LOCAL IMPACTS OF CLIMATE CHANGE-INDUCED MIGRATION

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To Sohyun, Brigitte, Juan, and Raymond

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I would like to express my deepest appreciation and gratitude for the guidance and persistent help of my committee members, help from PCRD staff members, and persistent support from my family and wife.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

Kim, Yong J. Ph.D., Purdue University, December 2019. Local Impacts of Climate Change-induced Migration. Major Professors: Brigitte S. Waldorf, Juan P. Sesmero.

First Essay: We exploit temporally disaggregated data on weather anomalies and temporary migration to examine the effect of the former on the latter, and the effectiveness of migration as a coping mechanism to maintain consumption in the face of adverse weather conditions. We construct a continuous measure of migration that increases both with the number of people leaving, and with the length of time they stay away. Our results show that, while weather anomalies do trigger temporary migration, they only do so when they occur before or rather early in the growing season. This suggests that households have a limited ability to respond to unexpected shocks when they occur late in the season. We also find that weather anomalies can affect migration patterns several months after they take place and discuss possible mechanisms. We find that, conditional on these temporal patterns, households lacking on labor force endowment and social networks are particularly limited in their ability to use migration as a coping mechanism and remain, consequently, more vulnerable to shocks. Our analysis reveals how temporal aggregation of weather shocks, widely implemented in previous studies, can obscure substantial heterogeneity in migration response, as well as their ability to mitigate adverse impacts.

Second Essay: The study uses the same framework as the first essay. It uses temporally disaggregated data on weather anomalies and temporary migration. However, this study expands the first essay by considering agricultural labor use. Our results show that agricultural labor hiring will not increase, although there is an increase in temporary labor migration by abnormal weather driving the previous agricultural season. This suggests that households adjust their agriculture plan with temporary

labor migration consideration. When a drought happens in the current agricultural season, our result shows that irrigation has mediation effects on hired agricultural labor. Our analysis reveals how temporally disaggregated analysis yields more detailed results for market outcomes.

Third Essay: Sea-level rise induced migration studies usually investigate inter-county or inter-regional migration. However, sea level rise does not affect a county uniformly. Instead, it affects only specific areas with different socio-economic status. The objective of this study is to provide information on socio-economic geography change associated with sea-level rise. We simulate the spatial redistribution of households in the United States coastal areas affected by the expected sea-level rise. Towards that end, we use a spatial microsimulation. The spatial microsimulation proceeds in two steps. In the first step, a synthetic population is generated for each spatial unit. In the second step, the synthetic population is redistributed as a response to sea-level rise. Our results show that, most of the households that migrate due to the sea-level rise, will migrate within the same or to a neighboring census tract areas.

1. INTRODUCTION

Migration is the movement of people from one location to another in order to improve living conditions. Developments of origin and destination are highly affected by migration. Since Ravenstein (1885) demonstrated that economic factors are the main drivers in the decision to migrate, researchers have widely investigated issues relating to migration including migration-driving factors, economic effects of migration in both origins and destinations.

Recently in migration studies, climate change-induced migration has received special attention. The three effects of climate change expected to affect economic drivers of migration are: (1) an increase in the frequency and magnitude of climatic disasters, (2) adverse climatic conditions that affect agricultural output and clean water accessibility, (3) sea level rise. Furthermore, each climate change effect impacts various migration drivers in different ways. For instance, enhanced natural disasters affect migration drivers by increasing risk perception. Therefore, climate change accelerates internal migration and displacement.

As climate change accelerates internal migration, its local effects are expected to magnify. For instance, adverse impacts of climate change on agriculture will increase income differences between rural and urban populations, which will accelerate urbanization. Location preferences change when natural disasters occur, and sea-level rise is expected to affect housing prices. Climate change affects regional socio-economic factors by influencing the migration system.

In this dissertation, each chapter investigates potential local impacts of climate change-induced migration: change in welfare and local economy by temporary migration, change in economic geography by sea-level rise induced migration. The main focus of this dissertation is identifying economic mechanisms and local effects of climate change-induced migration.

In the first two essays, the way in which abnormal precipitation induces temporary migration and affects household welfare and hired agricultural labor is investigated. These essays show the importance of considering disaggregated temporal levels . The last essay measures sea-level rise induced migration and their destinations in disaggregated spatial units.

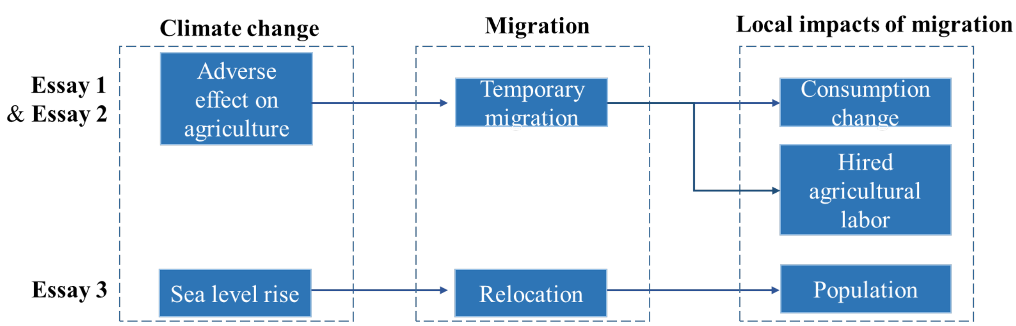
The first distinction of this dissertation is that the various disaggregated units in climate-related migration are considered. The first and second essays focus on the effects of temporary labor migration with disaggregated temporal units. The first essay, in particular, examines how the timing of abnormal precipitation can affect temporary labor migration differently, and how the timing of temporary labor migrations change the effects on welfare. The second essay uses the same setting as the first essay, but the topic is agricultural hired labor. This essay investigates how the timing of abnormal precipitation can affect temporary labor migration differently, and how it changes the hired agricultural labor. These two studies using disaggregated temporal units in analysis, show that the temporal unit can change the analysis results. In addition, it suggests that collecting temporally disaggregated data is critical for the related recovery policies. The third essay measures sea-level induced migration and their destinations in disaggregated spatial units. Previous studies explain the destinations of sea-level rise induced migration by county, but this study explains the migration with census tract level.

The essays in this dissertation about the various types of disaggregated units can lead to various policy implications for policymakers. The first essay provides policy implications for local governments. The results show that the timing of abnormal precipitation changes the effects of temporary labor migration on consumption. Thus, policymakers need to consider the timing of abnormal precipitation when establishing a recovery plan. The second essay also provides policy implications for local governments. When local governments consider temporary labor migration as a recovery plan, this could affect the local agricultural labor market. Thus, it should be considered carefully. The third essays show how socio-economic geography can be changed by sea-level rise. Therefore, it can be used for the establishment of future sea-level rise related adaptation policy.

The second distinction of this dissertation is that it includes different definitions of temporary labor migration variables. Traditionally, the temporary migration variable was defined as a binary variable due to a lack of data. In the first two essays, a continuous variable of temporary migration is defined by considering the duration of migration and the number of temporary migrants. Thus, this dissertation reduced bias by measurement errors by taking into account the new temporary migration variable.

To date, research on migration has been extensively conducted in many subjects such as economics and regional science. This dissertation does not begin with a completely new question, but it contributes to the literature by adding new data sets. This is the third distinction of this dissertation. In the first two essays, temporary labor migration is analysed by using a temporary disaggregated data set. The temporary disaggregated data set makes it possible to interpret how temporary labor migration can be changed by the timing of abnormal precipitation. In the third essay, intra-county level migration by sea-level rise is measured. Estimating this is challenging because the Census does not provide intra-county level migration data. This study uses traditional name matching between two consecutive years. This study, in particular, uses tax data at the parcel level. Thus, this study uses new data to bring new aspects to traditional studies.

The dissertation proceeds as follows. The next chapter investigates the effects of temporary labor migration on household consumption by using disaggregated temporal data. Chapter 3 extends on the second chapter by analyzing the effects of temporary labor migration on hired agricultural labor. Chapter 4 simulates intra-county migration by sea-level rise. Then finally, the conclusion summarizes the chapters.



Essay	Key quantifiable impacts
Essay 1	Climate effects on temporary migration and consumption
Essay 2	Climate effects on temporary migration and hired agricultural labor
Essay 3	Population composition changes

Fig. 1.1. Research structure

2. TEMPORARY MIGRATION AS A STRATEGY AGAINST WEATHER SHOCKS: EVIDENCE FROM RURAL INDIA

2.1 Introduction

Extreme weather conditions such as prolonged droughts or excessive precipitation and flooding-increasingly common given ongoing changes in climatic conditions-severely affect rural communities. Most notable, weather-induced poor harvests require coping mechanisms that allow farmers to deal with the associated economic hardships. This paper focuses on temporary migration as one such coping strategy, thereby shedding light on the relationship between weather, migration and welfare.

The literature has paid considerable attention to the questions of how extreme weather induces labor migration in agricultural economies and whether labor migration bolsters agricultural household consumptions (Stark and Bloom, 1985; de Brauw and Harigaya, 2007; Chandrasekhar et al., 2015). Our study makes three key contributions to this literature. First, we are primarily concerned with temporary labor migration as opposed to permanent migration. Temporary migrants leave their household in pursue of employment for a limited time period only. As a result, temporary migration is fundamentally different from permanent migration in that it is mostly shaped by push factors (adverse conditions at the origin), rather than by pull factors (favorable conditions at the destination). Although the importance of temporary labor migration in the face of economic adversity has been extensively documented, most studies remain exclusively tied to permanent labor migration. We exploit data that tracks temporary migrants in rural India, to examine the determinants and returns from temporary migration.

Second, we exploit temporally disaggregated data to better understand the seasonal intricacies of the relationship between weather anomalies, migration, and consumption. Previous studies use annual data and thus the year as the unit of observation. However, many rural areas have two or more agricultural seasons during the year. Our framework recognizes that behavioral responses to extreme weather conditions may differ depending on the timing of the anomalies vis--vis the evolution of the agricultural seasons. For instance, drought conditions late in the season may be less likely to trigger migration than drought conditions early in the growing season. Moreover, we also allow for asymmetric effects across anomalies (flooding may have distinct effects from those of droughts). Additionally, weather anomalies may have immediate effects on farm productivity, triggering immediate migration; or could have more lasting effects on farm productivity, triggering migration in the subsequent growing season.

Third, we construct a continuous measure of temporary labor migration, measured in person-months. We therefore depart from previous studies in this literature that measure migration as a binary phenomenon without accounting for the number of temporary migrants and the length of their sojourns away (Foster and Rosenzweig, 2008). Our strategy allows us to examine not only whether climatic anomalies trigger migration, but also the magnitude of that action by households. Our analysis underscores the importance of such departure from the literature. In particular, our results reveal that the impact of weather anomalies on migration and consumption varies widely across households according to whether they have access to irrigation, and along the labor endowment spectrum.

In this paper, we focus on abnormal precipitation in rural India as an exogenous weather shock and ask whether temporary labor migration can serve as an abnormal precipitation adaptation strategy. India is well-suited as a study area for several reasons. First, India is one of the most drought-vulnerable countries among agricultural economies. Second, sending family members to seek employment elsewhere for short periods of time is a common migration pattern in India (Deshingkar and Grimm, 2004). In fact, Deshingkar and Start (2003) point out that short-term migration is the main reason for the slow rate of urban population growth. Lastly, for a set of villages in India, Village Dynamics in South Asia (VDSA) survey provides detailed monthly data on households and their individual members, and these data can be spatially and temporally matched to meteorological data.

To assess the weather-migration-welfare nexus, we estimate the effect of precipitation anomalies on temporary labor migration, and the mediating effect of labor migration on household consumption. Identifying a causal relationship between household consumption and temporary labor migration is challenging for at least two reasons. First, temporary labor migration is more likely to be used as a coping strategy by deprived households (Chandrasekhar et al., 2015), making migration endogenous in the household consumption model. Second, unobservable characteristics that are correlated both with migration and consumption are likely present. We follow previous literature (Nguyen and Winters, 2011) and employ an instrumental variable approach (using an indicator of migration network at the village level and its interaction with the households labor force as instruments) to control for endogeneity of migration. Additionally. we estimate our model using household fixed effects to control for time-constant unobservables, and also cluster standard errors at the household level.

Our findings indicate that the effects of abnormal weather on temporary labor migration and consumption differ depending on the timing of abnormal weather occurrence. In particular, rural Indian households seem to use temporary migration as a coping mechanism to abnormal weather conditions before planting and early in the growing season. But households do not increase migration when the anomaly occurs later in the growing season. This might be associated with the availability (or lack thereof) of migration opportunities and with less harmful effects of weather anomalies when they take place after crops are in an advanced stage of development. Consistently with this finding, our results also show that temporary migration is more sensitive to weather shocks the stronger the households migration network and the larger the households labor endowment. Finally, our results indicate that adverse precipitation shocks have drastic effects on consumption, but less so among households with higher temporary migration. Therefore, our results suggest that households with low labor force endowments and limited networks are particularly vulnerable to weather shocks because they are more limited in their ability to exploit temporary migration as a coping mechanism. Our findings also call for policies supporting livelihood diversification strategies.

The rest of this paper proceeds as follows. Sections 2 and 3 provide literature review of labor migration strategy as a coping mechanism and temporary labor migration in India. Section 4 and section 5 present the conceptual framework and empirical methodology, respectively. Data sources and descriptive statistics are presented in section 6. Results are presented in section 7. Section 8 discusses policy implications and offers concluding remarks.

2.2 Literature review

There is a rich literature on the nexus among adverse conditions, labor migration, and welfare. A good deal of the literature is situated in African and Asian countries, including India, where temporary labor migration is quite pervasive. First, the evidence seems to suggest that temporary labor migration is used by households as a strategy to cope with adverse conditions in rural areas (Findley, 1994; Haberfeld et al., 1999; Deshingkar and Start, 2003; Badiani and Safir, 2010; Jlich, 2011). Second, effects of temporary labor migration are mixed rather than unified (Taylor et al., 2003; de Brauw and Harigaya, 2007; Atamanov and Van den Berg, 2012; Chandrasekhar et al., 2015). Third, disaggregated temporal level data with temporary labor migration are needed for disaggregated temporal analysis (Coffey et al., 2015).

Another strand of literature, which is closer in nature to our focus, looks at the link between weather anomalies and migration. Perch-Nielsen (2004) found evidence suggesting droughts can trigger migration, and also posed that drought is a very special type of disaster in that its development process differs from that of other natural disasters. Usually, natural disasters are one-time events. For example, floods or cyclones damage assets in the short-run, with recovery starting right after the event. In contrast, droughts develop slowly; i.e., they degrade assets like land over time, thereby forcing farmers to use migration instead of other forms of adaptation as a coping mechanism. These insights were later extended beyond drought, to include extreme rain and temperature events. Marchiori et al. (2012) found that these weather extremes trigger domestic and international migration in sub-Saharan Africa.

The studies just reviewed focused on permanent migration. However, subsequent analyses turned their attention to temporary migration. Findley (1994) found that droughts triggered temporary, rather than permanent, migration patterns in rural Mali between 1983 and 1985. Other studies have similarly established that weather anomalies trigger temporary labor migration (Badiani and Safir (2010); Jlich (2011). In particular, Badiani and Safir (2010) found that a mild drought can trigger temporary labor migration, while Jlich (2011) found that a severe drought in 2003 prompted an increase in temporary migration.

The New Economics of Labor Migration (NELM) views sending migrants away as a household-level decision aimed at increasing welfare or, at the very least, mitigating negative shocks (Stark and Bloom, 1985). Consequently, many studies have investigated the effects of migration-including seasonal migration-on the households welfare in the origin. The empirical results are mixed. This inconclusiveness of the literature is not surprising as (temporary) migration is associated with positive welfare effects via remittances as well as negative effects due to lost labor at home and consequently reduced crop yields and income (Taylor et al., 2003; Deshingkar and Start, 2003; Brauw, 2010; Atamanov and Van den Berg, 2012; Chandrasekhar et al., 2015).

Two of these studies focused specifically on India. Deshingkar and Start (2003) investigated the characteristics of seasonal migrants as well as the effects of seasonal migration on household income in India. They found that remittances from seasonal migrants are the main income source of poor communities in Andhra Pradesh and

Madhya Pradesh. In addition, the study found the effects of seasonal migration are mixed. While remittances from seasonal migrants significantly help households in the origin, they are highly volatile as migrants labor contracts are often unreliable.

Chandrasekhar et al. (2015) studied the effects of seasonal migration on household consumption in rural India. They estimated seasonal migration effects on consumption by using instrumental variables with cross-sectional data from a nationally representative sample covering the 2007 2008 period. They find a negative correlation between seasonal migration and household consumption. They attribute the negative effects of seasonal migration to migrants deprived socio-economic status. Migrants have low education level and low skills, so they tend to be employed in low-quality jobs. This study showed seasonal migration is not effective strategy to increase household consumption.

Although Chandrasekhar et al. (2015) did not mention it explicitly, their study indirectly alluded to the need of temporally disaggregated data. They showed that temporary labor migration does not effectively bolster household consumption per capita. However, since they did not adjust the per capita denominator for the absence of temporary migrants during part of the year, the study may have underestimated the impact on annual consumption. More direct evidence for the necessity of short temporal units is provided by Coffey et al. (2015). They convincingly show that annual data is insufficient when dealing with temporary migration. Investigating the determinants of temporary labor migration and using the agricultural season as the temporal unit, they conclude that the determinants indeed differ by agricultural periods.

2.3 Conceptual framework

In this section we document key features of temporary labor migration in India and then develop a conceptual framework that captures those features, while allowing us to examine the causes and consequences of migration decisions. Determinants and effects of temporary labor migration have been researched at length by many researchers in the Indian context (Haberfeld et al., 1999; Deshingkar and Grimm, 2004; Badiani and Safir, 2010; Jlich, 2011; Chandrasekhar et al., 2015; Coffey et al., 2015). These studies delivered important insights regarding the link between weather anomalies, temporary migration, and household welfare.

While some evidence points to increased temporary migration after natural disasters (Badiani and Safir, 2010), other studies fail to detect a change or even find decreased migration activity after these shocks (Gray and Mueller 2012a, Tse 2011). Phan and Coxhead (2010) argue that such ambiguity may be explained by the fact that shocks increase incentives to migrate but may also reduce households ability to afford the cost of migration. Additionally, these studies found that households that are more likely to send migrants away have lower-than-average income and send migrants to urban areas. The latter fact suggests that village- and city-level shocks are independently distributed, and households use migration to self-insure against rural shocks.

Weather anomalies are perhaps among the most frequent and powerful village-level shocks. In this study, we use the Village Dynamics in South Asia (VDSA) dataset provided by International Crops Research Institute for the Semi-Arid Tropics. We explore our data to determine whether there is any evidence supporting or rejecting the two empirical regularities identified in previous studies: 1) the positive correlation between village-level shocks and migration, and 2) the negative correlation between households endowment and migration.

Temporary migration is usually directed toward urban areas, and temporary migrants mainly engage in non-farm work. Figure 2.1 shows that the temporary labor migration flows extracted from the 2010 VDSA data are predominantly destined towards highly populated areas. In addition, the data show that only one percent of temporary labor migrants has identified themselves as farm laborers. Therefore, the outside option of temporary migrants is less affected by weather conditions and provides an opportunity for income diversification and risk management; which explains why migration is positively correlated with weather anomalies. Secondly, we report

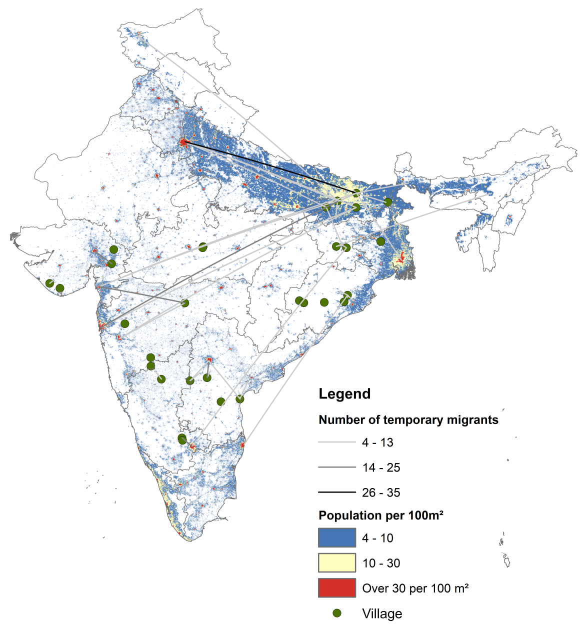


Fig. 2.1. Temporary labor migration flows (Based on 2010 VDSA)

some key descriptive statistics in Table 2.1 that illustrate the link between household endowment and migration in our context. For various socio-economic characteristics, Table 1 shows results of difference-in-means tests between households with versus households without migrants. Reported values reveal that households with temporary labor migrants in our data are, in fact, more socio-economically deprived than households without temporary migrants. In particular, households with temporary labor migrants have lower expenditure per capita and own less land. Moreover, most households with temporary labor migrants belong to a lower caste.

