a poverty alleviation program can help them to choose migration as a diversification option. Evidence of NREGS reducing risk aversion can be seen in the case of farming too as there is evidence that farmers shifted to riskier and more profitable crops following the implementation of NREGS (Gehrke and Hartwig 2018).

While the average annual payment under NREGS was approximately 100 USD, in an RCT in Bangladesh, Bryan, Chowdhury, and Mobarak (2014) randomly assigned an $8.50 incentive to households in rural Bangladesh to temporarily outmigrate during the lean season. The incentive induces 22% of households to send a seasonal migrant, their consumption at the origin increases significantly, and treated households are 8–10 percentage points more likely to remigrate 1 and 3 years after the incentive was removed. Similar evidence can be seen in the case of migration of prime-aged adults following South Africa’s social pension program (Ardington Case and Hosegood 2009) or the mean tested pension schemes in China (Eggleston, Sun, and Zhan 2018) where such transfers relaxed the household credit constraints. There is also similar evidence in Mexico where public transfers (*Oportunidades*) reduced financial constraints for migration (Angelucci 2015). Apart from that, NREGS promoted women’s participation in the labor force by setting a state-level quota as well as guaranteeing equal wages by gender (Khera and Nayak, 2009; Pankaj and Tankha 2010; Azam 2011). Such an incentive can promote male migration as NREGS incomes are not sufficient and migration for work is predominantly male.

The main limitation of this study is to claim causality with only two periods of data. This can be only resolved once the third wave of IHDS becomes publicly available. Another limitation is that the non-resident instrument was created to account for transfer income to and from households and not to account for migration. Using the non-resident file to identify migration may have its limitations. However, in the absence of a reliable household survey with direct instruments on migration, we cannot test the robustness of these results using alternative surveys.

While our results corroborate studies, which find limitations in social networks in the face of slow-onset climate change, the positive results about the impact of the poverty alleviation program indicate the future direction of public policy in this area. Now it is also worth noting that India already has several such programs. The fact that the disadvantaged social groups are not able to capitalize on them indicates the broader problem of exclusion faced by members of these social groups. Poverty alleviation also has its limitations. One important development in this area is the growth of non-farm sectors as productivity in this sector is higher and generally, it is less sensitive to climate. However, recent studies indicate that because of several preexisting problems like low educational attainment as well as discrimination, such changes are bypassing the disadvantaged social groups (Bera and Dubey 2020; Himanshu et al. 2013).

Tables

Table 1. Percent of Migrant Households in IHDS Sample.

	Social Groups			
	Others	OBC	Scheduled	Total
% Migrant HH				
Wave I	4.7	5.2	3.9	4.7
Wave II	11.6	10.7	8.2	10.1

Table 2. Household Characteristics in IHDS Sample.

	Change in number of Migrants in HH		
	Same/Lower	Increase	Total
HH Size	5.98	6.53	6.03
Dependency ratio	0.59	0.58	0.59
Literate	74.2%	76.5%	74.4%
Poor	22.4%	21.7%	22.4%
Main Occupation			
Cultivation	39.7%	37.5%	39.5%
Ag Labor	19.8%	14.6%	19.3%
Non-Ag Labor	16.4%	16.5%	16.4%
Others	24.2%	31.4%	24.8%
Social Group			
Other	25.7%	29.7%	26.1%
OBC	40.3%	42.6%	40.5%
Scheduled	34.0%	27.7%	33.5%

Table 3. Effect of Social Group membership and SPEI changes with the increase in migration.

	(1)	(2)
	D#Migrant	D#Migrant
Social Group		
OBC	-0.0067	-0.0067
	(-1.37)	(-1.37)
Scheduled	-0.0205***	-0.0207***
	(-4.00)	(-4.02)
SPEI6		
D #Wet Months	-0.0007	
	(-0.86)	
D#Dry Months	0.0014**	
	(2.80)	
SPEI18		
D #Wet Months		-0.0010*
		(-2.51)
D#Dry Months		0.0004
		(1.33)
N	25570	25570

t statistics in parentheses

* *p < 0.05,* ** *p < 0.01,* *** *p < 0.001*

Note: All regression controls for a number of household members and a quadratic term dependency ratio, the main source of income for the household literate, poor, a control for the social network, and one for NREGS wage advantage. Other variables include the distance from the nearest town, whether villagers leave this village for a seasonal job, and the proportion of villagers belonging to the same social group as the household head. The specification also controls for a quarter of the survey in either wave.

