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Barbora Šedová, M.Sc.

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Dean/ Second supervisor: Prof. Dr. Maik Heinemann

Supervisor: Prof. Dr. Matthias Kalkuhl
Reviewer: Prof. Dr. Katrin Millock

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To my parents and my sister.

Summary

While estimated numbers of past and future climate migrants are alarming, the growing empirical evidence suggests that the association between adverse climate-related events and migration is not universally positive. This dissertation seeks to advance our understanding of *when* and *how* climate migration emerges by analyzing heterogeneous climatic influences on migration in low- and middle-income countries. To this end, it draws on established economic theories of migration, datasets from physical and social sciences, causal inference techniques and approaches from systematic literature review. In three of its five chapters, I estimate causal effects of processes of climate change on inequality and migration in India and Sub-Saharan Africa. By employing interaction terms and by analyzing sub-samples of data, I explore how these relationships differ for various segments of the population. In the remaining two chapters, I present two systematic literature reviews. First, I undertake a comprehensive meta-regression analysis of the econometric climate migration literature to summarize general climate migration patterns and explain the conflicting findings. Second, motivated by the broad range of approaches in the field, I examine the literature from a methodological perspective to provide best practice guidelines for studying climate migration empirically. Overall, the evidence from this dissertation shows that climatic influences on human migration are highly heterogeneous. Whether adverse climate-related impacts materialize in migration depends on the socio-economic characteristics of the individual households, such as wealth, level of education, agricultural dependence or access to adaptation technologies and insurance. For instance, I show that while adverse climatic shocks are generally associated with an increase in migration in rural India, they reduce migration in the agricultural context of Sub-Saharan Africa, where the average wealth levels are much lower so that households largely cannot afford the upfront costs of moving. I find that unlike local climatic shocks which primarily enhance internal migration to cities and hence accelerate urbanization, shocks transmitted via agricultural producer prices increase migration to neighboring countries, likely due to the simultaneous decrease in real income in nearby urban areas. These findings advance our current understanding by showing *when* and *how* economic agents respond to climatic events, thus providing explicit contexts and mechanisms of climate change effects on migration in the future. The resulting collection of findings can guide policy interventions to avoid or mitigate any present and future welfare losses from climate change-related migration choices.

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Introduction

Anthropogenic climate change, with its potential to independently drive the Earth system out of its safe operating space (Rockström *et al.*, 2009a,b; Steffen *et al.*, 2015), is one of the biggest threats faced by humanity. The warming climate accompanied by sea level rise (Mengel *et al.*, 2016), changing climatic conditions (Naumann *et al.*, 2018; Trenberth, 2011) and more frequent and intense extreme weather events (Lange *et al.*, 2020; Lehmann *et al.*, 2018; Rahmstorf and Coumou, 2011) pose significant risks to human security across scale (Carleton and Hsiang, 2016), jeopardizing physical (Carleton *et al.*, 2020) and mental (Obradovich *et al.*, 2018) health, food (Challinor *et al.*, 2014) and water (Schewe *et al.*, 2014) supplies, as well as political stability (Burke *et al.*, 2015a; Hsiang *et al.*, 2013). Taken together, the aggregate (economic) damages from climate change are tremendous (Burke *et al.*, 2015b; Dell *et al.*, 2009; Kalkuhl and Wenz, 2020).

Thus far, human activities have caused the warming of the Earth's surface of approximately 1°C above pre-industrial levels (IPCC, 2018). At the current rate, global warming is likely to reach 1.5 °C already between 2030 and 2052 (IPCC, 2018). Yet, any warming beyond 1.5 °C substantially increases the risks for natural and human systems by activating tipping elements in a domino-like cascade that could take the Earth system to even higher temperatures on the so-called "Hothouse Earth" pathway (Steffen *et al.*, 2018). Despite these looming threats, countries have delayed taking real action for decades, making climate change the greatest *tragedy of the commons* of our times (Battersby, 2017; Hardin, 1968).[1]

With continued global warming, *in situ* adaptation to the changing conditions might become increasingly difficult, especially since some regions are expected to become

[1]Climate change is the ultimate global common problem. The atmosphere can be perceived as a global common-pool resource in its function as a sink for CO2 and other greenhouse gas emissions (GHGs) (Edenhofer *et al.*, 2015; Ostrom, 1990; Paavola, 2008). A unit of sink services used by one user is not available to others, making the atmosphere a rival resource. The use of units of sink services is non-excludable, as the number of users, size of the sink and the range of activities using it make it extremely difficult to monitor the use of the sink and to exclude users (Ostrom, 1990; Paavola, 2008). As a result of these resource attributes, atmospheric sinks experience what Hardin (1968) described as *the tragedy of the commons*: users are motivated to act in self-interest and use sink services before others make them unavailable, and it is challenging to prevent them from doing so. Congesting the atmosphere with GHGs leads to dangerous and irreversible change of climate, with significant implications for natural and societal systems globally (IPCC, 2014).

uninhabitable in the future (Xu *et al.*, 2020). Under these circumstances, migration may serve as an important adaptation strategy for affected populations. It has been increasingly established that climate impacts already affect the patterns of human migration (Cattaneo *et al.*, 2019; Hoffmann *et al.*, 2020; Millock, 2015). The estimates show that in 2019 alone, almost 24 million people were displaced due to weather-related events (NRC and IDMC, 2019). Without any concrete climate action, up to 143 million people in Sub-Saharan Africa, South Asia, and Latin America will be forced to move by 2050 in response to gradual climate change (Rigaud *et al.*, 2018).