Information reported in Figure 2.1 and Table 2.1 offer, in the context of India, strong support for the following:

- Empirical Regularity 1: households use temporary migration to cope with weather anomalies.

Table 2.1.
Difference-of-means tests for migrant and non-migrant households

Variables	Total (n=3,216)		Migrant households (n=679)		Non-migrant households (n=3,216)		Difference-of-means Test	
	Mean	Std.	Mean	Std.	Mean	Std.	Diff.	Sig
Monthly household expenditure per capita	1028.1	40.3	968.7	25.9	1040.9	17.8	-72.2	*
Number of labor force	4.77	0.03	5.80	0.03	4.55	0.03	1.25	***
Land own (Acres)	4.81	0.09	3.12	0.14	5.18	0.10	-2.06	***
Rent in (Acres)	0.73	0.04	0.76	0.14	0.73	0.04	0.03	
Rent out (Acres)	0.24	0.02	0.31	0.04	0.23	0.02	0.08	
Year of householder education	5.39	0.06	5.42	0.16	5.39	0.07	0.03	
Forward Caste	0.09	0.00	0.18	0.01	0.07	0.00	0.11	***
Scheduled or Backward Caste	0.56	0.01	0.66	0.02	0.54	0.01	0.12	***
Total effects	-0.040 (0.041)	-0.043** (0.019)	-0.167*** (0.060)	0.043 (0.036)	-0.128*** (0.045)	-0.154*** (0.015)		

- Empirical Regularity 2: more disadvantaged households are more likely to engage in migration.

We develop a conceptual model that allows us to test for empirical regularity 1. In other words, we will examine whether and to what extent households send temporary migrants to cope with weather anomalies; as well as to quantify the effectiveness of such strategy in mitigating the impact of adverse weather on consumption. Furthermore, our empirical strategy directly addresses the selection problem resulting from empirical regularity 2.

We draw upon the model of seasonal migration and expenditure by de Brauw and Harigaya (2007). Our framework adheres to the NELMs notion that migration and consumption decisions are made cooperatively within the households. While the absence of information on the intra-household decision making process makes it impossible to examine the degree of cooperativeness, we believe this is an appropriate assumption in our context because our focus is on temporary, rather than permanent migration. By its very nature, temporary migration creates a repeated interaction pre- and post-migration decision between the migrant and the household. Therefore, it seems reasonable to assume that the repeated nature of the interaction is likely to generate some cooperation between the migrant and the rest of the household.

Without settling on specific units of measurement, we consider a farm household with a labor force of size N, a vector of household characteristics X, living in a village where abnormal weather patterns are indexed by D. Suppose that the households production function $f(N, X, D)$ is strictly increasing and concave in all inputs. For simplicity, we assume that all household workers derive their income from farm production and operate under a binding budget constraint. Therefore, household consumption can be expressed as $C = f(N, X, D)$. Moreover, if a weather anomaly D_1 is more severe than another D_0, then $D_0 < D_1$ and $f(N, X, D_0) > f(N, X, D_1)$. As illustrated in Figure 2.2, consumption in a mild drought situation, D_0, will be higher than consumption in a severe drought situation, D_1.

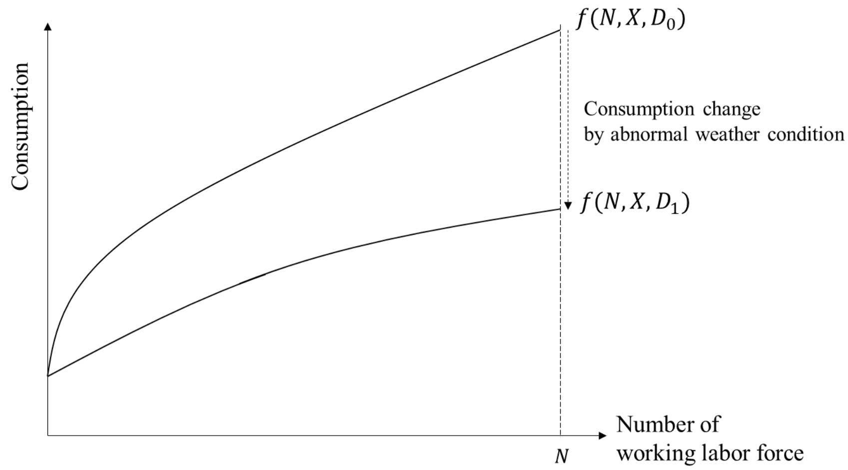


Fig. 2.2. Abnormal weather-induced change in consumption, without temporary labor migration

The structure of income and, consequently, consumption, is altered when households send temporary migrants away. Income is now derived not only from food production, but also remittances from temporary labor migrants. To begin with, households need to decide the proportion, m, of their labor to be send for work elsewhere. The expected remittance is influenced by wages in the destination, w. Assume that net expected remittances is $\phi(Nm, w)$ where $\phi(\cdot)$ is increasing in its arguments. Household income and consumption can then be decomposed into income from farm production, $f(N(1-m), X, D)$, and income from remittances from temporary labor migrants, $\phi(w, c, Z, D)$. In the latter portion of income, we have allowed remittances to depend upon the severity of the weather anomaly. This is to accommodate the fact that anomalies continue to evolve even after migrants left, and migrants may increase remittances as new information arrives if conditions on the farm continue to worsen. Finally, following the NELM, we assume that migration level m is the result of an optimal, cooperative decision made by the household, which we denote by m^*, and may be a corner or interior solution:

1. $m^* = 0$ if $\frac{\partial f}{\partial m}|_{m=1} > \frac{\partial \phi}{\partial m}|_{m=1}$

2. $m^* = 1$ if $\frac{\partial f}{\partial m}|_{m=1} < \frac{\partial \phi}{\partial m}|_{m=1}$

3. $0 < m^* < 1$ if $\frac{\partial f}{\partial m}|_{m=1} = \frac{\partial \phi}{\partial m}|_{m=1}$

The migration decision will likely be affected by the household labor force endowment, household characteristics, and weather anomalies. Therefore, we generically characterize the migration decision as $m^*(N, X, D)$. Given the optimal proportion of temporary labor migrant m^*, the consumption function takes on the form:

$$C = f((N(1 - m^*), X, D) + \phi(Nm^*, w, c, Z) \tag{2.1}$$

Our primary concern in this study is with the effect of weather anomalies on household consumption, and the meditating role of temporary migration on the effect. Differentiating with respect to the severity of weather anomalies yields:

$$\frac{\partial C}{\partial D} = \frac{\partial f}{\partial D} + (\frac{\partial f}{\partial m^*} + \phi N)\frac{\partial m^*}{\partial D} + Nm^*\frac{\partial \phi}{\partial D} \tag{2.2}$$

The first term on the right-hand side of equation 2.2 captures the direct effect of weather on consumption; i.e. this is the effect of weather anomalies in the absence of any migratory response by the household. The second and third terms capture the mediating role of migration on the effect of weather anomalies on consumption. The second term characterizes the variation in income due to change in farm labor caused by migration, $\frac{\partial f}{\partial m^*}\frac{\partial m^*}{\partial D}$, and the variation in income due to change in the number of migrants sending remittances caused by migration, $\frac{\partial f}{\partial m^*}\frac{\partial m^*}{\partial D}$. Finally, the third term captures changes in remittances sent by existing migrants due to changes in the severity of weather anomalies.

The channels formally characterized in equation2.2, are illustrated in Figure 2.3. The level of consumption under each counterfactual are as follows. Consumption in the absence of a weather anomaly, $D = D_0$, is $f(N, X, D_0)$; consumption after a weather anomaly but without migration is $f(N, X, D_1)$; consumption after a weather anomaly, with a change in migration, but with constant remittances per migrant is denoted by $[f(N(1 - m^*), X, D_1) + Nm^*\phi(w, c, Z, D_0)]$; and consumption after a weather anomaly, where both the number of migrants and remittances per migrant change is denoted by $[f(N(1-m^*), X, D_1) + Nm^*\phi(w, c, Z, D_1)]$.

The direct effect of a weather anomaly on consumption is denoted as effect 1 in Figure 2.3; i.e. $f(N, X, D_0) - f(N, X, D_1)$. This effect corresponds to a counterfactual in which the household does not send migrants away in response to an increase in the severity of the weather anomaly (an increase in $D_1 - D_0$). The two components of the second term of equation (2) are graphically illustrated by 2.a and 2.b. respectively. The effect 2.a. $(f(N, X, D_1) - f(N(1-m^*), X, D_1))$ reflects our hypothesis that consumption drops due to decreased farm productivity as migration reduces the labor force. The effect 2.b. $([f(N(1-m^*), X, D_1) + Nm^*phi(w, c, Z, D_0)] - f(N(1-m^*), X, D_1))$ reflects our hypothesis that consumption increases due to increased revenue from remittances, conditional on the number of migrants. Finally, the last term in equation (2) is graphically illustrated by effect 3, $[f(N(1-m^*), X, D_1) + Nm^*\phi(w, c, Z, D_1)] - [f(N(1-m^*), X, D_1) + Nm^*\phi(w, c, Z, D_0)]$.

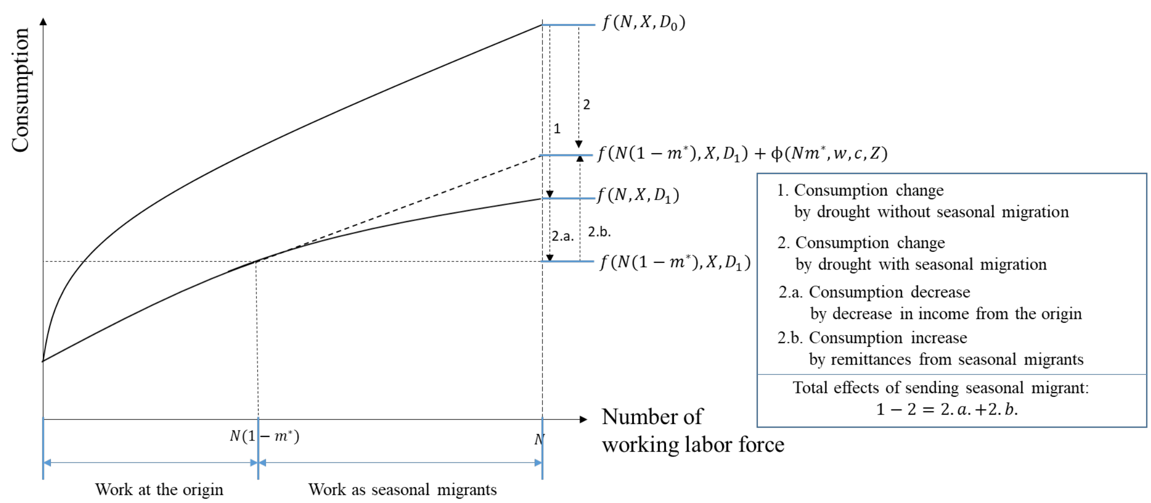


Fig. 2.3. Abnormal weather-induced change in consumption, with temporary labor migration

We hypothesize that effect 1 is negative, effect 2 (2.a plus 2.b) is positive, and effect 3 is positive. However, we also hypothesize that the sum of effects 2 and 3 are smaller, in absolute value, than effect 1; i.e. $1 + 2.a + 2.b + 3 < 0$. Using the formal characterization of equation (2), these hypotheses amount to: $\frac{\partial f}{\partial D} < 0$, $(\frac{\partial f}{\partial m^*} + \phi N)\frac{\partial m^*}{\partial D} + Nm^* \frac{\partial \phi}{\partial D} > 0$, and $\frac{\partial f}{\partial D} + (\frac{\partial f}{\partial m^*} + \phi N)\frac{\partial m^*}{\partial D} + Nm^* \frac{\partial \phi}{\partial D} < 0$. Our empirical analysis computes these partial derivatives. In the next section we first develop our estimating equation, we then discuss our identification strategy, and lastly, we describe the data used to execute that strategy. If confirmed, our hypotheses would indicate that migration is an effective strategy to cope with weather shocks, but that it cannot fully offset the negative impact of weather anomalies on household consumption.

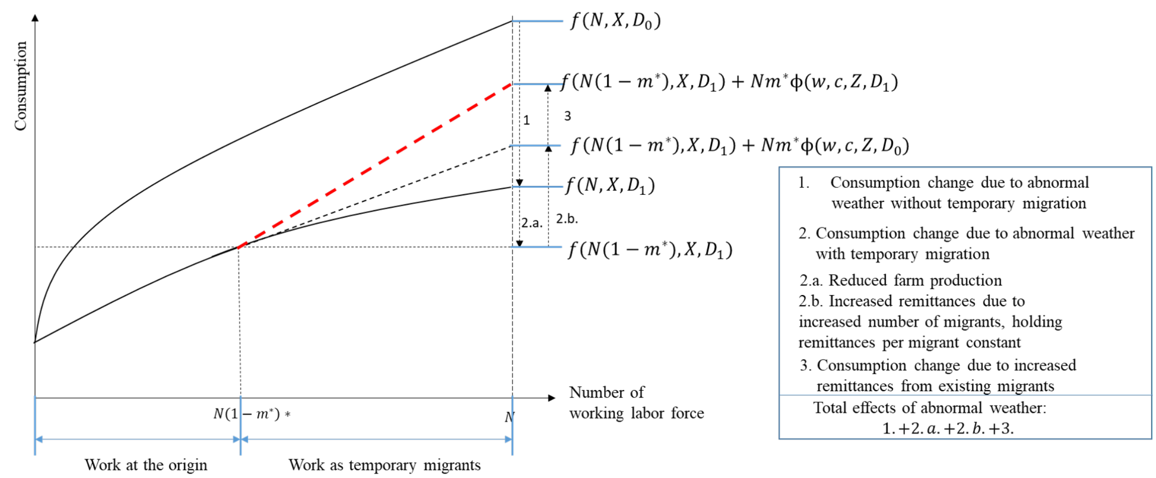


Fig. 2.4. Final conceptual model for Abnormal weather-temporary migration-consumption nexus

2.4 Empirical Strategy

2.4.1 Econometric model and identification

The objective of our study is to examine the degree to which temporary migration mitigates the effect of precipitation shocks on household expenditure. Therefore, our household consumption model includes precipitation anomalies by themselves, as well as anomalies interacted with temporary migration. We are primarily concerned with the sign and size of the coefficient on the interaction term which allows us to infer the effectiveness of migration as a strategy to cope with precipitation anomalies. The conceptual model shows that temporary migration mitigates the effects of precipitation shocks on consumption in two ways, change of number of temporary migrants and change of effects of temporary migration. Thus, we use a two-stage least squares regression design as depicted in Figure 2.5.

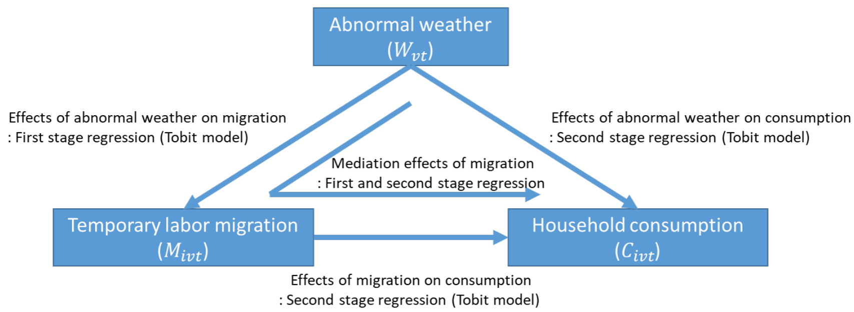


Fig. 2.5. Diagram of econometric model

The first stage is a temporary labor migrant number decision model. Instead of a simple binary variable for temporary migration, this study uses a continuous measure, defined as the number of temporary labor migrants per month. The second stage is household consumption model. We use the log of household consumption per capita per month as the output variable of the second stage. For the second stage, we use estimated number of temporary labor migrant. Thus, the basic equation is below Equation 2.3:

$$\begin{aligned} &\log C_{ivt} = \alpha \hat{M}_{ivt} + D_{vt}\beta_1 + \hat{M}_{ivt}D_{vt}\beta_2 + R_{ivt}D_{vt}\beta_3 + X_{ivt}\beta_4 + U_{ivt}E + \varepsilon_{ivt} \\ &\text{and } \hat{M}_{ivt} = \hat{\lambda}_i + \hat{\lambda}_t + D_v t\hat{\gamma}_1 + R_{ivt}D_{vt}\hat{\gamma}_2 + X_{ivt}\hat{\gamma}_3 \end{aligned} \tag{2.3}$$

C_{ivt} is household consumption per capita per month for household i in village v on period t, D_{kvt} is a set of precipitation anomaly variables of village v on period t with sub-temporal dimension k, and M_{ivt} is number of temporary labor migrant per month of household i in village v on period t, and R_{ivt} is a set of mediator variables, which has mediation effects between precipitation anomalies and household consumption. This study considers irrigation. X_{it} is a set of control variables, and U_{ivt} is a set of unobservable variables, which affect on temporary labor migration and household consumption.

The model has two econometrics issues: unobservable confounding variables and bi-directional causality. First, Equation 2.3 includes many confounding variables that affect the number of temporary labor migrant and household consumption, like wage in destination. Since wage is a confounding variable of consumption and migration, omitting wage creates bias in the estimation. To correct the bias from unobservable variables, we use fixed effects of household, and agricultural season. We, therefore, dropped the U_{ivt} variable of Equation 2.3 by assuming those variables are absorbed in household or agricultural season fixed effects. We can write the estimator as:

$$\begin{aligned} \log C_{ivt} &= \theta_i + \theta_t + \alpha \hat{M_{ivt}} + D_{vt}\beta_1 + \hat{M_{ivt}} D_{vt}\beta_2 + R_{ivt}D_{vt}\beta_3 + X_{ivt}\beta_4 + \varepsilon_{ivt} \\ \hat{M_{ivt}} &= \hat{\lambda}_i + \hat{\lambda}_t + D_v t\hat{\gamma_1} + R_{ivt}D_{vt}\hat{\gamma_2} + X_{ivt}\hat{\gamma_3} + \hat{\tau}_1 m_{vt} + \hat{\tau}_2 L_{ivt} m_{vt} \end{aligned} \tag{2.4}$$

where θ_i, θ_t are fixed effects of household and time in consumption model, and λ_i and λ_t are fixed effects of time in number of temporary labor migration model.

Second, the model has bi-directional causality between temporary labor migration and consumption. For example, low level of consumption increases the number of temporary labor migrants so as to bolster consumption. In addition, sending temporary labor migrants can increase consumption because of remittances from temporary labor migrants. This study uses instrumental variables to correct bias from bi-directional causality.

We follow a rather extensive literature documenting migration network as a valid instrumental variable because migration networks decrease uncertainties and costs of migration, while it does not directly affect consumption(de Brauw and Harigaya, 2007; Chandrasekhar et al., 2015). Information on migration networks are likely shared with other households in the village. Thus, studies use proportion of migrants-both temporary and permanent migrants- in the village as the instrumental variable. In addition, as suggested by Nguyen and Winters (2011), we introduce an interaction term between migration network and the size the of household labor force for two reasons: 1) to generate within-household variability over time on the instrument, and 2) to accommodate the fact that the households labor endowment is typically associated with the households ability to send migrants away in response to weather shocks. Since the number of household workers is included as a control variable in the second stage, the interaction term does not directly affect consumption and is itself an instrument.