Unless stated otherwise, all the following regression controls for the same set of variables.

Table 4a. Spatial heterogeneity of SPEI6 changes with increase in migration.

	(1)	(2)
(SPEI6)	D#Migrant	D#Migrant
Categorical: D #Wet Months		
MT to LT Median	-0.0047	
	(-0.39)	
LT to MT Median	-0.0322*	
	(-2.32)	
MT to MT Median	-0.0506***	
	(-3.35)	
Categorical: D #Dry Months		
MT to LT Median	0.0069	
	(0.54)	
LT to MT Median	0.0304*	
	(2.41)	
MT to MT Median	0.0140	
	(1.01)	
Binary: D #Wet Months		
LT to MT Median		-0.0123
		(-1.23)
Binary: D #Dry Months		
LT to MT Median		0.0316**
		(3.15)
N	25570	25570

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4b. Spatial heterogeneity of SPEI18 changes with increase in migration.

	(1)	(2)
(SEPI18)	D#Migrant	D#Migrant
Categorical: D #Wet Months		
MT to LT Median	-0.0313*	
	(-2.50)	
LT to MT Median	-0.0379**	
	(-2.67)	
MT to MT Median	-0.0547***	
	(-3.57)	
Categorical: D #Dry Months		
MT to LT Median	-0.0000	
	(-0.00)	
LT to MT Median	0.0448***	
	(3.57)	
MT to MT Median	0.0097	
	(0.71)	
Binary: D #Wet Months		
LT to MT Median		-0.0056
		(-0.55)
Binary: D #Dry Months		
LT to MT Median		0.0443***
		(4.38)
N	25570	25570

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5. Interaction effect of spatial heterogeneity of SPEI6 changes by social group membership on the increase in migration.

	(1)	(2)
	D#Migrant	D#Migrant
Binary: D #Wet Months (SPEI6)		
OBC × LT to MT Median	-0.0059	
	(-0.57)	
Scheduled groups × LT to MT Median	0.0028	
	(0.27)	
Binary: D #Dry Months (SPEI6)		
OBC × LT to MT Median	0.0018	
	(0.16)	
Scheduled groups × LT to MT Median	-0.0295**	
	(-2.86)	
Binary: D #Wet Months (SPEI18)		
OBC × LT to MT Median		-0.0081
		(-0.76)
Scheduled groups × LT to MT Median		-0.00208
		(-0.19)
Binary: D #Dry Months (SPEI18)		
OBC × LT to MT Median		0.00261
		(0.23)
Scheduled groups × LT to MT Median		-0.0298**
		(-2.80)
N	25570	25570

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6a. Interaction effect of spatial heterogeneity of SPEI6 changes by social group membership with the increase in migration for different subsamples based on social network quality.

	(1)	(2)	(3)
	D#Migrant	**D#Migrant**	**D#Migrant**
Binary: D #Dry Months (SPEI6)			
OBC × LT to MT Median	-0.0067	0.0258	0.0010
	(-0.48)	(1.36)	(0.07)
Scheduled groups × LT to MT Median	-0.0303*	-0.0275	-0.0257*
	(-2.39)	(-1.45)	(-2.04)
OBC × LT to MT Median × SocNetQ			0.0102
			(0.49)
Scheduled groups × LT to MT Median × SocNetQ			-0.0060
			(-0.28)
N	17697	7873	25570

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Regressions also control for interaction terms related to a binary identifier for changes in wetness and other relevant interactions in the triple difference specification (3).

Table 6b. Interaction effect of spatial heterogeneity of SPEI6 changes on social group membership on the increase in migration for different subsamples based on social network membership.