To account this issue, we use a Tobit model in the first stage equation. A Tobit model has various advantages over other potential models. First, a Tobit model does not allow negative prediction. Second, it accounts for censored observations for the dependent variable. Therefore, the final econometric model takes on the form:

$$\begin{aligned} \log C_{ivt} &= \theta_i + \theta_t + \alpha \hat{M}_{ivt} + D_{vt}\beta_1 + \hat{M}_{ivt} D_{vt}\beta_2 + R_{ivt} D_{vt}\beta_3 + X_{ivt}\beta_4 + \varepsilon_{ivt} \\ \text{and Tobit}(\hat{M}_{ivt}) &= \hat{\lambda}_i + \hat{\lambda}_t + D_v t\hat{\gamma}_1 + R_{ivt} D_{vt}\hat{\gamma}_2 + X_{ivt}\hat{\gamma}_3 + \hat{\tau}_1 m_{vt} + \hat{\tau}_2 L_{ivt} m_{vt} \end{aligned} \tag{2.5}$$

2.4.2 Marginal effects of weather anomalies

This study uses average marginal effects to interpret the effects of abnormal precipitation condition. The Equation 2.6 is derived from the differentiation of the last econometrics model by AP_{ivtk}, abnormal precipitation condition. The subscriptions l is the type of abnormal prcipitation, excessive precipitation or dryness condition, and k is the period, sub-agricultural season unit.

$$\begin{aligned} &\frac{\partial \log C_{ivt}}{\partial AP_{lvtk}} = \alpha \frac{\partial \hat{M}_{ivt}}{\partial AP_{lvtk}} + \frac{\partial D_{vt}}{\partial AP_{lvtk}}\beta_1 + \frac{\partial \hat{M}_{ivt}}{\partial AP_{lvtk}} D_{vt}\beta_2 + \hat{M}_{ivt}\frac{\partial D_{ivt}}{\partial AP_{lvtk}}\beta_2 + R_{ivt}\frac{\partial D_{vt}}{\partial AP_{lvtk}}\beta_3 \\ &\text{where } \frac{\partial \hat{M}_{ivt}}{\partial AP_{lvtk}} = \frac{\partial D_{vt}}{\partial AP_{lvtk}}\hat{\gamma}_1 + R_{ivt}\frac{\partial D_{vt}}{\partial AP_{lvtk}}\hat{\gamma}_2 \end{aligned} \tag{2.6}$$

Then, Equation 2.6 can be rearranged, yielding:

$$\frac{\partial \log C_{ivt}}{\partial AP_{lvtk}} = \frac{\partial D_{vt}}{\partial AP_{lvtk}}\beta_1 + \frac{\partial \hat{M}_{ivt}}{\partial AP_{lvtk}}(\alpha + D_{vt}\beta_2) + \hat{M}_{ivt}(\frac{\partial D_{ivt}}{\partial AP_{lvtk}}\beta_2) + R_{ivt}\frac{\partial D_{ivt}}{\partial AP_{lvtk}}\beta_3 \tag{2.7}$$

Equation 2.10 shows abnormal weather condition has four types of marginal effects on household consumption. First, $\frac{\partial D_{vt}}{\partial AP_{lvtk}}\beta_1$ is the direct effects of abnormal weather on consumption. Second, $\frac{\partial \hat{M}_{ivt}}{\partial AP_{lvtk}}(\alpha + D_{vt}\beta_2)$ is mediation effects of temporary labor migration. Third,$\hat{M}_{ivt}(\frac{\partial D_{ivt}}{\partial AP_{lvtk}}\beta_2)$ is indirect effects of abnormal weather by change of number of temporary labor migrant. Lastly, $R_{ivt}\frac{\partial D_{ivt}}{\partial AP_{lvtk}}\beta_3$ is mediation effects of other coping strategies, like irrigation. Figure 2.6 presents the analysis process.

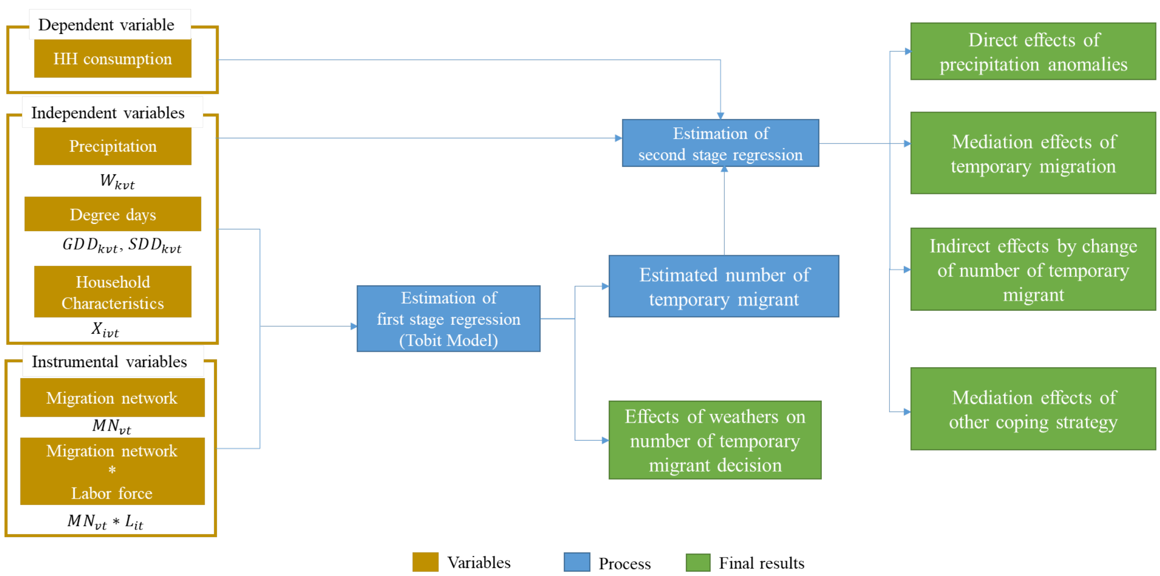


Fig. 2.6. Diagram of analysis process

The key hypothesis of this study-adverse weather shocks decrease household welfare, but less for households with migrants-can be re-written based on the econometric model:

$$\frac{\partial D_{vt}}{\partial AP_{lvtk}}\beta_1 < 0$$

$$\text{and } \frac{\partial \hat{M}_{ivt}}{\partial AP_{lvtk}}(\alpha + D_{vt}\beta_2) + \hat{M}_{ivt}(\frac{\partial D_{ivt}}{\partial AP_{lvtk}}\beta_2) > 0 \tag{2.8}$$

2.5 Data

This study merges temporally and spatially socio-economic household data and meteorological data. The socio-economic information is extracted from the Village Dynamics in South Asia (VDSA) dataset provided by International Crops Research Institute for the Semi-Arid Tropics. VDSA is a monthly micro panel dataset for 30 villages in India during the 5-year period from 2010 to 2014. In the analysis, we include only agricultural households, and exclude 2010 data as we do not observe lagged values of important variables. In addition, we only include villages in non-arid climate, as this is the region where most of agricultural production takes place. The meteorological data consists of daily temperature and precipitation dataset obtained from the Climate Prediction Center of NOAA. The CPC meteorological data is a global raster dataset with 0.5 by 0.5-degree resolution. The meteorological data is matched by villages geographical coordinates.

Our analysis critically depends on our definition of dependent and independent variables. We start by discussing our choice of study area within India, we then move on to our definition and measurement of agricultural seasons and weather anomalies. finally, we describe our definition and measure of our dependent variables: household welfare and migration.

2.5.1 Definition of climatic regime

To geographically identify the non-arid climatic regime as our study area, we use the Kppen-Geiger climate classification. Kppen-Geiger climate classification is one of the most well-known climate classification systems. This classification divides climate into five groups, tropical, arid, temperate, continental, and polar. Then, each group is further divided by precipitation and temperature patterns. Initially, climate regimes are defined based on vegetation systems. Thus, many studies use Kppen-Geiger climate classification to distinguish between agro-ecological areas. We use a Kppen-Geiger-based spatially explicit classification of climatic regimes by Kottek et al. (2006) and match climatic regimes to village-level data. The data shows that 10 villages have Arid/Steppe/Hot climate, 14 villages have Tropical/Savannah climate, and 6 villages have Temperate/Dry winter/Hot summer climate.

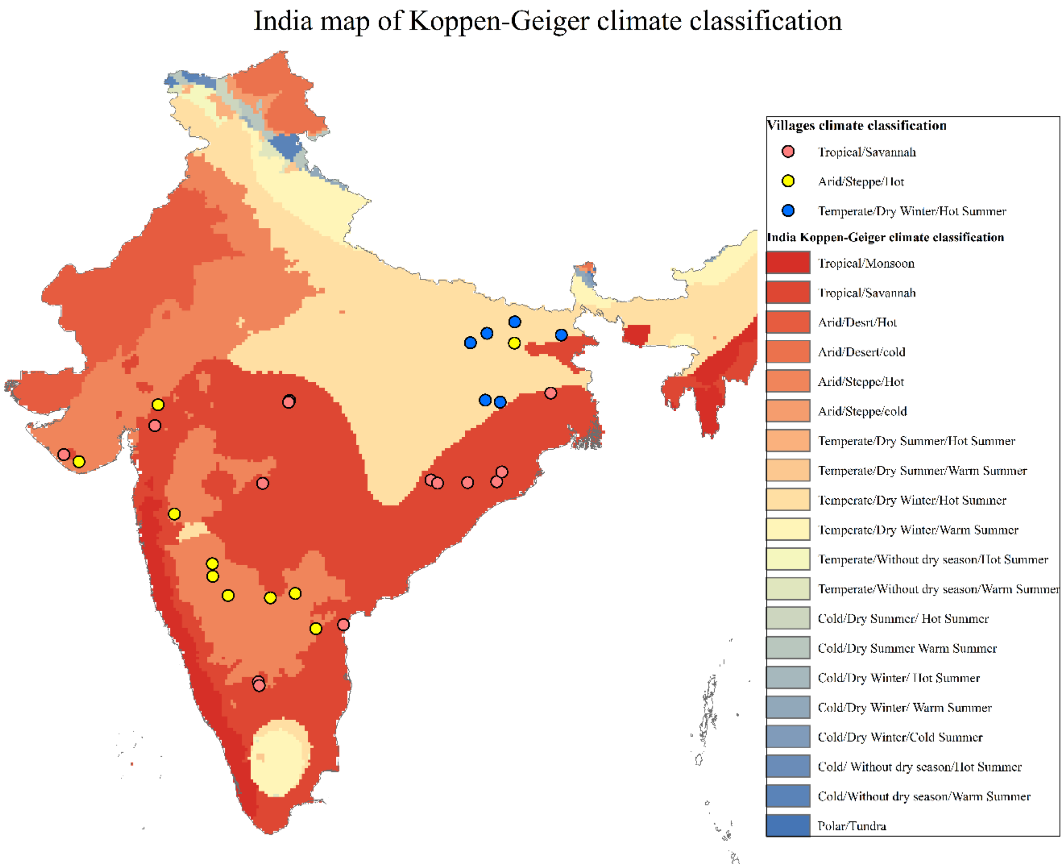


Fig. 2.7. India map of Koppen-Geiger climate classification

Although our study areas have three climatic regimes, we use only non-arid climate regions in our analysis. Precipitation patterns vary widely across climate regimes. Figure 7 shows precipitation patterns across climatic regimes. These rather drastic differences in precipitation patterns across climate regimes introduce substantial heterogeneity and possible bias in our estimates. Consequently, to avoid heterogeneity-related bias and considering that most agricultural production happens in non-arid climate, we only include in our sample the 20 villages with non-arid climatic regime.

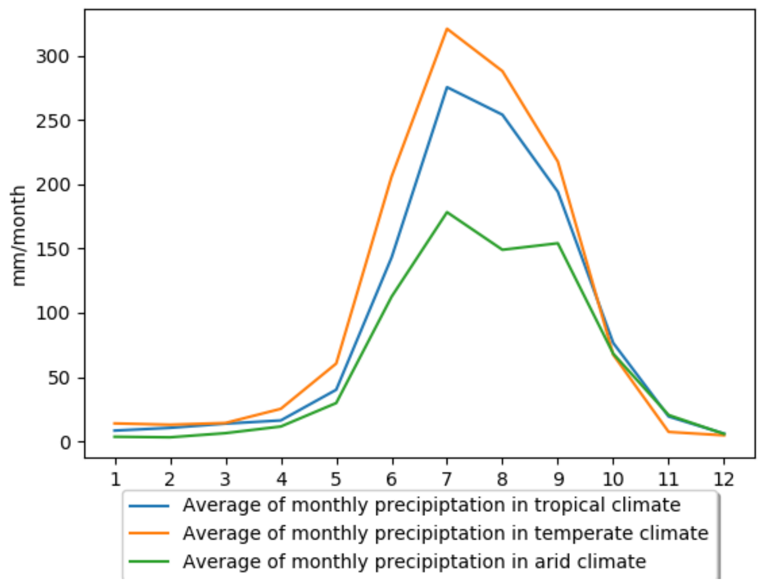


Fig. 2.8. Average of monthly precipitation

2.5.2 Definition of temporal dimension

Temporary labor migration, as a coping strategy to abnormal weather, is closely related to the agricultural cycles. In this area of India, there are two agricultural seasons within a year. Many studies aggregate data to the annual level because of lack of season-level information. Coffey et al. (2015) illustrates potential problems associated with this aggregation by showing how temporary labor migration decisions can vary by agricultural season. We exploit temporally disaggregated data to conduct our analysis. We define agricultural seasons based on information regarding seeding and harvest activities included in the VDSA cultivation module. The beginning and end of agricultural seasons may vary depending on specific weather patterns. For example, the beginning of the growing season for rice may vary widely in response to a drought, as planting rice requires puddled soils. There are two growing seasons within a year in our sample: (1) Kharif (Autumn agricultural season) and (2) Rabi (Winter-

Table 2.2.
Temporal definitions of variables

	Agricultural season t-1		Agricultural season t	
	Early	Later	Early	Later
Weather variables	Weather 1	Weather 2	Weather 3	Weather 4
Migration variable			Migration	
Expenditure variable			Expenditure	
Control variables			Control variables	

Spring agricultural season). We use information on seeding and harvesting activities to specify year- and village-specific growing seasons as described in Appendix 1.

Weather anomalies can have contemporaneous effects on behavior and consumption. But they may also have lagged effects as they slowly degrade growing conditions over time. We use our village- and year-specific definition of growing seasons to distinguish between weather anomalies according to their occurrence relative to those defined periods. Considering contemporaneous and lagged effects, we classify weather anomalies according to their timing in four categories: early in the previous agricultural season, late in the previous agricultural season, early in the current season and late in the current season. See Table 2.2 for a diagrammatic representation of our temporal disaggregation of weather shocks.

2.5.3 Definition of weather anomaly

We focus on precipitation abnormalities because most parts of India has high temperature. To measure abnormal precipitation in each sub-period of time described in Table 2.2, we use the statistical Z-score of precipitation on that specific sub-period. We focus on deviations from historical patterns as they are, by definition, unexpected. Unexpected shocks are likely to trigger implementation of coping strategies including temporary migration, and they are also likely to have a sizable impact on welfare.

The Z-score allows us to define anomalies as drastic deviations from a historical mean. We consider patterns over the last 50 years to define historical means.

Deviations from historical precipitation patterns result in either flooding or drought. These phenomena need not have symmetric effects on farm productivity and migration. First, the effect of deficit and surplus precipitation on yields are typically not the same. Second, the ability to offset the effects of weather anomalies with labor differ depending on the type of anomaly. For instance, some activities that offset the effects of flooding require substantial labor, which may discourage households from sending migrants away. Moreover, flooding make an instantaneous damage to farm productivity prompting immediate responses by households. In contrast, droughts deteriorate growing conditions more slowly, perhaps triggering distinct behavioral responses over time. Therefore, different types of anomalies (droughts and flooding) may trigger different migration responses both in terms of timing and magnitude, resulting in distinct overall effects on consumption. Thus, we separate the statistical Z-score in two variables separately included in estimation: positive abnormal precipitation, and negative abnormal precipitation. We calculate positive abnormal precipitation, and negative abnormal precipitation in a village as:

$$
\begin{aligned}
PP_{vt} &= \begin{cases} \frac{P_{vt}-\bar{P}_v}{\sigma_v} & \text{if } P_{vt}-\bar{P}_v \geq 0 \\ 0 & \text{if } P_{vt}-\bar{P}_v < 0 \end{cases} \\
NP_{vt} &= \begin{cases} -\frac{P_{vt}-\bar{P}_v}{\sigma_v} & \text{if } P_{vt}-\bar{P}_v < 0 \\ 0 & \text{if } P_{vt}-\bar{P}_v \geq 0 \end{cases}
\end{aligned}
\tag{2.9}
$$

where PP_{vt} is positive abnormal precipitation in village v at time t, NP_{vt} is negative abnormal precipitation, P_{vt} is precipitation in village v at time t, $\bar{P}_v$ is mean of last fifty years precipitation in village v at given month, and σ_v is standard deviation in village v at given month. To control non-linearity between household consumption or number of temporary labor migrant and abnormal weather conditions, we include quadratic terms in the econometric model.

2.5.4 Definition of temporary labor migration

The Indian Census defines temporary labor migration as a household member leaving for not more than six months. Instead, we follow the VDSA criterion and define a temporary labor migrant as a person residing outside of the village for employment purposes, without forming a new household regardless of the time spent away. Despite the fact that the amount of time spent away does not alter the definition of temporary migration, we depart from previous studies measuring migration as binary (Mendola, 2008; Chandrasekhar et al., 2015), and recognize the fact that time away should be reflected in the migration decision. Therefore, we define migration as the ratio of total migration months to total workable months:

$$M_{it} = \frac{\sum_j M_{ijt}}{T_t} \tag{2.10}$$

Where M_{it} is defined temporary labor migration variable for household i at period t, M_{ijt} number of migration months of member j in household i, and T_t is number of months of period t.

2.5.5 Definition of household welfare

Our final outcome variable is household welfare. In general, household income per capita is considered as an appropriate measure of household welfare. However, measuring household income is difficult because households are consumers as well as producers. Alternatively, we use household consumption per capita as a proxy for household welfare. We calculate the household consumption per capita as:

$$C_{ivt} = \frac{TC_{ivt}}{HH_{ivt} - M_{ivt}} \tag{2.11}$$

where C_{ivt} is household consumption per capita of household i in village v at period t, TC_{ivt} is household total consumption, HH_{ivt} is total household member of household i in the origin at period t, and Mig_it is average number of temporary labor migrants per month from household i in period t

2.5.6 Definition of abnormal precipitation

To measure abnormal precipitation, we use the statistical Z-score of precipitation on the given period. Coping abilities to abnormal precipitation are closely connected to the probability of abnormal precipitation occurrence. Villages in which flooding, or drought happens frequently tend to prepare the occurrence of the abnormal precipitation events. This shows necessities of consideration for mean and standard deviation in definition of abnormal precipitation. Thus, this study uses statistical Z-score of precipitation given period by using last fifty years precipitation data.

Based on the statistical Z-score of precipitation, we additionally consider type of abnormal precipitation. In the literature on labor migration, households respond differently by types of abnormal precipitation because of differences of damage types. Households in which suffered severe flooding tend to response instantaneously because damages are acknowledged instantly. On the other hand, response to drought damage needs more time than flooding. Drought damages need certain period to be developed. So, there are more uncertainty in damages than flooding. Thus, we separate the statistical Z-score in two variables, positive abnormal precipitation, and negative abnormal precipitation.

2.5.7 Descriptive statistics

We present descriptive statistics of key variables at the household-season unit of observation in Table 2.3. Therefore, means are household-level means over all seasons, and standard deviations represent within-household variability over time. We present these values as our fixed-effect estimator relies on within-household variability of the main identifying variables. To ensure comparability across regions and over time, we adjust the expenditures by the state-level monthly food price indices and consumer price indices, from 2011 to 2014. These indices were not available after 2014, so we computed indices from January 2015 to June 2015 through linear extrapolation of past indices. The main take away from Table 3 is that all variables of interest display substantial within-household variability over time, which facilitates estimation of our fixed-effect model.

2.6 Estimation Results

This section presents the results of an array of different regression specifications to model temporary migration. We estimate a model without detailed temporal dimensions (variables are aggregated at the annual, rather than seasonal, level), and another model that includes temporally disaggregated variables. Both models are estimated by 2SLS. Contrasting results across these models highlights a key contribution of our paper; a better understanding of households ability to cope with weather anomalies depending on the timing of the shocks, as well as the speed with which households can respond to those shocks. Our preferred model is the instrumental variable estimation with temporally disaggregated variables, but we also present an OLS estimation of the model with temporally disaggregated variables to explore the issue of selection bias and the effectiveness of our chosen instrument to address it.

Results from Model 1 (with temporally aggregated variables) are presented in Table 4. This model distinguishes anomalies according to whether they are water deficit or excess precipitation, and according to the year in which they take place, but not the season in which they take place, generating a total of 4 distinct weather anomalies: drought last year, flooding last year, drought this year, and flooding this year. This model fails to detect any sizable effect of weather anomalies on migration. In other words, households do not seem to use migration as a strategy to deal with the hardships from precipitation anomalies. Even more puzzling is the fact that weather anomalies seem to have a positive effect on consumption. However, instead of providing sensible insights regarding behavioral responses to anomalies, results from this model are likely biased by temporal aggregation. Rainfall patterns are highly seasonal, as more than 50% of precipitation in India occurs during the monsoon period. Moreover, temporary migration, by its nature, may also display strong seasonality.

Table 2.3.
Descriptive Statistics

Variable	Mean	Std. Dev	Minimum	Maximum
Dependent variable				
Monthly household expenditure per capita (2011 ₹)	1028.13	1094.38	37.85	21050.95
Migration variable				
Number of temporary migrant	0.219	0.560	0	4.25
Precipitation variables				
Excessive wet conditions at previous harvest period	0.414	0.877	0	4.89
Excessive wet conditions at current pre-harvest period	0.222	0.444	0	2.96
Excessive wet conditions at current harvest period	0.513	0.955	0	4.89
Excessive dry conditions at previous harvest period	0.246	0.321	0	1.43
Excessive dry conditions at current pre-harvest period	0.201	0.248	0	1.10
Excessive dry conditions at current harvest period	0.203	0.291	0	1.43
Instrumental variable				
Proportion of migrants in village	0.074	0.082	0.001	0.341
Interaction between proportion of migrants in village and number of labor force member	0.384	0.582	0.001	6.016
Control variables				
Number of household member with age between 0 to 4	0.409	0.687	0	3
Number of household member with age between 5 to 10	0.635	0.907	0	5
Number of household member with age between 11 to 25	1.645	1.37	0	8
Number of household member with age between 26 to 40	1.283	1.095	0	7
Number of household member with age between 41 to 60	1.187	0.811	0	5
Number of household member with age over 60	0.484	0.701	0	4
Forward Caste (binary)	0.093	0.29	0	1
Backward Caste (binary)	0.495	0.5	0	1
Scheduled Caste (binary)	0.062	0.242	0	1
Year of householder education	6.724	3.339	0	16.333
Owned land (acres)	4.815	6.441	0	66
Land rent-in (acres)	0.732	3.036	0	48.75
Land rent-out (acres)	0.241	1.482	0	37
Land with irrigation (acres)	2.902	4.893	0	45
Disaster assistance - East	0.038	0.191	0	1
Disaster assistance - Central	0.108	0.31	0	1
Labor force	4.771	2.388	0.167	40
Number of household member with none-agricultural job	0.617	1.215	0	7
Growing degree days at previous harvest period	577.26	199.972	236.354	1125.59
Growing degree days at current pre-harvest period	365.737	133.451	103.557	635.105
Growing degree days at current harvest period	564.355	198.58	247.417	1129.855
Stress degree days at previous harvest period	59.662	90.158	0	687.853
Stress degree days at current pre-harvest period	19.224	25.17	0	121.767
Stress degree days at current harvest period	46.941	60.813	0	278.456

Table 2.4.
Marginal effects at the mean of model (1)

	Model 1 (without detailed temporal dimensions)			
Time	Last year		Current year	
Type of abnormal weather	Excessive Dry	Excessive Wet	Excessive Dry	Excessive Wet
1st stage	Migration number model			
Effects of precipitation anomalies	0.095 (0.256)	0.028 (0.104)	0.375 (0.338)	0.339 (0.315)
2nd stage	Household consumption model			
Direct effects of precipitation anomalies	0.246** (0.109)	0.055* (0.03)	0.274** (0.129)	0.126* (0.067)
Mediation effects of irrigation	0.03 (0.06)	-	-0.01 (0.07)	-
Total Migration effects	-0.007 (0.043)	-0.011 (0.024)	0.108 (0.067)	0.072 (0.062)
Mediation effects by migrant	-0.014 (0.029)	-0.012 (0.019)	0.049 (0.039)	0.019 (0.031)
Effects by change in number of temporary migrant	0.008 (0.03)	0.001 (0.012)	0.059 (0.055)	0.053 (0.048)
Total effects	0.269*** (0.083)	0.044 (0.038)	0.198** (0.083)	0.372*** (0.114)

***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$, : $p < 0.15$

The use temporally aggregated data seems to mask these seasonal patterns and wipe out the link between anomalies and migration. The temporal mismatch between weather shocks and consumption also seems to bias the estimates of total effects.

2.6.1 Results without considerations of detailed temporal dimensions and climatic regime

We further examine our hypotheses by estimating a model with seasonal, rather than annual, data. This model distinguishes anomalies according to whether they are water deficit or excess, and according to the timing of their occurrence, generating a total of 8 distinct weather anomalies: drought early in the first agricultural season, flooding early in the first agricultural season, drought late in the first agricultural season, flooding late in the first agricultural season, drought early in the second agricultural season, flooding early in the second agricultural season, drought late in the second agricultural season, and flooding late in the second agricultural season. The model is first estimated by 2SLS and results are reported in Table 5a.

The use of temporally disaggregated data dramatically alters our results. Table 5a reports the average marginal effect of weather anomalies on migration and consumption. The migration module in Table 5a shows that anomalies due in fact trigger temporal migration as a coping strategy. Our results also indicate that households with abundant labor and a strong network seem to be better equipped to use temporary migration as a coping mechanism in the face of adverse weather. Abundant labor in our context means young adults, especially males since most labor opportunities are circumscribed to physically demanding jobs. Therefore, the demographic profile and social network of the household seem to shape its ability to buttress itself against adverse weather shocks. However, not all anomalies have the same effect on migration behavior. In fact, droughts seem to have a lagged effect (droughts in one-year trigger migration in the following year) while floodings seem to have an immediate effect on migration. This is in line with previous studies that asserted droughts result in a gradual degradation of the soil, while flooding cause immediate damages to crops. Our model with annualized data seems to average out the temporal nuances of the link between weather anomalies and migration. Moreover, and in line with our hypotheses, our results show that migration is an effective strategy to cope with adverse weather shocks. In particular, migration mitigates the negative impacts of weather anomalies on consumption. But this is true only for anomalies that take place early in the current growing season (positive and statistically significant Total Migration Effects for shocks early in agricultural season t; 0.049 for drought and 0.05 for flooding). This seems to suggest that households have a very limited ability to respond to shocks that take place late in the growing season. This may explain why temporal aggregation fails to identify migration as an effecting tool to deal with adverse weather shocks. Also in line with our hypotheses, while migration can offset some of the adverse effects of weather anomaly, it only does so partially. In other words, the overall effect of weather anomalies on household per capita consumption is still negative, but lower for households that send migrants away. Migration reduces the effect of a drought early in the current season by about 40% (from -0.136 to -0.087; i.e. -0.136+0.049). On the other hand, migration reduces the effect of flooding early in the season by about 50% (from -0.149 to -0.099; i.e. -0.19+0.05).

2.6.2 Results with detailed temporal dimensions

Model (2) defines variables with detailed temporal dimensions. As we discussed on 2.5.2, this study defines abnormal weather variables by four temporal dimensions, early of previous agricultural season, late of previous agricultural season, early of current agricultural season, and late of current agricultural season. The estimation results of model (2) are displayed on Table 2.5.

The migration module of model (2) shows that abnormal precipitation triggers temporary labor migration differently by types and time of anomalies. In the last agricultural season, excessive dry conditions trigger temporary labor migration, while excessive wet conditions have insignificant effects. On the current agricultural season, only excessive wet conditions at early of the season have significant effects on temporary labor migration. This result is expected. Households can recognize the results of flooding immediately. The property of flooding will make people to decide migrate immediately. Thus, flooding on early of current agricultural season will trigger temporary labor migration. Unlike flooding, drought conditions are developed slowly. In addition, agricultural households cannot recognize the results until end of the agricultural season. Thus, drought conditions have lagged effects on temporary migration.

The results of mediation effects of temporary labor migration show that temporary labor migration has significant positive effects only on early current agricultural season. Although excessive wet condition show insignificant result, it is closed to significant in 85% confidence interval. The results imply that effects of temporary labor migration are mainly depends on precipitation anomalies at early of current agricultural season. Beside of mediation effects, the results of effects by change in number of temporary migrant show that they are positive when precipitation anomalies trigger temporary labor migration. Thus, the model (2) shows that Indian agricultural households use temporary labor migration strategy differently by type and time of precipitation anomalies, either by increase number of temporary migrants or increase effect of temporary migration.

Table 2.5.
Marginal effects at the mean of model (2) estimated by 2SLS

	Model 2 (with detailed temporal dimensions)							
Time	Agricultural season t-1				Agricultural season t			
	Early period		Late period		Early period		Late period	
Type of abnormal weather	Excessive dry condition	Excessive wet condition	Excessive dry condition	Excessive wet condition	Excessive dry condition	Excessive wet condition	Excessive dry condition	Excessive wet condition
1st stage	Migration number decision model							
Effects of precipitation anomalies	0.115 (0.075)	0.079 (0.057)	0.098 (0.066)	0.072 (0.050)	0.057 (0.096)	0.149** (0.061)	-0.049 (0.065)	0.04 (0.041)
2nd stage	Household consumption model							
Direct effects of precipitation anomalies	-0.227*** (0.071)	0.02 (0.036)	-0.032 (0.05)	-0.054* (0.028)	-0.136* (0.074)	-0.016 (0.034)	-0.198*** (0.051)	-0.072*** (0.022)
Effects of irrigation	0.067* (0.038)	-	0.009 (0.031)	-	-0.069 (0.046)	-	0.068* (0.038)	-
Total Migration effects	0.012 (0.024)	0.000 (0.025)	0.000 (0.026)	0.01 (0.024)	0.049 (0.033)	0.05** (0.02)	-0.01 (0.025)	-0.01 (0.017)
Mediation effects by migrant	-0.004 (0.023)	-0.01 (0.026)	-0.012 (0.025)	0.000 (0.021)	0.038 (0.025)	0.025 (0.021)	-0.004 (0.022)	-0.015 (0.016)
Effects by change in number of temporary migrant	0.016 (0.010)	0.01 (0.01)	0.012 (0.009)	0.01 (0.011)	0.01 (0.021)	0.025 (0.017)	-0.007 (0.012)	0.004 (0.006)
Total effects	-0.148** (0.059)	0.02 (0.043)	-0.024 (0.042)	-0.044 (0.033)	-0.156*** (0.056)	0.034 (0.035)	-0.14*** (0.043)	-0.082*** (0.023)

***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$, : $p < 0.15$

Table 2.6.
Marginal effects at the mean of model (2) estimated by OLS

	Model 2 (without climate regime, with detailed temporal dimensions)							
Time	Agricultural season t-1				Agricultural season t			
	Early period		Late period		Early period		Late period	
Type of abnormal weather	Excessive dry condition	Excessive wet condition	Excessive dry condition	Excessive wet condition	Excessive dry condition	Excessive wet condition	Excessive dry condition	Excessive wet condition
Household consumption model								
Direct effects of precipitation anomalies	-0.285*** (0.056)	-0.033 (0.033)	-0.005 (0.044)	-0.087*** (0.018)	-0.296*** (0.062)	-0.102** (0.031)	-0.117** (0.048)	-0.083*** (0.015)
Effects of irrigation	0.116*** (0.034)	-	0.001 (0.029)	-	-0.012 (0.040)	-	0.033 (0.034)	-
Total Migration effects	-0.003 (0.014)	-0.005 (0.013)	-0.013 (0.013)	0.007 (0.007)	0.035* (0.015)	0.030** (0.011)	-0.012 (0.014)	-0.011 (0.006)
Total effects	-0.171*** (0.040)	-0.039 (0.031)	-0.018 (0.031)	-0.079*** (0.018)	-0.274*** (0.045)	-0.072** (0.029)	-0.096** (0.035)	-0.094*** (0.015)

***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$, : $p < 0.15$

To examine the robustness of our results, we estimate the same model as in Table 5a, but by OLS. Results from this model are reported in Table 2.6. These results highlight the importance of using an IV approach to control for selection bias. Since households that rely more in migration also tend to be more socio-economically deprived (as reflected in Table 1), estimation by OLS should result in an underestimation of the mitigating effects of migration. This is precisely what we observe when we compare the Total Migration Effects rows in Tables 5a and 5b. The estimated mitigating effect of migration on consumption are 0.049 and 0.05 for drought and flooding (early in the current season) using an IV approach, but only 0.035 and 0.03 respectively using an OLS approach. Selection, therefore, seems to introduce a bias that underestimates the effectiveness of migration as a coping strategy by between 30 and 40%.

2.7 Discussion and Conclusion

This paper examines the degree to which rural households use temporary migration as a coping strategy in response to adverse and unexpected weather shocks. While this issue has received attention in the literature, this study deepens our understanding of this link by estimating a model that accommodates a more nuanced treatment of shocks, and also allows for contemporary and delayed responses to shocks. We also develop a continuous measure of migration displaying a desirable property not captured by cruder, binary measures previously used in the literature: our measure increases with the number of persons leaving the household, and also with the time spent away by migrants.

Our refined framework delivers interesting insights regarding the link between migration and weather anomalies. Our results show that droughts, in contrast to floodings, tend to trigger delayed behavioral responses; i.e. households send migrants away several months after the drought happens, possibly due to the water soil profile failing to recover after a drought. Our analysis also indicates that migration can serve as an effective coping strategy, but only when shocks happen rather early in the growing season. This is consistent with the view that investments and decisions made by the household as the growing season progresses are at least partially irreversible, severely curtailing the households ability to cope with shocks late in the season.

Our results call for policies that enhance households access to inputs and resources that reduce the effects of weather anomalies on farm productivity, including but not limited to irrigation and tile drainage. However, policies that may help households better diversify and insure income sources (e.g. training for off-farm work, insurance against weather anomalies, etc.) may be more effective in long run, and especially considering the likely drastic effects of climate change on the frequency and severity of weather anomalies. Finally, our analysis suggests there is still much to be examined about the link between weather shocks, migration, and other possible coping strategies such as formal and informal insurance and financing mechanisms.

3. THE EFFECTS OF TEMPORARY MIGRATION ON HIRED AGRICULTURAL LABOR IN RURAL INDIA

3.1 Introduction

The causes and consequences of migration are an important topic in economic development and much research has already been done on how rural communities are changed by rural to urban migration. While a good deal of both quantitative and qualitative studies have focused on permanent rural to urban migration, temporary migration is –primarily because of data limitations– almost exclusively investigated in qualitative ways. However, temporary migration plays a pivotal role in developing countries and its consequences need a more precise quantification. In fact, in the previous chapter, we showed that temporary migration is a coping strategy for dealing with abnormal precipitation and its magnitude influences households' welfare gain. This chapter addresses temporary migration brought on by abnormal precipitation as a cause for changes in the demand for hired labor, thereby shedding light on the relationship between climate, migration and agricultural behaviors. The question asked is, what are the consequences of temporary migration on the demand for hired agricultural labor?

The literature has repeatedly addressed the question of how rural migration changes the demand for agricultural labor (Acharya et al., 2019; Ochieng et al., 2017; Maharjan et al., 2013). However, the empirical results are mixed. Some studies (Hull, 2007; de Haas, 2006; McCarthy et al., 2009) show that migration stimulates hiring agricultural labor, arguing that migration creates an agricultural labor shortage, and households will use remittances to hire substitute labor that allows them to maintain their agriculture production levels. Others find that migration discourages households to hire additional agricultural labor. The argument is that households decrease the amount of land used for agriculture as their incomes increase due to remittances.

This paper aims at better understanding the relationship between temporary migration and demand for agricultural labor by situating it in the context of weather variability. That is, we focus on precipitation anomalies as treatment variable and ask whether precipitation anomalies change the relationship between temporary migration and the hiring of agricultural labor. The empirical analysis uses households in a sample of Indian villages as a case study. India is well-suited as a study area because temporary migration from rural to urban areas is a common migration pattern in India. Moreover, the Village Dynamics in South Asia (VDSA) survey provides detailed monthly data on household and agriculture, including information on temporary migration and hired labor.

Methodologically, the challenge is to unearth the causalities of the weather-migration-agriculture linkages. Towards that end, we estimate the average causal effects of (1) abnormal precipitation on temporary migrations, and (2) of temporary migration on hired agricultural labor. Identifying these relationships has three main bias sources. First, there is a possibility of self-selection bias. Temporary migration is a coping strategy for deprived households. However, deprived households rarely use hired agricultural labor. Thus, this relationship creates a self-selection bias unless an adequate model is used. Second, hired agricultural labor itself also prompts temporary migration, inducing endogeneity via bi-directional causality. Third, there are many unobservable characteristics confounding between temporary labor migration and hired labor.

To control for these biases, we use a two-stage least squares model. At the first stage, we estimate household-level temporary migration using village-level migrant proportions and their interaction with the labor force as instrumental variables. In addition, we use fixed effects to control for self-selection bias and bias from unobservable characteristics.

Our findings indicate that the effects of abnormal weather on temporary labor migration and hired agricultural labor differ by the time and type of abnormal precipitation. We found the same relationship between abnormal precipitation and temporary migration as in the previous chapter. Abnormal precipitation in the previous agricultural season triggers temporary labor migration, while the effects of abnormal precipitation on the current agricultural season are different by types and time. Consistent with the findings of the previous chapter on temporary labor migration, our results show that the weather conditions of the previous agricultural season do not affect hired agricultural labor. Therefore, our results suggest that abnormal precipitation can reduce agriculture, and the demand for agricultural labor.

Our study makes two key contributions to the literature and ultimately enhances our understanding of the links between climate, migration and the demand for hired agricultural labor. First, the study includes a more nuanced treatment of the temporal dimensions of both temporary migration and hired agricultural labor, whereby weather (precipitation amount) serves as the contextual exogenous variable. Foremost, the temporal dimension is important when choosing a temporal unit of observation. This study does not use a traditional unit like a month or a year, but one that is defined by agricultural activities. As such, time is divided into seasons, and each season is further divided into the early season (seeding) and late season (harvesting). The study thus recognizes that households decisions to send away migrants or to hire agricultural labor may very much be influenced by the conditions at pivotal times of the agricultural calendar.

Second, the study focuses on temporary rather than permanent migration and, moreover, captures temporary migration as a continuous variable rather than just a dummy variable. The literatures neglect of temporary labor migration is primarily due to the lack of adequate data for temporary labor migration. Temporary labor migrants leave their village for a short period of time only, typically for less than a year. The data collection cycle, however, is almost exclusively a year or even longer. As a result, events starting and ending within a year such as temporary migration and hiring seasonal labor, are easily missed.[1] Since the VDSA data collects monthly data, our study can capture all temporary migrants that stay away from their village for at least a month. Moreover, taking advantage of the monthly panel data we are able to design a continuous variable for temporary migration. We do so by combining information on how many migrants a household has with information on how many months the migrants stay away from their village.

The remainder of this paper proceeds as follows. Following this introduction, Sections two provides a literature review of the relationship between labor migration and hired labor in the agricultural sector of developing countries. The third section presents our conceptual framework of the relationships between migration, hired labor, and abnormal weather conditions. The fourth section includes the econometric model and the derivation of salient marginal effects. Data and estimation results are presented in sections five and six, respectively. The last section concludes with a discussion of the results, including policy implications.

3.2 Literature review

Over the last century, a rich literature has developed that centers on how rural to urban migration modifies patterns of agricultural behavior. A good deal of those studies have focused on the question whetherand to what extentrural households that lost members to migration subsequently hire additional agricultural labor. The empirical results are mixed. Studies with negative effects argue that remittances have subsidizing effects on agricultural income. Thus, households will actually reduce the number agricultural workers. In contrast, studies with positive effects suggest that rural to urban migration increases investment in agriculture which subsequently leads to rising demand for agricultural labor. Moreover, some studies show that the effect of migration depends very much on the contextual setting.

[1] For example, temporary migration is easily missed if the questionnaire simply asks for the place of residence one year ago.