	(1)	(2)	(3)
	D#Migrant	D#Migrant	D#Migrant
Binary: D #Dry Months (SPEI6)			
OBC × LT to MT Median	-0.0055	0.0325	-0.0087
	(-0.43)	(1.31)	(-0.70)
Scheduled groups × LT to MT Median	-0.0314**	-0.0008	-0.0323**
	(-2.77)	(-0.03)	(-2.90)
OBC × LT to MT Median × SocNetM			0.0485
			(1.77)
Scheduled groups × LT to MT Median × SocNetM			0.0368
			(1.29)
N	20575	5182	25757

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Here, social network is measured using a binary variable indicating participation in religious and caste organizations. Regressions also control for interaction terms related to a binary identifier for changes in wetness and other relevant interactions in the triple difference specification (3).

Table 7. Interaction effect of spatial heterogeneity of SPEI6 changes by social group membership on the increase in migration for different subsamples based on NREGS wage advantage.

	(1)	(2)	(3)
	D#Migrant	**D#Migrant**	**D#Migrant**
Binary: D #Dry Months (SPEI6)			
OBC × LT to MT Median	-0.0013	0.0119	-0.0030
	(-0.09)	(0.66)	(-0.22)
Scheduled groups × LT to MT Median	-0.0499***	-0.0028	-0.0457***
	(-3.60)	(-0.17)	(-3.47)
OBC × LT to MT Median			0.0164
			(0.73)
Scheduled groups × LT to MT Median × NREGAdv			0.0452*
			(2.12)
N	14314	11256	25570

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Regressions also control for interaction terms related to a binary identifier for changes in wetness and other relevant interactions in the triple difference specification (3).

References

- Adger, W Neil. 2010. "Climate change, human well-being and insecurity." *New Political Economy* 15 (2): 275-292.
- Adger, W Neil, and Helen Adams. 2013. "36. Migration as an adaptation strategy to environmental change." *World Social Science Report*: 261.
- Aguinis, Herman, Ryan K Gottfredson, and Steven Andrew Culpepper. 2013. "Best-practice recommendations for estimating cross-level interaction effects using multilevel modeling." *Journal of Management* 39 (6): 1490-1528.
- Angelucci, Manuela. 2015. "Migration and financial constraints: Evidence from Mexico." *Review of Economics and Statistics* 97 (1): 224-228.
- Ardington, Cally, Anne Case, and Victoria Hosegood. 2009. "Labor supply responses to large social transfers: Longitudinal evidence from South Africa." *American Economic Journal: Applied economics* 1 (1): 22-48.
- Azam, Mehtabul. 2011. "The impact of Indian job guarantee scheme on labor market outcomes: Evidence from a natural experiment." *Available at SSRN 1941959*.
- Banerjee, Abhijit V, and Andrew F Newman. 1991. "Risk-bearing and the theory of income distribution." *The Review of Economic Studies* 58 (2): 211-235.
- Banerjee, Lopamudra. 2010. "Effects of flood on agricultural productivity in Bangladesh." *Oxford Development Studies*

38 (3): 339-356.