For studies suggesting a negative effect, Figure 1 shows at least two possible trajectories yielding such a negative effect. First, labor migration leads to labor shortages, prompting households to reduce the amount of agriculture, and implicitly the need for hired agricultural labor. Second, the remittances have a subsidizing effect on agricultural income. When remittances are sufficiently high, the remittances-receiving households will need less agricultural income for their livelihood. Thus, these households will be in a position to reduce their agricultural activity and implicitly the number of hired workers. (Schmook and Radel, 2008; Lukasiewicz, 2011; Ochieng et al., 2017; Acharya et al., 2019)

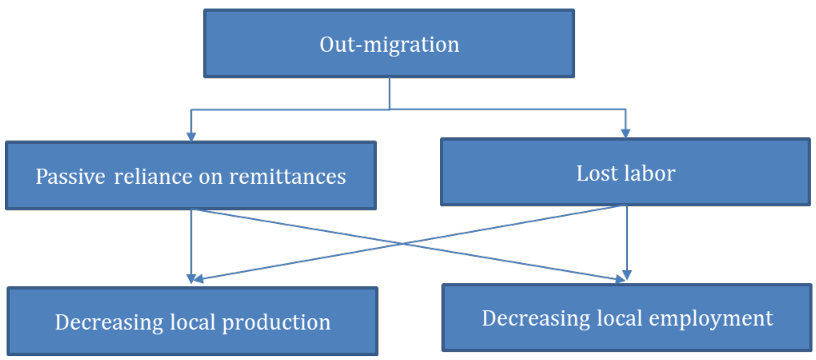


Fig. 3.1. Consequences of out-migration (Modified from Hass, 2010)

Ochieng et al. (2017) investigated the change of expenditure on agricultural inputs by temporary migration in Central Africa. They used Tobit models with IV to correct the corner solution problem of agricultural labor, and the endogeneity issue associated with the relationship between migration and agricultural labor. They showed that migration decreases the use of fertilizers and improved varieties. Moreover, they showed that migration has no significant effect on the number of hired laborers. They explained that a decrease or no change in inputs is due to households financial constraints. Households usually use the remittances for their livelihood, such as paying off debts and buying food and are not enough to hire agricultural labor. Ochieng et al. (2017) did not directly investigate the relationship between weather anomalies, migration, and hired agricultural labor. However, we can say adverse weather can modify effects of temporary labor migration on the agricultural hired labor.

In line with the New Economics of Labor Migration (NELM), several studies shows that households with migrants have more hired agricultural labor than non-migration households. These studies argue that rural households use the additional income from migrants remittances to make agricultural investment. Thus, the households substitute migrants labor for technology or hired labors (Hull, 2007; de Haas, 2006; McCarthy et al., 2009).

Hull (2007) investigated the relationship between migration and hired labor in Northeastern Thailand for two different years, 1994 and 2000. He categorized the households in four groups; non-rice growing households, rice-growing households without hired labor, rice-growing households with hired labor but no payment, and rice-growing households with hired labor with payment. Using the four household categories as dependent variable, he estimated a multinomial logistic regression model whereby migrants with remittances and migrants without remittances served ass the treatment variables. The results showed that increasing the number of migrants with remittances increases the probability of hiring more labor for agriculture. Moreover, the relationship was stronger in 2000 than in 1994. Interestingly, he mentioned that fluctuations of precipitation may be one of the factors that strengthening the relationship.

Notable is also the group of studies suggesting that the effects of migration on agricultural activities are context-specific. Several effect modifiers are identified, including the type of migration, the type of agriculture, the amount of remittances, and weather conditions. In an early study, Lucas (1997) showed that temporary migration decreases crop production whereas long-term or permanent labor migration have the opposite effect. Wouterse and Taylor (2008) showed that international migration has negative effects on traditional agricultural activities but not on cash crop agriculture. Maharjan et al. (2013) investigated the effects of temporary migration on the number of hired laborers. Using a survey from two villages in Nepal they find that the effects of migration on the number of hired laborers are heterogeneous depending on the amount of remittances. When remittances are high, the household starts to consume more leisure and other goods. However, when the remittance are lower, then households treat them as the supplementary income, and invest more in agricultural activity.

Of particular interest for this study is the heterogeneous relationships between climatic shocks, temporary migration, and hired labor. For example, Badiani and Safir (2010) investigated different behavioral reactions to weather shocks. They found that idiosyncratic shocks led to increase in local labor supply, while weather shocks led to temporary labor migration away from the village. They explain this as the effects of shocks on the labor market. Weather shocks led to a decrease in labor demand because of reduced agricultural production. Thus, shocks on agricultural production led to temporary labor migration. Maharjan et al. (2013) investigated how the weather shocks affected the gender wage gap. She surveyed 509 migrant and non-migrant households in two Nepalese regions, Syangja (western region) and Batitadi (far-western region). Employing an IV strategy using migration network as an instrument, she found that rainfall shocks increase the gender wage gap in the rain-fed rice growing regions of Nepal. She explained this phenomenon by connecting it to female migration. In Nepal, female migration is not common, except in marriage migration. When the village is affected by exogenous shocks, men in agricultural households leave for jobs, whereas women usually stay in the region, and start to participate in agricultural labor for livelihood. As a result, wages are decreased, and the gender wage gap is increased.

3.3 A conceptual model

In this section, we present a conceptual model that addresses how temporary labor migration can change the demand for hired agricultural labor, taking into account weather abnormalities. To address the relationship among abnormal precipitation, temporary labor migration, and hired agricultural labor, we begin by specifying some simple initial conditions. We consider a farm household with household characteristics X, living in a village with which experiences deviations from the normal weather patterns, D. The household has N members capable of working on the farm, and the total labor required for the farm is denoted as L. The number of hired workers can then be portrayed as the function $h(N, X, L, D)$ and is shown in Figure 3.2.

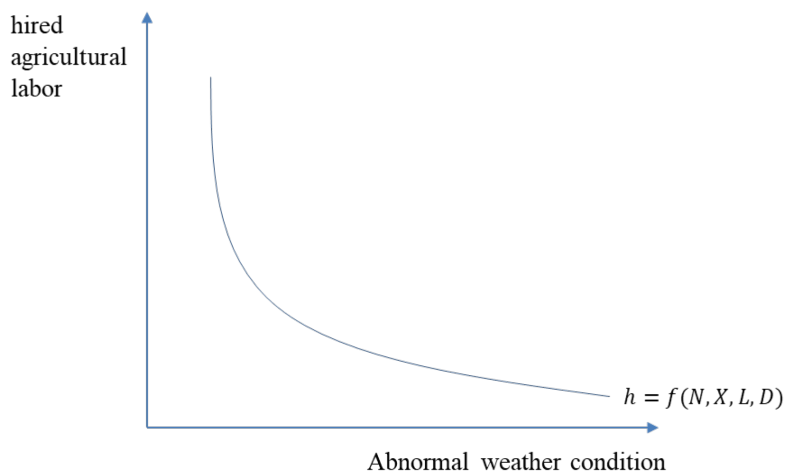


Fig. 3.2. Hired labor by abnormal weather conditions

This initial set-up can be modified by allowing one or more household members to temporarily leave the household to work elsewhere. Assume that m is the proportion of temporary migrants in the household and that L remains unchanged. Then, the household will require more hired agricultural labor, yielding $h(N, X, L, D) < h(N(1-m), X, L, D)$ and - as illustrated in Figure 3.3 - shifting the curve upward.

The household receives remittances from its migrants and the magnitude of the remittances will depend on the number of total labor force, N, and proportion of temporary migrants, m, and wage, w. Then the net expected remittances can be expressed as $\phi(Nm, w, c, Z)$[2]. We assume that $\phi(\cdot)$ is increasing inNm and wage w.

[2]We recognize that the net benefit is also affected by the cost of migration and the characteristics of the migrant. Not explicitly including them in ϕ does not affect the salient relationships among temporary migration, hired labor, and weather abnormalities.

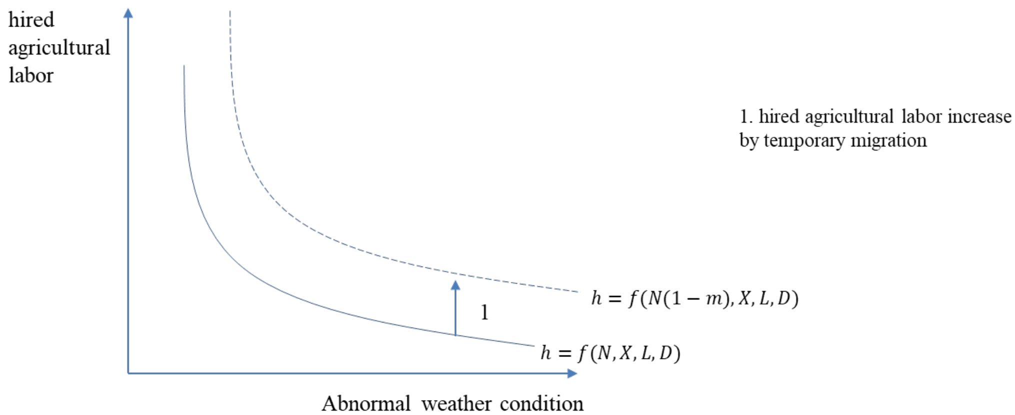


Fig. 3.3. Hired labor by abnormal weather conditions with temporary migration

The remittances can be used to hire additional labor, yielding a modified hired labor function h^* that takes on the form $h^* = h(N(1-m), X, D) + \phi(Nm, w, c, Z)$. Recalling that temporary migration m depends on weather conditions (see the previous chapter), changes in hired labor in response to changing weather conditions yields:

$$\frac{\partial h^*}{\partial D} = \frac{\partial h}{\partial D} + \frac{\partial h}{\partial m} \cdot \frac{\partial m}{\partial D} + \frac{\partial \phi}{\partial m} \cdot \frac{\partial m}{\partial D} \tag{3.1}$$

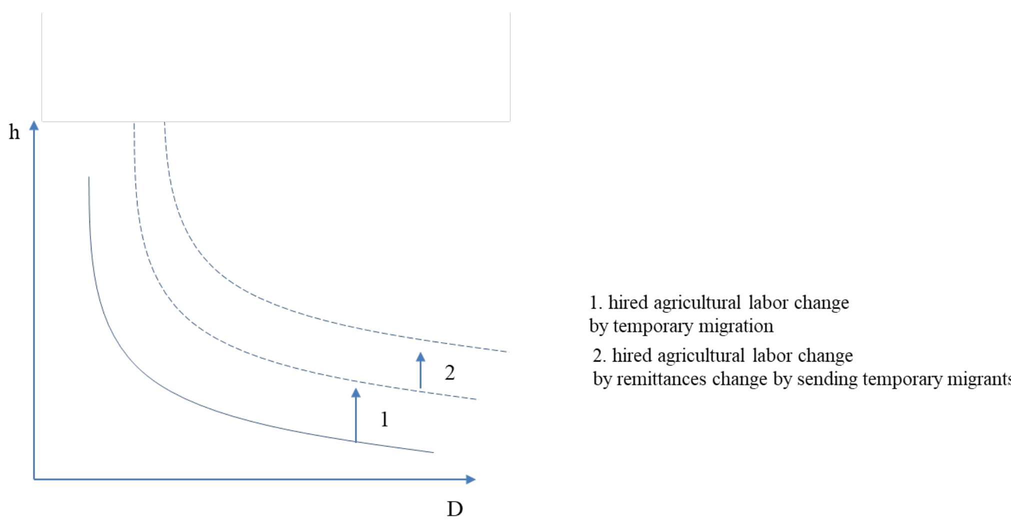


Fig. 3.4. Hired labor by abnormal weather conditions with temporary migration and change of remittances

Assume now that remittances are also a function of weather conditions D such that temporary migrants send more money home when their origin experiences abnormal weather shocks, i.e.,$\phi^{**}(Nm, w, D, c, Z)$. Then, the hired labor function takes on the form

$$h^{**} = h(N(1-m), X, D) + \phi^{**}(Nm, w, D, c, Z) \tag{3.2}$$

And differentiation with respect to weather condition D yields:

$$\begin{aligned} \frac{\partial h^{**}}{\partial D} &= \frac{\partial h}{\partial D} + \frac{\partial h}{\partial m} \cdot \frac{\partial m}{\partial D} + \frac{\partial \phi^{**}}{\partial m} \cdot \frac{\partial m}{\partial D} + \frac{\partial \phi^{**}}{\partial D} \\ &= \frac{\partial h}{\partial D} + \frac{\partial m}{\partial D}(\frac{\partial h}{\partial m} + \frac{\partial \phi^{**}}{\partial m}) + \frac{\partial \phi^{**}}{\partial D} \end{aligned} \tag{3.3}$$

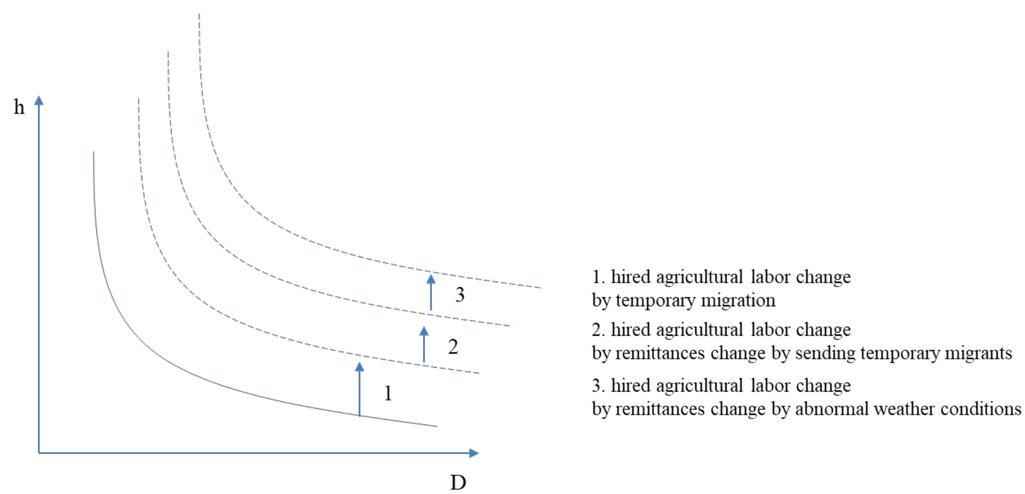


Fig. 3.5. Final conceptual model

3.4 Empirical design

3.4.1 The econometric model

The objective of our study is to examine how the complex relationship between abnormal weather and temporary labor migration changes decisions surrounding hired agricultural labor. Figure 3.6 visualizes these relationships whereby abnormal weather

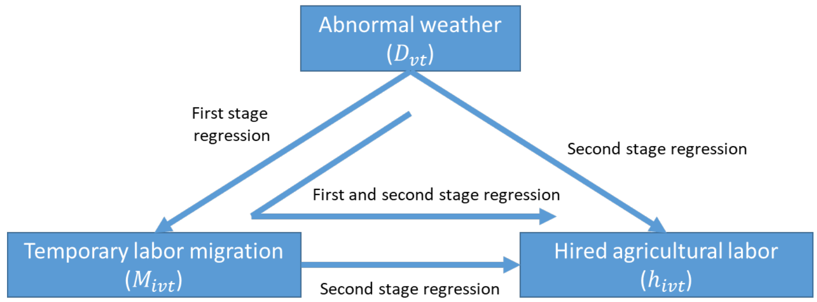


Fig. 3.6. Schematic framework of analysis

affects hired labor directly, but also indirectly through its influence on temporary migration.

Econometrically, the direct and indirect influence of abnormal weather conditions can be captured in a two-stage model. The model is specified for a household i, living in village v at time t as the unit of observation. The key variables are hired labor, h_{ivt}, temporary migration, M_{ivt}, and a vector of deviant weather conditions, D_{vt}. Note that the abnormal weather conditions only vary across villages and across time, but not across households within a village. In addition, the econometric model also includes a set of mediator variables, R_{ivt} . Mediator variables have a mediating effect between deviations from the normal weather pattern and hiring practices. Whether or not a household uses irrigation is an example of such a mediator variable. Finally, the vector X_{ivt} includes the control variables measured for household i in village v at time t, and U_{ivt} are unobservable confounding household characteristics, which affect temporary labor migration and household consumption.

With this notation, and including the salient interactions between abnormal weather variables and temporary migration as well as between abnormal weather conditions and mediator variables, the two-stage model is specified as a single-log[3] model of the form:

$$\begin{aligned} &\log h_{ivt} = \theta_i + \theta_t + \alpha \hat{M_{ivt}} + D_{vt}\beta_1 + \hat{M_{ivt}} D_{vt}\beta_2 + R_{ivt} D_{vt}\beta_3 + X_{ivt}\beta_4 + \varepsilon_{ivt} \\ &\text{and } \hat{M_{ivt}} = \hat{\lambda}_i + \hat{\lambda}_t + D_v t\hat{\gamma}_1 + R_{ivt} D_{vt}\hat{\gamma}_2 + X_{ivt}\hat{\gamma}_3 \end{aligned} \tag{3.4}$$

where θ_i and θ_t are fixed effects of household and time in the hired labor model, and $\hat{\lambda}_i$ and $\hat{\lambda}_t$ are the estimated fixed effects of household and time in the temporary labor migration model.

Second, the model suffers from bias due to reverse causality between temporary labor migration and hired agricultural labor as discussed earlier with hired labor and affecting and being affected by temporary labor migration. To account for the reverse causality problem, we used instrumental variables. In line with the literature, we chose the village-level migrant proportion at time t, m_{vt} as a main instrumental variable (Nguyen and Winters, 2011). Moreover, to increase the variability, we included the interaction between the village-level migrant proportion and the household-level labor force L_{ivt}. Then the estimated number of temporary migrants is obtained as:

$$\hat{M_{ivt}} = \hat{\lambda}_i + \hat{\lambda}_t + D_v t\hat{\gamma}_1 + R_{ivt} D_{vt}\hat{\gamma}_2 + X_{ivt}\hat{\gamma}_3 + \hat{\tau}_1 m_{vt} + \hat{\tau}_2 L_{ivt} m_{vt} \tag{3.5}$$

Aside from those endogeneity issues, the limited data range is the final econometric issue requiring consideration. Temporary labor migration is a non-negative variable and thus a limited dependent variable in the first stage of the estimation. Moreover, temporary labor migration is a strategy of deprived households and only few households have at least one temporary migrant (Chandrasekhar et al., 2015; Haberfeld et al., 1999). Thus, temporary labor migration can be thought of as a corner solution problem.

To account for this problem, we used a Tobit model in the first stage regression. The Tobit model is ideally suited for limited dependent variables as it does not predict

[3]We use the log specification because the number of hired agriculutral labor is highly skewed

negative numbers for the temporary labor migration variable. Therefore, the final econometric model takes on the form:

$$\begin{aligned}\log h_{ivt} &= \theta_i + \theta_t + \alpha \hat{M}_{ivt} + D_{vt}\beta_1 + \hat{M}_{ivt}D_{vt}\beta_2 + R_{ivt}D_{vt}\beta_3 + X_{ivt}\beta_4 + \varepsilon_{ivt} \\ \text{and Tobit}(\hat{M}_{ivt}) &= \hat{\lambda}_i + \hat{\lambda}_t + D_v t\hat{\gamma}_1 + R_{ivt}D_{vt}\hat{\gamma}_2 + X_{ivt}\hat{\gamma}_3 + \hat{\tau}_1 m_{vt} + \hat{\tau}_2 L_{ivt}m_{vt}\end{aligned} \tag{3.6}$$

3.4.2 Marginal effects of the abnormal precipitation condition

This study uses average marginal effects to interpret the effects of abnormal precipitation condition. The Equation 3.7 is derived from the differentiation of the last econometrics model by AP_{ivtk}[4], one of the abnormal precipitation conditions. The subscriptions l is the type of abnormal prcipitation, excessive precipitation or dryness condition, and k is the period, sub-agricultural season unit.

$$\begin{aligned}&\frac{\partial \log h_{ivt}}{\partial AP_{lvtk}} = \alpha\frac{\partial \hat{M}_{ivt}}{\partial AP_{lvtk}} + \frac{\partial D_{vt}}{\partial AP_{lvtk}}\beta_1 + \frac{\partial \hat{M}_{ivt}}{\partial AP_{lvtk}}D_{vt}\beta_2 + \hat{M}_{ivt}\frac{\partial D_{ivt}}{\partial AP_{lvtk}}\beta_2 + R_{ivt}\frac{\partial D_{vt}}{\partial AP_{lvtk}}\beta_3 \\ &\text{where } \frac{\partial \hat{M}_{ivt}}{\partial AP_{lvtk}} = \frac{\partial D_{vt}}{\partial AP_{lvtk}}\hat{\gamma}_1 + R_{ivt}\frac{\partial D_{vt}}{\partial AP_{lvtk}}\hat{\gamma}_2\end{aligned} \tag{3.7}$$

The Equation 3.7 can be rearranged as following:

$$\frac{\partial \log h_{ivt}}{\partial AP_{lvtk}} = \frac{\partial D_{vt}}{\partial AP_{lvtk}}\beta_1 + \frac{\partial \hat{M}_{ivt}}{\partial AP_{lvtk}}(\alpha + D_{vt}\beta_2) + \hat{M}_{ivt}(\frac{\partial D_{ivt}}{\partial AP_{lvtk}}\beta_2) + R_{ivt}\frac{\partial D_{ivt}}{\partial AP_{lvtk}}\beta_3 \tag{3.8}$$

The Equation 4.4 shows that precipitation anomalies have four types of marginal effects on hiring agricultural labor. First, $\frac{\partial D_{vt}}{\partial AP_{lvtk}}\beta_1$ is the direct effects of abnormal weather on hired agricultural labor. Second, $\frac{\partial \hat{M}_{ivt}}{\partial AP_{lvtk}}(\alpha + D_{vt}\beta_2)$ is indirect effects of abnormal weather on hired agricultural labor by a change in the number of temporary labor migrants. Third, $\hat{M}_{ivt}(\frac{\partial D_{ivt}}{\partial AP_{lvtk}}\beta_2)$ is the mediation effects of temporary labor migration on hired agricultural labor. Lastly, $R_{ivt}\frac{\partial D_{ivt}}{\partial AP_{lvtk}}\beta_3$ is the mediation effects of other coping strategies, like irrigation, to abnormal precipitation. The figure 4.6 represents the analysis process.