- Barnett, Jon, and Michael Webber. 2009. "Accommodating migration to promote adaptation to climate change." *Commission on Climate Change and Development*.
- Beine, Michel, and Lionel Jeusette. 2019. "A Meta-Analysis of the Literature on Climate Change and Migration."
- Bell, Martin, Elin Charles-Edwards, Philipp Ueffing, John Stillwell, Marek Kupiszewski, and Dorota Kupiszewska. 2015. "Internal migration and development: Comparing migration intensities around the world." *Population and Development Review* 41 (1): 33-58.
- Bera, Manasi, and Amaresh Dubey. 2020. "Structure and Changes in Household Income and Employment Across Social Groups in Rural India." *The Indian Journal of Labour Economics* 63: 407-435.
- Bhattacharya, Prabir C. 2002. "Rural-to-urban migration in LDCs: A test of two rival models."*Journal of International Development* 14 (7): 951-972.
- Black, Richard, W Neil Adger, Nigel W Arnell, Stefan Dercon, Andrew Geddes, and David Thomas. 2011. "The effect of environmental change on human migration." *Global environmental change* 21: S3-S11.
- Black, Richard, Nigel W Arnell, W Neil Adger, David Thomas, and Andrew Geddes. 2013. "Migration, immobility and displacement outcomes following extreme events." *Environmental Science & Policy* 27: S32-S43.
- Bryan, Gharad, Shyamal Chowdhury, and Ahmed Mushfiq Mobarak. 2014. "Underinvestment in a profitable technology: The case of seasonal migration in Bangladesh." *Econometrica* 82 (5): 1671-1748.
- Burgess, Robin, Olivier Deschenes, Dave Donaldson, and Michael Greenstone. 2017. "Weather, climate change and death in India."
- Carleton, Tamma A. 2017. "Crop-damaging temperatures increase suicide rates in India."*Proceedings of the National Academy of Sciences* 114 (33): 8746-8751.
- Carter, Michael R, and John A Maluccio. 2003. "Social capital and coping with economic shocks: an analysis of stunting of South African children." *World Development* 31 (7): 1147-1163.
- Cattaneo, Cristina, Michel Beine, Christiane J Fröhlich, Dominic Kniveton, Inmaculada Martinez-Zarzoso, Marina Mastrorillo, Katrin Millock, Etienne Piguet, and Benjamin Schraven. 2019. "Human migration in the era of climate change." *Review of Environmental Economics and Policy* 13 (2): 189-206.
- Christensen, Jens Hesselbjerg, Bruce Hewitson, Aristita Busuioc, Anthony Chen, Xuejie Gao, R Held, Richard Jones, Rupa Kumar Kolli, WK Kwon, and René Laprise. 2007. "Regional climate projections." In *Climate Change, 2007: The Physical Science Basis. Contribution of Working group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, University Press, Cambridge, Chapter 11*, 847-940.
- Dallmann, Ingrid, and Katrin Millock. 2017. "Climate variability and inter-state migration in India."*CESifo Economic Studies* 63 (4): 560-594.
- Das, Upasak. 2015. "Can the rural employment guarantee scheme reduce rural out-migration: Evidence from West Bengal, India." *The Journal of Development Studies* 51 (6): 621-641.
- Datar, Chhaya. 2007. "Failure of National Rural Employment Guarantee Scheme in Maharashtra." *Economic and Political Weekly*: 3454-3457.
- De la Fuente, Alejandro. 2007. "Climate shocks and their impact on assets."*Occasional paper for UNDP*.

- Defrance, Dimitri, Esther Delesalle, and Flore Gubert. 2020. *Is Migration Drought-induced in Mali?: An Empirical Analysis Using Panel Data on Malian Localities Over the 1987-2009 Period.* Institut de recherche économiques et sociales, UC Louvain.
- Deininger, Klaus, and Yanyan Liu. 2013. *Welfare and Poverty Impacts of India S National Rural Employment Guarantee Scheme: Evidence from Andhra Pradesh*. Vol. 1289. Intl Food Policy Res Inst.
- Dell, Melissa, Benjamin F Jones, and Benjamin A Olken. 2014. "What do we learn from the weather? The new climate-economy literature." *Journal of Economic Literature* 52 (3): 740-98.
- Dercon, Stefan. 2005. *Insurance against poverty*. Oxford University Press.
- Desai, Sonalde, Reeve Vanneman, and New Delhi National Council of Applied Economic Research. 2018. India Human Development Survey (IHDS), 2005. Inter-university Consortium for Political and Social Research [distributor].
- ---. 2019. India Human Development Survey Panel (IHDS, IHDS-II), 2005, 2011-2012. Inter-university Consortium for Political and Social Research [distributor].
- Deshingar, P, S Akter, P Sharma, and J Farrington. 2010. "The impacts of social protection on labour markets and migration with particular reference to the NREGA." *Overseas Development Institute, London*.
- Deshingkar, Priya. 2008. "Circular internal migration and development in India." *Migration and development within and across borders: research and policy perspectives on internal and international migration. Geneva: International Organization for Migration/Social Science Research Council*: 161-87.
- Deshingkar, Priya, and Daniel Start. 2003. *Seasonal migration for livelihoods in India: Coping, accumulation and exclusion*. Vol. 111. Overseas Development Institute London.
- Drèze, Jean, and Reetika Khera. 2011. "Employment guarantee and the right to work." In *The battle for employment guarantee*, edited by N.G. Jayal and P. Mehta, In The Oxford Companion to Politics in India, 3-20. New Delhi: Oxford.
- Dutta, Puja, Rinku Murgai, Martin Ravallion, and Dominique Van de Walle. 2014. "Does India's employment guarantee scheme guarantee employment?".
- Eckstein, David, Vera Künzel, Laura Schäfer, and Maik Winges. 2019. "Global climate risk index 2020." *Bonn: Germanwatch*.
- Eggleston, Karen, Ang Sun, and Zhaoguo Zhan. 2018. "The impact of rural pensions in China on labor migration." *The World Bank Economic Review* 32 (1): 64-84.
- Fafchamps, Marcel, and Flore Gubert. 2007. "The formation of risk sharing networks." *Journal of development Economics* 83 (2): 326-350.
- Feng, Shuaizhang, Alan B Krueger, and Michael Oppenheimer. 2010. "Linkages among climate change, crop yields and Mexico–US cross-border migration." *Proceedings of the national academy of sciences* 107 (32): 14257-14262.
- Field, Christopher B, and Vicente R Barros. 2014. *Climate change 2014–Impacts, adaptation and vulnerability: Regional aspects*. Cambridge University Press.
- Fishman, Ram. 2018. "Groundwater depletion limits the scope for adaptation to increased rainfall variability in India." *Climatic change* 147 (1): 195-209.
- Fussell, Elizabeth, Lori M Hunter, and Clark L Gray. 2014. "Measuring the environmental dimensions of human migration: The demographer's toolkit." *Global Environmental Change* 28: 182-191.