[4] AP is one element of matrix D_{vt}

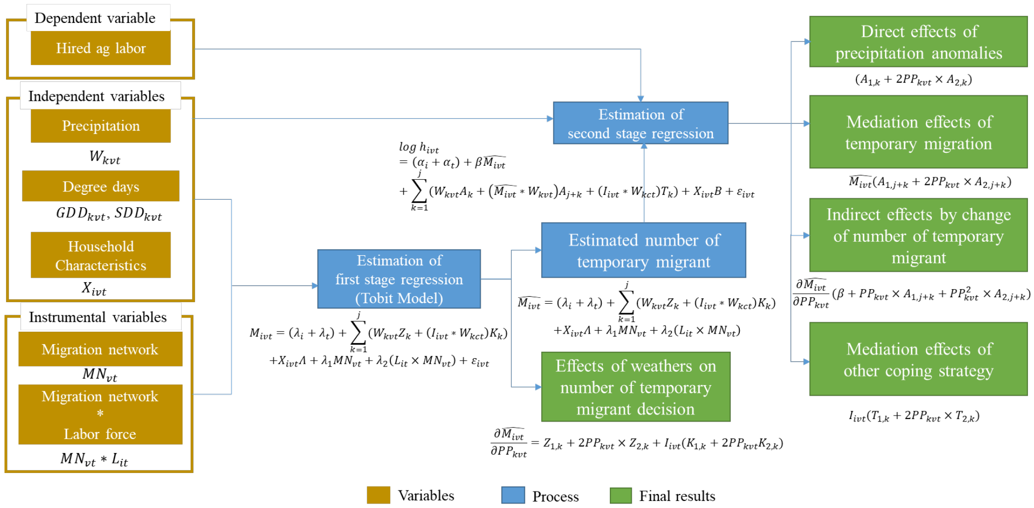


Fig. 3.7. Analysis process

3.5 Data

3.5.1 Sources and variable operationalization

This study uses two data sets, one including panel data on socio-economic household characteristics, the other including meteorological data. The socio-economic household data is taken from the Village Dynamics in South Asia (VDSA) dataset provided by the International Crops Research Institute for the Semi-Arid Tropics. VDSA is monthly panel data for households in 30 villages in India from 2010 to 2014. It includes household and individual socio-economic data, and details of agricultural activities. We concentrate on villages in non-arid climates, and only select households engaging in some agricultural activity.

The meteorological data are extracted from the daily temperature and precipitation records of NOAA. The dataset uses a suitably small scale of 0.5 degree by 0.5 degree whichat 25 degrees latitude translates into grid cells of about 55km by 55km. Using village coordinates, we can easily match villages to grid cells and their associated weather information. Our research concentrates on abnormal weather conditions D_{vt}. We define abnormal weather conditions as abnormal precipitation amounts. For the operationalization, two variables are needed, one describing excessively large precipitation amounts or positive deviations from the mean, PP. The other describing abnormally low precipitation amounts, or negative deviations NP. Allowing precipitation abnormalities to enter the model in a nonlinear fashion, we can define a composite abnormal weather variable defined as $D = PP + PP^2 + NP + NP^2$. Both PP and NP –and implicitly D– are measured at the village level v. We distinguish whether the abnormal precipitation occurred during the previous agricultural season, or during the current agricultural season. Furthermore, a distinction is made whether the abnormal precipitation amount occurred during the early portion of an agricultural season, i.e., coincides with seeding tasks, or occurred during the later portion of the season, i.e., coinciding with harvesting. For a given season t, this yields $k = 1, \ldots, 4$ relevant time periods:

- $k = 1$ previous season, $t - 1$, seeding period.
- $k = 2$ previous season, $t - 1$, harvesting period.
- $k = 3$ current season, t, seeding period.
- $k = 4$ current season, t, harvesting period.

For the two remaining key variablestemporary migration and hired laborthe operationalization relies in information extracted from the VDSA panel data set. In this study, temporary migration for household i living in village v during time period t, M_{ivt}, is measured as a continuous variable rather than as a simple binary variable (household has / does not have temporary migrants). Specifically, temporary migration is defined as the average number of temporary migrants per month during agricultural season t. Note that the number of months per season may vary depending on the observed weather conditions.

Finally, for the operationalization of hired labor, we utilize VDSA information on all agricultural activities during each agricultural season and month, as well as information on hours of labor, by family members and hired workers. We constructed the hired agricultural labor variable, h_{ivt} ,by first aggregating the hours of hired agricultural workers in household i living in village v during season t, subsequently normalizing it by the number of days in the villages season and assuming 8-hour workdays:

$$h_{ivt} = \frac{\text{Hours}_{ivt}}{8 \times \text{Days}_{vt}} \tag{3.9}$$

This normalization makes the two key variablesnumber of temporary migrants and the number of hired agricultural laborcompatible and the coefficients of first stage and second stage can be compared without any transformation.

3.5.2 Characteristics of households with hired agricultural labor

Our sample includes a total of n=3,184 households. A vast majority (62.81%) have hired labor. In contrast, only a small minority of the households (21.26%) have at least one temporary migrant who left home to work elsewhere. If we consider only households with temporary migrants, then 68 percent of households have hired agricultural labor; among households without temporary migrants only 61 percent have agricultural hired labor. Although this constitutes only a weak gap of 7 percentage points, it does allude to structural differences in the practice of hiring agricultural labor between households with and households without migration. We also saw that households with temporary migrant have different characteristics than households without migrants from previous chapter. Thus, the empirical strategy needs an appropriate model to prevent self-selection bias. The Table 3.1 shows the structural difference between migration and non-migration household groups.

To explore the possibility of self-selection bias we performed a difference of means test number of hired agricultural labor in households with versus households without temporary migrants. On average, households hire 3.96 workers per month in an agricultural season, with a large standard deviation is 12 workers. Moreover, 35% of household do not have any hired agricultural labor. Households with temporary migrants hire, on average, only 3.35 workers per month, compared to 4.087 workers for households without temporary migrants. The difference of 0.737 workers is not significant different from zero, not even at a generous 20% significance level. Comparing

Table 3.1.
Relationship between hired labor and temporary migration

		Hired Labor		
		present	absent	Sum (%)
Temporary Migration	present	459	218	677 (21.26%)
	absent	1,541	966	2,507 (78.64%)
Sum (%)		2,000 (62.81%)	1,184 (37.18%)	3,184 (100%)

Table 3.2.
Descriptive statistics and difference test

Variables	Total (n=3,184)		Hired labor households (n=2,507)		Non-hired labor households (n=677)		Difference of Means Test	
	Mean	Std.	Mean	Std.	Mean	Std.	Diff.	P
Monthly household food expenditure per capita (Ruphee)	974.6	1021.9	1054.0	1161.7	840.5	707.5	-213.5	***
Number of labor force	1.54	2.26	1.16	1.53	2.19	3.01	1.03	***
Land own (Acres)	4.35	6.29	5.18	7.33	2.95	3.54	-2.23	***
Rent in (Acres)	0.74	3.26	1.01	4.02	0.28	0.99	-0.73	***
Rent out (Acres)	0.234	1.42	0.240	1.55	0.22	1.16	-0.01	
Year of householder education	5.63	4.46	6.03	4.46	4.95	4.39	-1.07	***
Forward Caste	1.46	0.35	0.167	0.37	0.11	0.31	-0.05	***
Scheduled or Backward Caste	0.53	0.49	0.51	0.49	0.57	0.49	0.05	***

households with hired agricultural labor and households without hired agricultural labor, we also performed similar difference of means test for a number of variables. The results are shown in Table3.2.

The Table 3.2 shows that compared to household without hired labor, households that do hire workers, on average, spend more money on food, own more land, rent more land, are better educated and are more likely to have a higher caste standing. Thus, hiring agricultural labor is significantly linked to a better socio-economic status.

3.6 Estimation Results

The estimation results of the model are displayed in Table X. The results of the first stage modelthe temporary migration model suggest that abnormal precipitation triggers temporary labor migration. However, the effects of abnormal precipitation on temporary labor migration are different by type and time of abnormal precipitation. The results of the migration module are consistent with the previous chapter. Drought conditions during the previous season are weakly linked to increased temporary migration; excessive rainy conditions during the early period of the current season are a strong predictor of people leaving the village to work elsewhere.

The second stage of the model suggests that the effects of abnormal precipitation on hiring agricultural workers also vary according to when the precipitation abnormality occurred and according to what type of abnormality it was. We find that households hire significantly fewer workers after they experienced drought conditions anytime in the previous season. However, flooding or excessive wet conditions in the previous season do not significantly influence households hiring behavior.

Abnormal precipitation patterns during the current agricultural season has the opposite effect. We find significant increases in the amount of hired labor given two scenarios. First, households hire more labor if there is excessive precipitation during the early (seeding) period of the season. This suggests that the wet conditions have immediate effects on agricultural damages and households respond by not only sending temporary migrants to work elsewhere, but also by increasing the number of hired workers that substitute the loss of manpower due to temporary migration.

Second, during the late period of the current season, drought rather than wet conditions trigger additional hiring of workers. Excessive wet conditions do not significantly affect households hiring behavior or the propensity to send away migrants to work elsewhere.

Table 3.3.
Marginal effects at the mean of model

	Model (with detailed temporal dimensions)							
Time	Agricultural season t-1				Agricultural season t			
	Early period		Late period		Early period		Late period	
Type of abnormal weather	Excessive dry condition	Excessive wet condition	Excessive dry condition	Excessive wet condition	Excessive dry condition	Excessive wet condition	Excessive dry condition	Excessive wet condition
1st stage	Migration number decision model							
Effects of precipitation anomalies	0.115 (0.075)	0.079 (0.057)	0.098 (0.066)	0.072 (0.050)	0.057 (0.096)	0.149** (0.061)	-0.049 (0.065)	0.04 (0.041)
2nd stage	Hired agricultural labor model							
Direct effects of precipitation anomalies	-0.2* (0.102)	0.009 (0.047)	-0.151*** (0.057)	0 (0.025)	-0.056 (0.099)	0.072 (0.058)	0.159** (0.066)	-0.013 (0.029)
Effects of irrigation	-0.008 (0.067)	-	-0.042 (0.046)	-	-0.1 (0.088)	-	0.093* (0.049)	-
Total Migration effects	0.005 (0.034)	0.022 (0.021)	-0.035 (0.031)	-0.038 † (0.024)	-0.004 (0.025)	0.035 (0.055)	0.021 (0.031)	0.009 (0.013)
Mediation effects by migrant	-0.003 (0.039)	0.017 (0.024)	-0.034 (0.029)	-0.043* (0.025)	0.0 (0.024)	0.029 (0.052)	0.025 (0.029)	0.009 (0.014)
Effects by change in number of temporary migrant	0.008 (0.017)	0.005 (0.011)	-0.001 (0.008)	0.005 (0.01)	-0.004 (0.008)	0.006 (0.011)	-0.004 (0.009)	0.000 (0.006)
Total effects	-0.202** (0.085)	0.031 (0.04)	-0.228*** (0.057)	-0.038 (0.036)	-0.164 (0.118)	0.107† (0.072)	0.274*** (0.071)	-0.004 (0.028)

***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$, †: $p < 0.15$

3.7 Discussion and conclusion

This paper analyzes the effects of temporary labor migration on hired agricultural labor by conditions of weather anomalies. We use abnormal weather variables with two different agricultural seasons. Furthermore, we define two sub-agricultural seasons by using the information on agricultural activities. For abnormal weather, we focus on precipitation. We define the weather anomalies by using average precipitation records from the last 50 years and standard deviation, by calculating the statistical z-score. Based on this definition, we ask 1) how agricultural households change hired agricultural labor by the different times of precipitation anomalies and 2) how temporary migration changes the number of hired agricultural laborers by mediating precipitation anomalies. To answer these two questions, we set up a two-stage least square model. The first stage was set up as a Tobit model to estimate temporary labor migration numbers. For the second stage, we included interaction variables between the abnormal precipitation and the temporary labor migration variable in order to estimate the mediation effects of temporary labor migration. Our main empirical findings are as follows.

First, the temporally disaggregated analysis reveals that the effects of precipitation anomalies on hired agricultural labor are different by time and type. On the other hand, the annual level analysis fails to detect these heterogeneous effects by time and type. This discrepancy underscores the importance of our temporally disaggregated strategy in the labor market.

Second, agricultural households consider the precipitation anomalies to plan the next agricultural season. They plan to send more temporary labor migration when they have suffered precipitation anomalies during the last agricultural season. This plan also affects on hired agricultural labor. Households decided temporary migration and agriculture simultaneously. Thus, precipitation anomalies during the last agricultural season do not increase hired agricultural labor. On the other hand, households do not change the number of hired agricultural labor by the precipitation anomalies of the previous agricultural season. This shows that households change their agricultural plans by considering a changed family labor force. Lastly, our analysis reconfirms that the effects of temporary labor migration on agricultural labor hiring are heterogeneous by context. We showed that households change their hired agricultural labor strategy heterogeneously by the time of abnormal precipitation. Thus, we extend temporal contexts on reasons of heterogeneous effects from literature.

While policy implications are beyond the scope of this study, our paper suggests that temporary labor migration can be a highly effective coping strategy for abnormal precipitation based on time and climatic regime. Temporary labor migration has been considered an effective coping strategy for precipitation anomalies. However, if we consider the effects of temporary labor migration and abnormal precipitation, time of abnormal precipitation should be considered in the local labor policy. For example, when a precipitation anomaly is in the last agricultural season, the agricultural hired labor will be decreased, while temporary migration increase. This means that households in deprived socio-economic status will suffer more because of decreased labor demand. However, when precipitation anomalies occur in the current agricultural season, then the hired agricultural labor will be increased, while temporary labor migration does not significantly increase. This shows that hired agricultural labor will be increased. Thus, the local government can use a labor wage supplement policy to support deprived households.

4. SEA LEVEL RISE INDUCED INTRA-COUNTY MIGRATION: SPATIAL MICROSIMULATION WITH ENVIRONMENTAL CHANGES

4.1 Introduction

Historically, many coastal areas have offered locational advantages, foremost in the form of access to ports and trade routes. Not surprisingly then, a substantial portion of the world population has settled along the coast, often clustered in large metropolitan areas. However, proximity to the ocean also bears risks, primarily in the form of flooding. These risks are become higher as climate change and the associated increasing global temperatures led directlyand indirectly through melting glaciersto global see-levels rise as well as to more severe weather events. At the same time, population growth and development of vulnerable coastal land imply ever greater losses when extreme weather events cause flooding and the sea water encroaches further inland. Taken together, the effects of flooding in coastal areas have taken on new proportions, most noticeable in the increasing number of people losing their homes. The large number of flood-induced displacements suggests that mass displacement by extreme weather events may become the norm.

At the global level, the Internal Displacement Monitoring Centre (IDMC) in Geneva reports that, during the first half of 2019, disasters were responsible for about seven million internally displaced persons (IDMC, 2019). The vast majority of these displacements were associated with storms and floods. Cyclone Fani in May of 2019 had the worst impact, displacing almost 3.5 million people in India and Bangladesh. Kulp and Strauss (2019) emphasize that–while the climate change driven global mean sea level rise was modest during the last century–the sea level is expected to rise more substantially in the years ahead, even when carbon emissions are cut sharply. They juxtapose the state-of-the-art sea-level projections with the population size and distribution and conclude that, by 2050, up to 340 million people will live on land below the flood level. By the end of the century, the flood threatened population will have increased to up to 630 million.

The urgency to address these issues is growing. Indicative is the emergency statement, signed by thousands of scientists from across the world and published just days before the 2019 Climate Summit in Madrid. The scientists declare, "[. . .] clearly and unequivocally that planet Earth is facing a climate emergency. Exactly 40 years ago, scientists from 50 nations met at the First World Climate Conference (in Geneva 1979) and agreed that alarming trends for climate change made it urgently necessary to act. Since then, similar alarms have been made through the 1992 Rio Summit, the 1997 Kyoto Protocol, and the 2015 Paris Agreement, as well as scores of other global assemblies and scientists explicit warnings of insufficient progress (Ripple et al., 2017). Yet greenhouse gas (GHG) emissions are still rapidly rising, with increasingly damaging effects on the Earth's climate. An immense increase of scale in endeavors to conserve our biosphere is needed to avoid untold suffering due to the climate crisis (IPCC, 2018)." (Ripple et al., 2017)

With sea level rise being one of climate change's most visible, long-lasting adverse outcomes threatening the livelihood of millions of people, the focus needs to shift towards how to respond to the inevitable consequences. Given the large number of people living in the flood-prone areas threatened by an eventual complete inundation, the costs are expected to be very high. For the United States, for example, studies suggest that–although uncertainty exists regarding the exact magnitude–the sea level rise is expected to adversely affect almost one million people. Moreover, flood costs in the United States are expected to exceed 2,000 billion dollars per year by the end of the century (Hinkel et al., 2014; Strauss et al., 2012).

In the past, the population often returned to flooded areas once the water receded and adapted by, for example, strengthening levies. Such a strategy will eventually no longer be feasible as adaptation strategies, become too costly or even become unavailable given the ever rising waters. Siders et al. (2019) therefore argue that policy makers and planners need to strategically integrate retreat into their set of tools tackling sea level rise. They refer to it as strategic and managed climate retreat. Already, we witness relocation and migration in reaction to a rising sea level. For instance, Kivalina village in Alaska requested funds from the federal government for relocation because of rising sea levels. In most cases, however, people move away from flood-prone areas in a more ad hoc fashion, independent of any larger strategic plan. Such ad hoc relocation decisions by individual households may, however, be inherently inequitable as low-income households will have comparatively fewer resources to tackle the risks (Siders et al., 2019).

This essay focuses on the ad hoc migration decisions of households in flood-prone areas and its potential to foster the spatial concentration low-income households. Migration as a mechanism leading to poverty concentration has received increased attention over the past decade. Although there is growing support for the claim that sea level rise induces migration, there has been relatively little research on the timing and patterns of such migration. However, recent research has provided the general properties regarding the timing and destination of sea level rise-induced migration. First, sea level rise-induced migration is voluntary migration rather than forced migration (Gold and Nawyn, 2013) because sea level rise is a slow and gradual process. For example, increased flood frequency alerts people to the risk of sea level rise, and consequently induces households to move away before complete inundation by the sea. Second, sea level rise-induced migration follows established migration networks (Curtis and Schneider, 2011; Gold and Nawyn, 2013; Hugo, 2010). That is, while sea level rise induces migration, sea level rise does not change housing preferences. Lastly, sea level rise effects are local. Therefore, current migration patterns can be used to examine patterns of sea level rise-induced migration.