- Garg, Teevrat, Maulik Jagnani, and Vis Taraz. 2020. "Temperature and Human Capital in India."*Journal of Environmental and Resource Economists* 7 (6): 1113-1150.
- Gehrke, Esther, and Renate Hartwig. 2018. "Productive effects of public works programs: What do we know? What should we know?" *World development* 107: 111-124.
- Gelman, Andrew, and Jennifer Hill. 2006. *Data analysis using regression and multilevel/hierarchical models*. Cambridge University Press.
- Gough, Ian. 2004. "Welfare regimes in development context: a global and regional analysis." In*Insecurity and welfare regimes in Asia, Africa and Latin America: Social policy in development contexts*, edited by Ian Gough, Geof Wood, Armando Barrientos, Philippa Bevan, Graham Room and Peter Davis. Cambridge University Press.
- Government of India. 2015. All India Report on Agriculture Census 2010-11. edited by cooperation & Farmer's Welfare, Department of Agriculture. New Delhi: Ministry of Agriculture and Farmer's Welfare.
- Gray, Clark, and Richard Bilsborrow. 2013. "Environmental influences on human migration in rural Ecuador." *Demography* 50 (4): 1217-1241.
- Gray, Clark, and Valerie Mueller. 2012a. "Drought and population mobility in rural Ethiopia."*World development* 40 (1): 134-145.
- ---. 2012b. "Natural disasters and population mobility in Bangladesh."*Proceedings of the National Academy of Sciences* 109 (16): 6000-6005.
- Guiteras, Raymond. 2008. "The Impact of Climate Change on Indian Agriculture."
- Harrington, Luke J, David J Frame, Erich M Fischer, Ed Hawkins, Manoj Joshi, and Chris D Jones. 2016. "Poorest countries experience earlier anthropogenic emergence of daily temperature extremes." *Environmental Research Letters* 11 (5): 055007.
- Harris, Ian, Timothy J Osborn, Phil Jones, and David Lister. 2020. "Version 4 of the CRU TS monthly high-resolution gridded multivariate climate dataset." *Scientific data* 7 (1): 1-18.
- Himanshu, Peter Lanjouw, Rinku Murgai, and Nicholas Stern. 2013. "Nonfarm diversification, poverty, economic mobility, and income inequality: a case study in village India." *Agricultural Economics* 44 (4-5): 461-473.
- Hnatkovska, Viktoria, and Amartya Lahiri. 2015. "Rural and urban migrants in India: 1983–2008."*The World Bank Economic Review* 29 (suppl_1): S257-S270.
- Horrace, William C, and Ronald L Oaxaca. 2006. "Results on the bias and inconsistency of ordinary least squares for the linear probability model." *Economics Letters* 90 (3): 321-327.
- Hugo, Graeme. 1996. "Environmental concerns and international migration."*International migration review* 30 (1): 105-131.
- Imbert, Clement, and John Papp. 2015. "Labor market effects of social programs: Evidence from India's employment guarantee." *American Economic Journal: Applied Economics* 7 (2): 233-63.
- Islam, S Nazrul, and John Winkel. 2017. "Climate Change and Social Inequality." *United Nations, Department of Economics and Social Affairs*.
- Iversen, Vegard, Adriaan Kalwij, Arjan Verschoor, and Amaresh Dubey. 2014. "Caste dominance and economic performance in rural India." *Economic Development and Cultural Change* 62 (3): 423-457.

- Jacoby, Hanan G, and Emmanuel Skoufias. 1997. "Risk, financial markets, and human capital in a developing country." *The Review of Economic Studies* 64 (3): 311-335.
- Jessoe, Katrina, Dale T Manning, and J Edward Taylor. 2018. "Climate change and labour allocation in rural Mexico: Evidence from annual fluctuations in weather." *The Economic Journal* 128 (608): 230-261.
- Johnson, Craig A, and Krishna Krishnamurthy. 2010. "Dealing with displacement: Can “social protection” facilitate long-term adaptation to climate change?" *Global Environmental Change* 20 (4): 648-655.
- Kanbur, Steven M. 1979. "Of risk taking and the personal distribution of income."*Journal of Political Economy* 87 (4): 769-797.
- Keshri, Kunal, and Ram B Bhagat. 2010. "Temporary and seasonal migration in India."*Genus* 66 (3): 25-45.
- Khan, Amir Ullah, and MR Saluja. 2007. "Impact of the NREGP on Rural Livelihoods."*New Delhi: India Development Foundation*.
- Khera, Reetika. 2011. *The Battle for Employment Guarantee*. Oxford University Press India.
- Khera, Reetika, and Nandini Nayak. 2009. "Women Workers and perceptions of the National rural employment Guarantee act." *Economic and Political Weekly*: 49-57.
- Liu, Yanyan, and Christopher B Barrett. 2013. "Heterogeneous pro-poor targeting in the national rural employment guarantee scheme." *Economic and Political Weekly*: 46-53.
- Masson-Delmotte, Valérie, Panmao Zhai, Hans-Otto Pörtner, Debra Roberts, Jim Skea, Priyadarshi R Shukla, Anna Pirani, W Moufouma-Okia, C Péan, and R Pidcock. 2018. "Global warming of 1.5 C." *An IPCC Special Report on the impacts of global warming of* 1: 1-9.
- Mathieu, John E, Herman Aguinis, Steven A Culpepper, and Gilad Chen. 2012. "Understanding and estimating the power to detect cross-level interaction effects in multilevel modeling." *Journal of applied psychology* 97 (5): 951.
- McLeman, Robert, and Barry Smit. 2006. "Migration as an adaptation to climate change."*Climatic change* 76 (1-2): 31-53.
- Millock, Katrin. 2015. "Migration and environment."*Annu. Rev. Resour. Econ.* 7 (1): 35-60.
- Mohanty, Abinash. 2020. *Preparing India for Extreme Climate Events: Mapping Hotspots and Response Mechanisms.* New Delhi: Council on Energy, Environment and Water.
- Mohanty, Bibhuti B. 2001. "Land distribution among scheduled castes and tribes."*Economic and Political Weekly*: 3857-3868.
- Mosse, David. 2010. "A relational approach to durable poverty, inequality and power."*The journal of development studies* 46 (7): 1156-1178.
- Munshi, Kaivan, and Mark Rosenzweig. 2016. "Networks and misallocation: Insurance, migration, and the rural-urban wage gap." *American Economic Review* 106 (1): 46-98.
- Novotný, Josef, Jana Kubelková, and Vanishree Joseph. 2013. "A multi-dimensional analysis of the impacts of the Mahatma Gandhi National Rural Employment Guarantee Scheme: A tale from Tamil Nadu." *Singapore Journal of Tropical Geography* 34 (3): 322-341.
- Pankaj, Ashok, and Rukmini Tankha. 2010. "Empowerment effects of the NREGS on women workers: A study in four states." *Economic and Political Weekly*: 45-55.