One of the more persistent characteristics of migration patterns in the U.S. is that poor migrants tend to move toward poorer areas (Foulkes and Schafft, 2010; Jivraj, 2011). This pattern will increase poverty rates in high poverty areas, while it will decrease poverty in other areas. In the case of minor sea-level rise, only the immediate coastal areas are affected, that is, areas where high-income households are typically concentrated. However, when sea level rises more than 2 - 5 feet, then it will also affect low-income regions further away from the coast. In addition, sea-level rise induced river level increase can damage poor areas (See Figure 4.1.). Thus, it is reasonable to expect sea-level rise induced migration will change the geography of poverty.

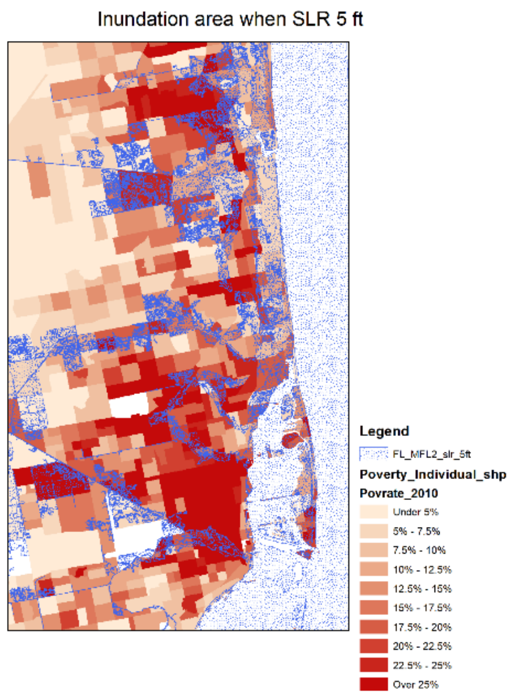


Fig. 4.1. Inundation area of Miami, FL given a 5ft SLR overlayered with 2010 poverty rate

The objective of this study is therefore to get a better understanding of the variations in migration propensities when faced with imminent flooding risks and changes in the spatial distribution/composition of the population flowing migration induced by sea-level rise / flooding. Two hypotheses are in the center. First, we hypothesize that out-migration rates in sea-level rise affected areas exceed those in areas not affected by sea-level rise. Second, sea level rise related population redistribution leads to increased poverty rates in high poverty neighborhoods.

The study uses well-known models for limited dependent variables, namely a logit model to estimate the probability of moving and a multinomial logit model to estimate the destination choice. The estimation results are subsequently used to simulate the population redistribution given specified inundation scenarios. The main methodological challenge is not the model itself, but there are two elements that make the method innovative. First, the predictors explicitly include variables measuring time-varying risk perception. Second, we derive parcel-level migration data that more adequately responds to the small-scale variation of flood risks than the typically large-scale migration data. The empirical case study uses data for Escambia County, Florida, 2010 to 2016.

The remainder of the study is organized as follows. Following this introduction, the second section provides a brief overview of the literature. The third section presents the study area. The fourth section is dedicated to the data and data preparation, including both the migration data and sea level rise data. The fifth section presents the model, its estimation results and simulation results. Finally, the essay ends with a summary and concluding discussion.

4.2 Literature review

In the absence of detailed and systematic data collection efforts that connect flooding/inundation events and relocations, many of the relevant studies concentrate on conceptual ideas about sea-level rise induced migration. Perch-Nielsen (2004), for example, conceptually differentiates sea-level rise induced migration as consisting of two components: a voluntary migration process and involuntary migration processes (see Figure 4.2). Involuntary migration will happen through governmental actions or when the area becomes completely inundated. Prior to inundation, however, flooding frequency increases, neighboring areas become inundated, and people begin to perceive the flooding risk as imminent, eventually resulting in voluntary migration.

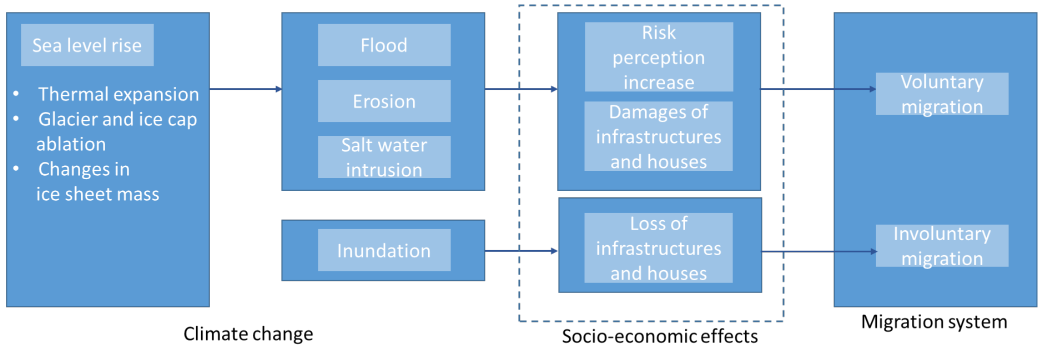


Fig. 4.2. Process of sea-level rise induced migration (Modified from Perch-Nielsen (2004))

Gold and Nawyn (2013) expanded the conceptual framework suggested by Perch-Nielsen (2004) by adding that migration patterns will be similar to those during the pre-flooding era. Their argument is that inundation will only affect the push and pull factors of a limited segments of coastal areas. As a result, most population migration patterns will remain the same as those currently observed. The historic example of retreat from Holland Island, MD, confirms these conceptual ideas. Gibbons and Nicholls (2006) investigated the abandonment of the island after the sea-level rose in the late 19th Century. From 1850 to 1900, the population of Holland Island had increased from 37 to 253. But when coastal erosion started, around 20 percent of the population left because of the loss of land. As the community continued to lose population, it was no longer able to sustain itself. induced loss. As a result, the island was completely abandoned in 1920 although most residents were not directly affected by the sea-level rise. This example shows that sea-level rise induced migration can trigger and thus be similar to economically moticated voluntary migration.

Hauer (2017) is one of the few studies going beyond conceptual and descriptive accounts of sea-level rise induced migration. He used US county-level migration data to estimate demographic changes by sea-level rise induced migration. Specifically, he studied the final destination of sea-level rise induced migration. By following previous studies, he assumes that sea level induced migration will follow past migration patterns. The author uses 1990 2013 inter-county migration data from the Internal Revenue Service. To make migration projection, he employed the unobserved components model, which decomposes time-series data to trends, seasons, and regression effects. For simplicity, he omitted seasons and regression effects. So, he assumed that migration systems would have the same trends from 1990 to 2013. The result showed that most of the migration would happen at Florida State, and almost half of sea level induced migrants in Florida will migrate to Florida. In addition, he showed Austin-Round Rock, Texas core-based statistical area will have the most significant population gain from sea-level rise induced migration. Thus, Hauer (2017) explained sea-level rise induced migration by concentrating on inter-regional migration.

Curtis and Schneider (2011) used spatial and temporal sea level rise data and linked it to migration. For spatial sea level rise data, they used Mulligan (2007) sea-level rise scenarios to identify inundation areas. For temporal sea level rise data, they used predictions from the 5th Assessment of the IPCC (2014). Thus, with these two datasets, they were able to identify the time and location of inundation. Using migration flows of metropolitan statistical areas from decadal Census data and assuming that migration flow patterns are time-invariant, they estimate the flooding-induced relocations. Most notable, they find that more than half of Floridas population would migrate to other states.

As of now, the literature has not adequately addressed the small-scale issue of the link between migration and sea-level rise. The problem is that sea level rise does not affect county residents uniformly but only affects residents in comparatively small areas along the coast and along rivers. This study fills this gap by investigating migration induced by sea-level rise at a parcel level.

4.3 Study area

Our study focuses on Escambia County in Florida, 2010 to 2016. The county borders Alabama to the West and the Gulf of Mexico to the South. It includes the low-lying Island of Santa Rosa which stretches form East to West parallel to the coast line. Most importantly, Escambia County experienced a major flooding event of its low-lying areas in April 2014, and a smaller flooding event in 2012, making it a suitable study area for observing migration responses relative to the flood occurrence.

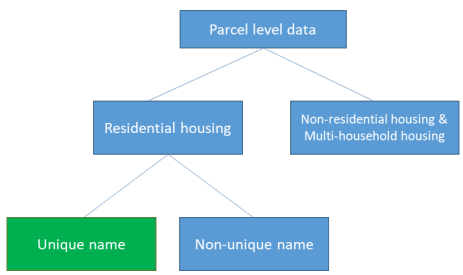
The US Census reports that Escambia County has about 315,000 inhabitants, with the non-Hispanic white population accounting for about two-third. The black or African American population is the largest minority group and accounts for about 23 percent of the population. Escambia County is not a very wealthy county when compared to the national averages. The median household income is only $47,000, the poverty rate amounts to 16.4 percent, and only 26 percent of the adult population has at least a bachelors degree. Escambia Countys housing stock is comprised of 142,000 housing units, 61 percent of them are owner-occupied. The median value of the owner-ocupied units is $126,000. In the rental housing sector, the median gross rent is $928.

4.4 Data

4.4.1 Migration data generation

The U.S. Census Bureau does collect data on individuals and households moving behavior, for example in the annual American Community Surveys (ACS) and the Current Population Surveys (CPS). However, the publicly accessible geographic identifiers for movers origins and destinations in these surveys refer to relatively large geographic areas, so-called PUMAs. Given the large spatial scale, they are not suitable for this study.

Instead, we generate a sample of movers and stayers from Escambia Countys property tax records which refer to a small spatial scale, namely individual parcels. The sample is confined to single family owner-occupied housing, and we further select only those properties that can be associated with a name that only shows up once in the records, i.e., a unique name (see Figure 4.4). Parcels owned by persons who own more than one property in Escambia County are thus eliminated. And so are parcels owned by persons who happen to have the exact same name as another parcel owner.



	2012	2014	2015
Total records	561,197	565,711	562,398
Single family	368,801	371,431	372,411
Residential housing	262,065	251,988	252,559
Unique name	245,466	235,604	235,787

Fig. 4.3. Parcel-level data refining process

To identify movers and stayers, we use a a parcel level name matching process suggested by Sun and Manson (2015). Persons are defined as stayers if they are attached to the same parcel in two consecutive years. Persons are defined as movers if they are attached to different parcels in consecutive years. Note that this procedure does not identify persons who are moving out of Escambia County, or who are moving from a single family house into rental housing.

Although parcel-level name matching is providing a novel way to construct micro-level migration, name matching may lead to false migration for various reasons. Table 4.1 is showing the common causes of false migration. To reduce the possibility of falsely identified migration, we this study separate co-owners as two persons. Parcel-level data usually shows names of co-owners in one column, without separation. This combination of two persons in one column creates problems in case of divorce and marriage. Moreover, we removed suffix/inheritor and middle names because there is variation as to whether people include or omit them.

Table 4.1.
Common errors of name matching (Modified from Sun and Manson (2015))

Reason	Example
Full name vs. Abbreviation	Yong Jee Kim vs. Yong J Kim
Married or Divorced Couples	Yong Jee Kim & Park vs. Yong Jee Kim
Suffix/ inheritor/ inheritance	Robert Bell Jr vs. Robert Bell
Order of first/last name	Kim, Yong vs. Yong Kim

Table 4.2.
Sample characteristics

Year	Number of Observations	Number of Movers	% Black	%Hispanic	Mean HH Income	Mean Risk
2012	13,235	566	16.8%	1.7%	$67,268	0.02
2013	13,429	400	16.6%	3.0%	$69,170	0.04
2014	12,973	518	15.0%	3.3%	$71,346	0.04
2015	14,097	677	17.1%	2.9%	$70,739	0.01
2016	14,083	708	15.4%	3.5%	$72,868	0.01

The property tax records do not include socio-economic attributes of property owners. Therefore we attach attributes that are derived from a synthetic population approach and thus have a a high likelihood of coinciding with the actual but unobserved attributes. Towards that end, we use socio-economic household and individual data from the American Community Surveys to first create a synthetic population for Escambia Countys census tracts. Subsequently, we employ an iterative proportional updating as proposed by Ye et al. (2009) to generate the synthetic population at the parcel level. Internal validations via univariate regressions between synthetic and actual data yielded showed that there are no significant differences.

Table 4.2 shows, for each year, the averages of the key data generated. The propensity to move varies between 3.0 percent in 2013 and 5.1 percent in 2016. These figures are compatible with observed intra-county relocation rates for home-owners. For renters, the migration propensities tend to be higher. With respect to the origin-destination linkages, Figure 4.4 is an example that summarizes the network of intra-county moves for 2013/14.

With respect to the assigned socio-economic attributes, Table 4.2 reveals that the share of black households is substantially smaller in the sample than in Escambia County as a whole. The gap, however, is not surprising given that the sample concen-

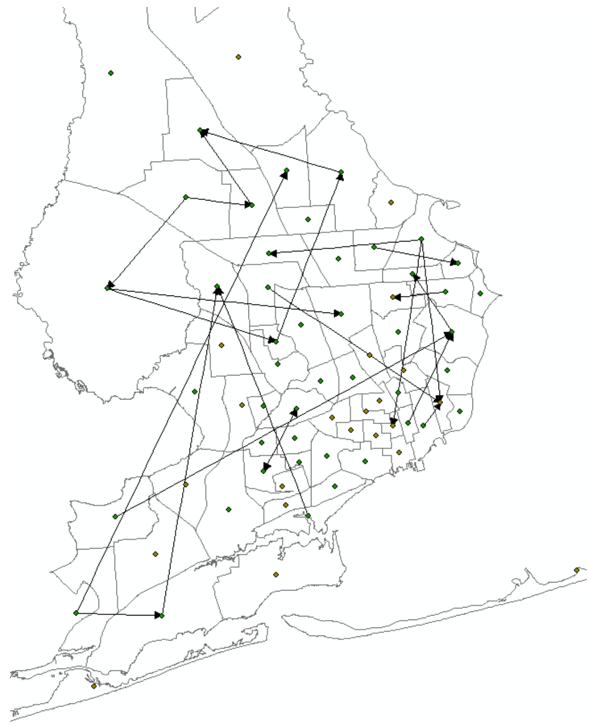


Fig. 4.4. Identified internal migration network of Escambia County at 2013 - 2014

trates on owner-occupied single-family homes where blacks are traditionally underrepresented. Furthermore, it is reasonable to assume that the selection of owner-occupied single-family homes only is also the reason why the average household income in the sample is so much higher than for the county as a whole.

4.4.2 Data on Sea-level rise

Sea-level rise data are obtained from the NOAA Office for Coastal Management. Based on NOAA data, we identified sea-level rise induced inundation areas and subsequently matched it to parcel-level data. Figure 4.5 shows the inundated areas in Escambia County when the sea-level rises by 5 ft and 10 ft, respectively. Interesting to note is that the 10ft rise includes a good deal of areas that are not in immediate proximity to the coast line.

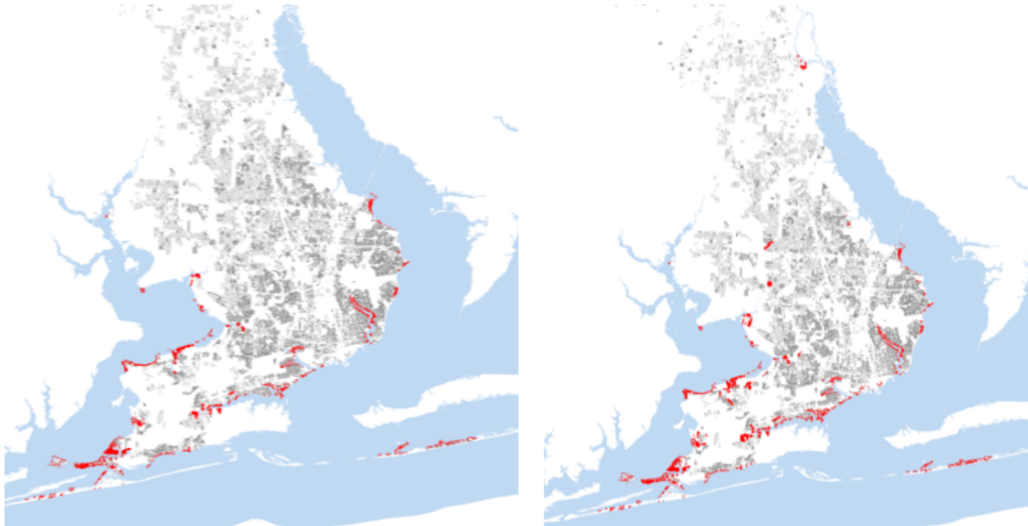


Fig. 4.5. Inundated areas when the sea level rises by 5ft (left) and 10ft (right).

4.5 Model

Adopting the standard random utility framework, we specify the probability that household i will choose to move as a function of the households utility of moving, U_{im}, exceeding the utility of staying, U_{is}. Let M_i be the random variable distinguishing household i moving, $M_i = 1$, versus household i staying $M_i = 0$. Then the probability of moving is:

$$P(M_i = 1) = P(U_{im} > U_{is}) \tag{4.1}$$

Assuming that the utility function U can be additively separated into its observable part V and unobservable ε, the probability of moving takes on the form:

$$P(M_i = 1) = P(V_{im} + \varepsilon_{im} > V_{is} + \varepsilon_{is}) \tag{4.2}$$

Finally, assuming that the unobserved parts of the utility are independent and identically Weibull distributed, and that the observable utility function is a linear combination of salient attributes, $X\beta$, then the probability of household i deciding to move can be expressed as the well-known logit expression:

$$P(M_i = 1) = \frac{\exp V_{im}}{\exp V_{im} + \exp V_{is}} = \frac{\exp X_{im}\beta}{\exp X_{im}\beta + \exp X_{im}\beta} \tag{4.3}$$

The key variable entering the linear predictor $X\beta$ is the perceived risk, which we operationalize as home insurance relative to the home value. Moreover, we allow the risk parameter to vary over time by including the interaction effects with the year fixed effects. As control variables we include the household income, the house mortgage, and we distinguish the owners by race and ethnicity, using the dummy variables BLACK and HISPANIC, respectively. The model is estimated with $n = 97,435$ observations, using maximum likelihood estimators.

Confining the sample to those who moved ($n = 414$), we designed a multinomial choice model for households decisions where to move. Let $S_i = 1, \ldots, K$ be the random variable indicating household is selection among K locations, then the probability that household i chooses location k takes on the form:

$$P(S_i = k) = \frac{\exp W_{ik}}{\sum_{r=1}^{K} \exp W_{ir}} = \frac{\exp Z_{ik}\beta}{\sum_{r=1}^{K} \exp Z_{ir}\beta} \tag{4.4}$$

The choice set of the destination choice model consists of $K = 3$, which are same census tract, adjunct census tract, and other census tracts, and the linear predictor, $Z\beta$, includes variables describing the racial and ethnic composition of the census tract (%black and %hispanic, respectively), insurance per acre, and a dummy variable indicating whether the census tract borders the coast.

Note that by not linking the destination choice model with the decision to move, we implicitly assume that the moving decision is not relevant to the subsequent locational choice. While this simplifying assumption is debatable, we decided to maintain it so as to make the subsequent simulations manageable.

The entire research design, including the data generation described in the previous section, and the two model described in this section, is summarized in the diagram below (Figure 4.6).

4.6 Results

Table 4.3 shows the estimation results for households decisions to move. To begin with, the parameter estimates for the control variables suggest that households migra-

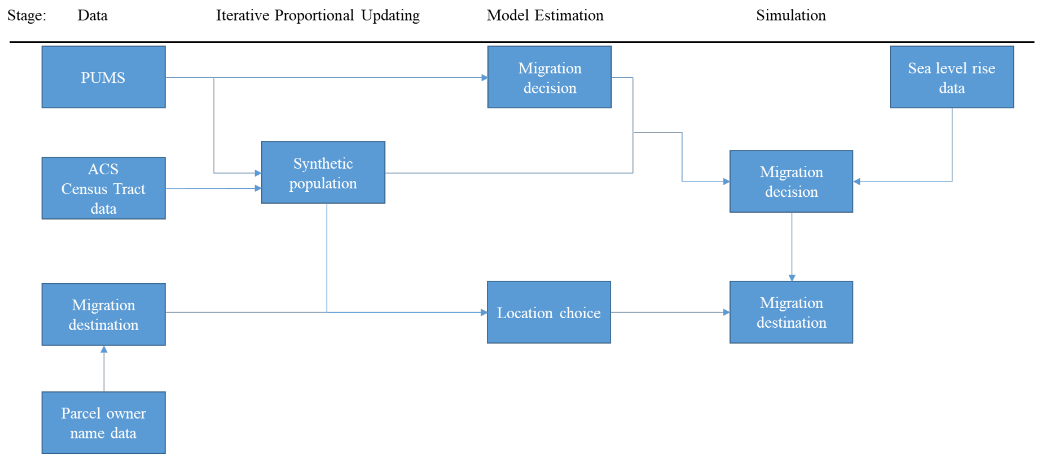


Fig. 4.6. Analysis process

tion propensities increase as budgetary constraints weaken, by lowering the amount of mortgage owed or through income increases. We do not find significant racial or ethnic differences in the probability of moving.