- Ravi, Shamika, and Monika Engler. 2015. "Workfare as an effective way to fight poverty: The case of India's NREGS." *World Development* 67: 57-71.
- Renaud, Fabrice G, Janos J Bogardi, Olivia Dun, and Koko Warner. 2007.*Control, adapt or flee: How to face environmental migration?*: UNU-EHS.
- Rosenzweig, Mark R, and Oded Stark. 1989. "Consumption smoothing, migration, and marriage: Evidence from rural India." *Journal of political Economy* 97 (4): 905-926.
- Sabates-Wheeler, Rachel, and Myrtha Waite. 2003. "Migration and Social Protection: A concept paper."*Institute of Development Studies, Sussex, December* 1645: 1980-2000.
- Sedova Barbora and Matthias Kalkuhl. 2020. "Who are the climate migrants and where do they go? Evidence from rural India." *World Development* 129: 104848.
- Skoufias, Emmanuel, Mariano Rabassa, and Sergio Olivieri. 2011. "The poverty impacts of climate change: a review of the evidence." *World Bank Policy Research Working Paper* (5622).
- Solinski, Thomas. 2012. "NREGA and labour migration in India: Is village life what the'rural'poor want?"*The South Asianist Journal* 1 (1).
- Stahlberg, S. 2012. "Title." Center on Democracy, Development, and the Rule of Law.
- Stark, Oded, and David E Bloom. 1985. "The new economics of labor migration."*The american Economic review* 75 (2): 173-178.
- Taraz, Vis. 2017. "Adaptation to climate change: Historical evidence from the Indian monsoon."*Environment and Development Economics* 22 (5): 517-545.
- ---. 2018. "Can farmers adapt to higher temperatures? Evidence from India."*World Development* 112: 205-219.
- ---. 2019. "Weather shocks, social protection, and crop yields: Evidence from India."*Social Protection, and Crop Yields: Evidence from India (October 11, 2019).*
- Thorat, Amit, and Omkar Joshi. 2020. "The continuing practice of untouchability in India."*Economic & Political Weekly* 55 (2): 37.
- Topalova, Petia. 2010. "Factor immobility and regional impacts of trade liberalization: Evidence on poverty from India." *American Economic Journal: Applied Economics* 2 (4): 1-41.
- Townsend, Robert M. 1994. "Risk and insurance in village India."*Econometrica: Journal of the Econometric Society*: 539-591.
- Vicente-Serrano, Sergio M, Santiago Beguería, and Juan I López-Moreno. 2010. "A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index." *Journal of climate* 23 (7): 1696-1718.
- Viswanathan, Brinda, and KS Kavi Kumar. 2015. "Weather, agriculture and rural migration: evidence from state and district level migration in India." *Environment and Development Economics* 20 (4): 469-492.
- Warner, Koko. 2010. "Global environmental change and migration: Governance challenges."*Global environmental change* 20 (3): 402-413.
- Warner, Koko, and Tamer Afifi. 2014. "Where the rain falls: Evidence from 8 countries on how vulnerable households use migration to manage the risk of rainfall variability and food insecurity." *Climate and Development* 6 (1): 1-17.
- Warner, Koko, and Kees Van der Geest. 2013. "Loss and damage from climate change: local-level evidence from nine

vulnerable countries." *International Journal of Global Warming* 5 (4): 367-386.

- Wilhite, Donald A, and Michael H Glantz. 1985. "Understanding: the drought phenomenon: the role of definitions." *Water international* 10 (3): 111-120.
- Wolf, Johanna. 2011. "Climate change adaptation as a social process." In *Climate change adaptation in developed nations*, 21-32. Springer.