The results are compatible with the notion that flooding, especially in high risk areas, operates like a push factor in the decision to move. Ceteris paribus, the estimated effects on the decision to move increases with increasing risk. In particular, the interaction variables for 2015 and 2016, i.e., the two post-2014 flood years, are particularly high for households living in high-risk areas. The graphical representation of the results for the interaction between year and insurance are shown in Figure 4.7.

The detailed results for the destination choice model are delegated to Table 4.4. They show that the most of households will stay on the same census tracts, instead of moving others. The results show that the housing price is the main determinants of migration. When housing price is high, then people will move to the same or adjunct census tracts. In addition, Hispanic is more likely move to other census tracts.

We used the estimations of the destination choice model to simulate what will happen when portions of the county are inundated due to sea level rise. By and large, the results suggest that the households having to retreat due to rising waters

Table 4.3.
Results of migration decision

	Coefficient	Std. error	Marginal Effects
Control variables			
Black	-0.078	0.091	-0.0027(0.0022)
Mortgage	-0.269***	0.083	-0.007***(0.003)
Hispanic	-0.064	0.188	-0.006** (0.002)
HH income	0.001*	0.001	0.00005***(0.00002)
Perceived risk			
Risk (=Insurance/house value)	-21586.22*	11355.36	165.47(166.37)
Year FE			
2010	-0.347*	0.213	-0.00007(0.0035)
2011	-0.009	0.243	0.0009(0.0039)
2012 (Flood year)	-0.272	0.228	-0.0010(0.0035)
2013	-0.551***	0.206	-0.0014(0.0034)
2014 (Flood year)	-0.297 ‡	0.195	0.0031(0.0031)
2015	-0.203	0.245	0.0061***(0.0028)
2016	-0.293	0.231	0.0020(0.0033)
Year x Perceived risk			
2010	21850.49	19450.24	Risk 75%: 0.0005 (0.0043) Risk 90%: 0.0020 (0.0060) Risk 95%: 0.0029 (0.0074)
2011	1678.17	18723.58	Risk 75%: 0.0015 (0.0045) Risk 90%: 0.0026 (0.0063) Risk 95%: 0.0032 (0.0076)
2012	27014.95 ‡	19556.02	Risk 75%: 0.0025 (0.0041) Risk 90%: 0.0062 (0.0058) Risk 95%: 0.0080 (0.0069)
2013	36714.39**	18118.48	Risk 75%: 0.0020 (0.0038) Risk 90%: 0.0057 (0.0055) Risk 95%: 0.0075 (0.0066)
2014	22531.93***	13070.54	Risk 75%: 0.0037 (0.0035) Risk 90%:0.0054 (0.0051) Risk 95%: 0.0063 (0.0062)
2015	28004.63	22446.45	Risk 75%: 0.0068** (0.0034) Risk 90%: 0.0086 (0.0054) Risk 95%: 0.0096 (0.0067)
2016	36000.23 ‡	22923.79	Risk 75%: 0.0059 (0.0039) Risk 90%: 0.0094* (0.0055) Risk 95%: 0.0111* (0.0064)

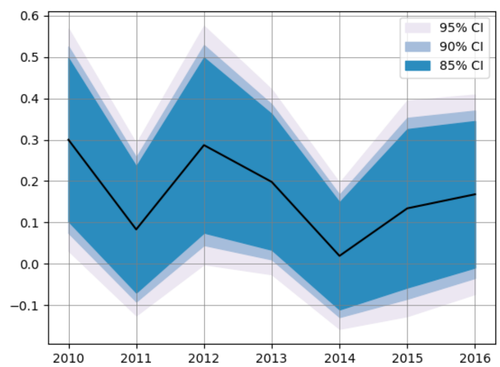


Fig. 4.7. results of interaction between risk and year dummy variables

will choose to move only short distances, many of them even moving to another place in the same census district.

When the sea level rises by 5 feet, a total of 3,395 single-family houses is affected. Among those 3,395 houses, 505 or 14.9 percent were occupied by African Americans households. Thus, African American households are slightly underrepresented among those having to retreat. Similarly, Hispanic households are underrepresented among those having to retreat. Only 43 houses or 1.3 percent of the affected houses were occupied by Hispanic households. Finally, less than 3 percent of the affected households have incomes below the threshold. Significant increases in poverty concentration in already poor neighborhoods cannot be confirmed.

When the sea level rises by 10 ft, a total of 6,238 single-family houses will be affected. Among the 6,238 houses, 1,106 or 17.7 percent of the houses were owned by African American families, approximately matching the overall sample share. Hispanic households again owned 78 of the affected houses, again representing only a small share of only 1.3 percent. Compared to the 5 ft rise, the share of poor household among those having to retreat was substantially higher, amounting to 5.7 percent or 356 households. However, compared to the population as a whole, the share is very low as can be expected given that the sample had to be confined to owner-occupied

Table 4.4.
Results of migration destination model

	Coefficient	Standard Error
migration to adjunct tract		
Housing value ($1 mil)	-0.192	0.0051
HH income	-0.00003	0.0000259
Black	-1.770	0.407
Asian	-15.5	983.5
More than two	-0.879	0.586
Hispanic	-13.15	1007.434
migration to other tract		
Housing value	-0.738	0.00366
HH income	-0.000007	0.0000081
Black	-0.737	0.266
Asian	-1.086	0.816
More than two	-0.098	0.403
Hispanic	0.742	0.858

single family homes. Moreover, their destination choices of the poor households did not exhibit significant any significant clustering in already high poverty areas.

4.7 Conclusion

This paper analyzes the effects of sea-level rise on migration decisions and destinations. Since Census and other public data have limited information about migration at a small spatial scale, we collect migration data from enumerative data from annual property tax data. We use a name matching procedure to identify homeowners who have migrated. Besides generating the migration data, we use three different data sources, PUMS, ACS, and property tax data, to produce the synthetic population for the parcel level. The research questions asked are (1) how do flooding/sea level rise affect residents decision to move, (2) where do households relocate when pushed to retreat from flooded or inundated areas.

Generating the data for Escambia County in Florida from 2010 to 2016, we subsequently estimate households decision and movers destination choice. We find increased migration propensities associated with the occurrence of flooding events. Moreover, risk prone locations have higher migration rates than locations with a lower perceived risk. With respect to the destination choice, we find that households who are affected by sea level rise are expected to move short distances, staying in the same census tract or moving to a neighboring district.

This study contributes to our knowledge of inner-county relocations following the flooding and or indundation by sea-level rise. Earlier studies, for example, Hauer (2017) examined inter-county migration following sea level rise. Based on our results, however, studies investigating retreat in response to flooding and sea level rise need to be conducted at a much smaller scale. Our findings suggest that households making ad hoc decisions on retreating from rising waters will in fact stay close to the hazard prone areas. This may eventually necessitate a further retreat, including a costly moves. In this sense, our study supports the case for strategic and managed retreats from rising waters, as Siders et al. (2019) recently expressed in general for adverse climate change outcomes.

The study's limitations are rooted in the lack of appropriate data at a small spatial scale. Flooding and inundation does not, as of now, threaten entire counties, but much smaller units like parcels, blocks, or block groups. Future research is needed that is based on surveys of households living in flood prone areas. Those surveys need to includes information on the socio-economic and demographic attributes of those who moved and those who stayed put, as well as geographic identifiers of origin and destination at very small-scales.

5. CONCLUSION

This dissertation explores the issues related to climate-induced migration. The first two essays investigate the impacts of precipitation anomalies on temporary labor migration and the effects of temporary migration on household welfare and agricultural labor hiring. The last essay deals with the economic geography changes due to sea-level rise induced migration. This chapter summarize the main conclusions of the dissertation.

The first and second essays use disaggregated temporal units to investigate the effects of temporary labor migration on household consumption and hired agricultural labor. The Village Dynamics of South Asia (VDSA) data set is employed, which comprises detailed information on agricultural activities and is collected monthly. These essays used a two-stage least square model with fixed effects to correct bidirectional causality between temporary labor migration and dependent variables, and self-selection bias. At the first stage, migrant proportions in village, and their interaction with the number of household laborforce are used as an instrumental variable. In addition, the Tobit model is used to reflect the corner solution problem of the number of temporary labor migration decisions.

The findings on the common module in the first and second essays indicate that the impact of abnormal precipitation on temporary labor migration is different, depending on the time and the type. Abnormal precipitation in the previous agricultural season increases the number of temporary labor migration. Dry conditions in the previous agricultural season have more significant effects. When the precipitation anomalies occur in the current agricultural season, the type and time of abnormal precipitation become more important. When there are dry conditions, households do not increase temporary labor migrants. Wet conditions increase temporary labor migrants only if it occurs early in the agricultural season. Therefore, abnormal precipitation leads to different decisions depending on the time and type.

The results in the first essay indicate that the effects of temporary labor migration on consumption can differ by the time and types of precipitation anomalies. The combination of temporary labor migration results show that temporary migration effects on consumption are enhanced when precipitation anomalies are in the early period of the current agricultural season. However, in dry conditions households do not increase the number of temporary migrants. In other words, households' decisions about temporary migration are not optimal when dryness occurs early in the current agricultural season. Therefore, local governments need to warn households about drought conditions to maximize consumption.

The findings in the second essay indicate that the effects of temporary labor migration on hired agricultural labor can also be different by the time and types of precipitation anomalies. With a combination of temporary labor migration results, the temporary migration interacted by the previous abnormal precipitation does not increase the number of hired agricultural labor. Non-change on hired agricultural labor shows that hired agricultural labor and temporary labor migration are simultaneously chosen with the agricultural plan.

The last essay investigates the consequences of sea-level induced migration using the Escambia County case. Various data sources were used to investigate intra-county migration. First, the 2010 to 2016 parcel level tax data was used. The parcel level tax data was used to produce intra-county level migration origin and destination by using a name matching process. Second, ACS Public Use Microdata was used to produce a synthetic population in Escambia County. A multinomial logit model was used to estimate the destination of sea-level induced migration. It was found that most of the sea-level rise induced migration will be towards the same, or adjunct, census tract.

The findings in the third essay indicate that sea-level rise induced migration will not change the economic geography significantly. Previous studies concentrated on inter-county or inter-regional migration. Consequently, there was a limitation on implication for local policies on sea-level rise. This study shows that sea-level induced migration will not change the community dramatically.

In this dissertation, traditional methods were applied: the two-stage least square with the Tobit model, and name matching methods for migration identification. However, new ideas were combined with the traditional method: the first and second essays include disaggregated temporal units, and the third essay used parcel level tax big data to identify intra-county migration. In the first two essays, disaggregated temporal units are introduced with the traditional two-stage least square model. In previous temporary migration studies, temporary migration was usually defined as a binary variable, or as the number of temporary migrants at an annual level, due to a lack of temporally disaggregated data. However, VDSA provides detailed monthly household data and therefore, the agricultural season data set was built. The agricultural season level analysis showed that the timing of abnormal precipitation can be one reason for non-unified temporary labor migration effects.

In the last essay, name matching was used with parcel level big data. Traditionally, a telephone book was used for migration identification. Since most of the households had one telephone number in the house, it was used to identify migration by comparing two different years telephone books. However, this method is hard to use today due to technological change. The third essay introduces parcel level tax data, which includes the name of the parcel owner. Using the name matching process for two different years parcel level tax data identified exact migration location, and the migration data was used in the economic analysis.

REFERENCES

Acharya, Y., Ghimire, Y., Upadhayay, N., and Poudel, B. (2019). Assessing Migration and Remittance Status and its Effect on Maize Production in Nepal. *Journal of Nepal Agricultural Research Council*, 5:88–95.

Atamanov, A. and Van den Berg, M. (2012). Heterogeneous Effects of International Migration and Remittances on Crop Income: Evidence from the Kyrgyz Republic. *World Development*, 40(3):620–630.

Badiani, R. and Safir, A. (2010). Coping with aggregate shocks: Temporary migration and other labor responses to climatic shocks in rural India. *World Bank Mimeo*.

Brauw, A. D. (2010). Seasonal Migration and Agricultural Production in Vietnam. *Journal of Development Studies*, 46(1):114–139. bibtex: brauw_seasonal_2010.

CFSR (2015). Global Weather Data for SWAT (http://globalweather.tamu.edu/). bibtex: cfsr_global_2015.

Chandrasekhar, S., Das, M., and Sharma, A. (2015). Short-term Migration and Consumption Expenditure of Households in Rural India. *Oxford Development Studies*, 43(1):105–122.

Coffey, D., Papp, J., and Spears, D. (2015). Short-term Labor Migration from Rural North India: Evidence from New Survey Data. *Population Research and Policy Review*, 34(3):361–380.

Curtis, K. J. and Schneider, A. (2011). Understanding the demographic implications of climate change: estimates of localized population predictions under future scenarios of sea-level rise. *Population and Environment*, 33(1):28–54.

de Brauw, A. and Harigaya, T. (2007). Seasonal Migration and Improving Living Standards in Vietnam. *American Journal of Agricultural Economics*, 89(2):430–447. bibtex: brauw_seasonal_2007.

de Haas, H. (2006). Migration, remittances and regional development in Southern Morocco. *Geoforum*, 37(4):565–580.

Deshingkar, P. and Grimm, S. (2004). Voluntary internal migration: An update. *London: Overseas Development Institute*, 44.

Deshingkar, P. and Start, D. (2003). *Seasonal Migration for Livelihoods in India: Coping, Accumulation and Exclusion*. Overseas Development Institute London.

Findley, S. E. (1994). Does Drought Increase Migration? A Study of Migration from Rural Mali during the 1983-1985 Drought. *The International Migration Review*, 28(3):539–553.

Foster, A. D. and Rosenzweig, M. R. (2008). Economic Development and the Decline of Agricultural Employment. Handbook of Development Economics, Elsevier.

Foulkes, M. and Schafft, K. A. (2010). The Impact of Migration on Poverty Concentrations in the United States, 1995-2000. *Rural Sociology*, 75(1):90–110.

Gibbons, S. and Nicholls, R. (2006). Island Abandonment and Sea-Level Rise: An Historical Analog from the Chesapeake Bay, USA. *Global Environmental Change-human and Policy Dimensions - GLOBAL ENVIRON CHANGE*, 16:40–47.

Gold, S. J. and Nawyn, S. J. (2013). *Routledge International Handbook of Migration Studies*. Routledge. Google-Books-ID: _JL8fqrgcCkC.

Haberfeld, Y., Menaria, R. K., Sahoo, B. B., and Vyas, R. N. (1999). Seasonal migration of rural labor in India. *Population Research and Policy Review*, 18(5):471–487.

Hauer, M. E. (2017). Migration induced by sea-level rise could reshape the US population landscape. *Nature Climate Change*, 7(5):321–325.

Hinkel, J., Lincke, D., Vafeidis, A. T., Perrette, M., Nicholls, R. J., Tol, R. S. J., Marzeion, B., Fettweis, X., Ionescu, C., and Levermann, A. (2014). Coastal flood damage and adaptation costs under 21st century sea-level rise. *Proceedings of the National Academy of Sciences*, 111(9):3292–3297.

Hugo, G. (2010). Climate change-induced mobility and the existing migration regime in Asia and the Pacific. In *Climate change-induced mobility and the existing migration regime in Asia and the Pacific*. Hart Publishing.

Hull, J. R. (2007). Migration, Remittances and Monetization of Farm Labor in Subsistence Sending Areas. *Asian and Pacific Migration Journal*, 16(4):451–484.

IDMC (2019). Global Report on Internal Displacement 2019.

IPCC (2014). *Climate Change 2014Impacts, Adaptation and Vulnerability: Regional Aspects*. Cambridge University Press.

IPCC (2018). Global Warming of 1, 5o C: an IPCC special report on the impacts of global warming of 1, 5o C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty. *Repblica da Coria: Summary for Policymakers*.

Jivraj, S. (2011). *The effect of internal migration on the socioeconomic composition of neighbourhoods in England*. PhD Thesis, University of Manchester.

Jlich, S. (2011). Drought Triggered Temporary Migration in an East Indian Village. *International Migration*, 49:e189–e199.

Kulp, S. A. and Strauss, B. H. (2019). New elevation data triple estimates of global vulnerability to sea-level rise and coastal flooding. *Nature Communications*, 10(1):1–12.

Lucas, R. E. B. (1997). Chapter 13 Internal migration in developing countries. In *Handbook of Population and Family Economics*, volume 1, pages 721–798. Elsevier.

Lukasiewicz, A. (2011). Migration and Gender Identity in the Rural Philippines. *Critical Asian Studies*, 43(4):577–593.

Maharjan, A., Bauer, S., and Knerr, B. (2013). *Migration for labour and its impact on farm production in Nepal*. Centre for the Study of Labour and Mobility Kathmandu, Nepal.

Marchiori, L., Maystadt, J.-F., and Schumacher, I. (2012). The impact of weather anomalies on migration in sub-Saharan Africa. *Journal of Environmental Economics and Management*, 63(3):355–374.

McCarthy, N., Carletto, C., Kilic, T., and Davis, B. (2009). Assessing the Impact of Massive Out-Migration on Albanian Agriculture. *The European Journal of Development Research*, 21(3):448–470.

Mendola, M. (2008). Migration and technological change in rural households: Complements or substitutes? *Journal of Development Economics*, 85(1):150–175.

Mulligan, M. (2007). Global sea level change analysis based on SRTM topography and coastline and water bodies dataset (SWBD). *URL: http://www. ambiotek. com/sealevel*.

Nguyen, M. C. and Winters, P. (2011). The impact of migration on food consumption patterns: The case of Vietnam. *Food Policy*, 36(1):71–87.

Ochieng, J., Knerr, B., Owuor, G., and Ouma, E. (2017). Migration and agricultural intensification at origin: evidence from farm households in Central Africa. *Migration and Development*, 6(2):161–176.

Perch-Nielsen, S. (2004). Understanding the effect of climate change on human migration. *ETH Zurich Research Collection*.

Ravenstein, E. G. (1885). The laws of migration. *Journal of the Statistical Society of London*, 48(2):167–235.

Ripple, W. J., Wolf, C., Newsome, T. M., Galetti, M., Alamgir, M., Crist, E., Mahmoud, M. I., and Laurance, W. F. (2017). World Scientists Warning to Humanity: A Second Notice. *BioScience*, 67(12):1026–1028.

Schmook, B. and Radel, C. (2008). International Labor Migration from a Tropical Development Frontier: Globalizing Households and an Incipient Forest Transition. *Human Ecology*, 36(6):891–908.

Siders, A. R., Hino, M., and Mach, K. J. (2019). The case for strategic and managed climate retreat. *Science*, 365(6455):761–763.

Stark, O. and Bloom, D. E. (1985). The New Economics of Labor Migration. *The American Economic Review*, 75(2):173–178.

Strauss, B., Tebaldi, C., and Zlemlinski, R. (2012). Surging Seas Sea Level Rise Analysis by Climate Central. *Florida and the Rising Sea*.

Sun, S. and Manson, S. M. (2015). Simple Agents, Complex Emergent City: Agent-Based Modeling of Intraurban Migration. In Helbich, M., Arsanjani, J. J., and Leitner, M., editors, *Computational Approaches for Urban Environments*, number 13 in Geotechnologies and the Environment, pages 123–147. Springer International Publishing.

Taylor, J., Rozelle, S., and de Brauw, A. (2003). Migration and Incomes in Source Communities: A New Economics of Migration Perspective from China. *Economic Development and Cultural Change*, 52(1):75–101.

VDSA (2013). Village Dynamics in South Asia (VDSA) database, generated by ICRISAT/IRRI/NCAP in partnership with national institutes in India and Bangladesh. (http://vdsa.icrisat.ac.in).

Wouterse, F. and Taylor, J. E. (2008). Migration and Income Diversification:: Evidence from Burkina Faso. *World Development*, 36(4):625–640.

Ye, X., Konduri, K., Pendyala, R. M., Sana, B., and Waddell, P. (2009). A methodology to match distributions of both household and person attributes in the generation of synthetic populations. In *88th Annual Meeting of the Transportation Research Board, Washington, DC.*

VITA

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