While science provides us with alarming estimates of past and future climate migration magnitudes, the growing empirical evidence aiming to establish a direct causal link between climatic events and migration remains mixed (Cattaneo *et al.*, 2019; Millock, 2015). Even though climate-related factors increasingly influence migration, the decision to migrate is further affected by a multitude of socio-economic and political conditions. Thus, the climate change-migration association is not universally positive (Black *et al.*, 2011b). Given this complexity, rather than only estimating and projecting climate change impacts on migration, it is crucial to comprehend the mechanisms and contextual conditions of *when* and *how* climate migration emerges. A greater understanding of the specific contexts in which and channels through which climatic events affect migration today and thus could influence migration in the future can guide the design and implementation of policy interventions that can help avoid or mitigate present and future welfare losses from climate change-related migration choices. This is the starting point of my thesis.

With my dissertation, I move beyond the more general questions regarding the direct impacts of local climate-related events that the empirical climate migration literature has primarily focused on thus far. Instead, the guiding questions of this dissertation are:

- *When and how do local and distant climate-related impacts affect human migration?*
- *Who is likely to migrate and who is likely to stay in response to climate change?*
- *What are the destination choices of climate migrants?*
- *How should climate migration research move forward?*

Thereby, I contribute to the recent scientific efforts that aim to better understand the heterogeneous effects of weather and climate on migration (Cattaneo *et al.*, 2019). Central to my analyses is the idea that a more nuanced understanding of climate-related impacts on migration can help to identify sustainable adaptation strategies and development pathways in a changing climate. My dissertation is composed of five articles which draw on established economic theories of migration and mobilize datasets from both physical and social sciences along with methodological innovations in causal inference and systematic literature review.

To study the effects of a changing climate, one ideally would observe two identical

Earths, slowly change the climate on one, and analyze how the outcomes diverge between the two planets. Researchers have applied different econometric designs to approximate this setting by creating a hypothetical counterfactual climate. In the econometric studies (i.e., chapters 1, 2 and 5) of my doctoral thesis, I draw on the state-of-the-art approaches from climate econometrics to study heterogeneous climatic effects on migration. While controlling for the unit of observation-specific intercepts and common time trends via fixed effects, I exploit the exogenous variation in climate-related events over time within a spatial unit. Thus, the identification of response coefficients comes from comparing a given entity under different climatic conditions and so they can be interpreted causally. To explore the heterogeneity across climate-related impacts, I either interact climatic variables with various household- and location-specific characteristics, or compare direct climatic impacts across various sub-samples of interest. In chapter 3, I then meta-analyze the most comprehensive sample of original econometric studies thus far to synthesize the existing climate migration literature. The multitude of research contexts and designs allows to better understand *when* and *how* climate migration emerges, how methodological pitfalls typical for the climate impact literature influence the evidence and more. In chapter 4, I provide a methodological guidance on how to address these pitfalls using state-of-the-art insights from climate econometrics and other disciplines with the intention to move the climate migration research forward.

In my original econometric analyses, I primarily focus on low- and middle-income countries, where agriculture is still a relevant source of livelihoods and the economies are thus particularly sensitive to variations in weather. In such environments, the spatial and temporal coverage of weather stations varies and the available datasets have many missing observations. To deal with these gaps, I draw on reanalysis data. I specifically apply the ERA5 data produced by the European Centre for Medium-Range Weather Forecasts (C3S, 2017). Reanalysis data combines observations from weather stations and remote sensing with a physics-based model, increasing the information from regions with existing observations to regions with sparse observations. Reanalysis data solves the endogeneity problem resulting from the weather stations placement, variation in the quality of data collection, and variation in the quantity of collected data and produces a consistent best estimate of atmospheric parameters over time and space (Auffhammer *et al.*, 2013; Donaldson and Storeygard, 2016). Because climatic events are correlated, in all model specifications both temperature and precipitation are controlled for to avoid potential omitted variable problems. In addition, by clustering of the standard errors at the treatment level, I account for the spatial and temporal correlation of climatic events. In what follows, I briefly introduce the individual chapters of this dissertation.

Chapter 1: Distributional Impacts of Weather and Climate in Rural India[2] In the first chapter (chapter 1, Šedová *et al.* (2019)), we lay the foundation by studying

[2]Joint work with Prof. Dr. Matthias Kalkuhl and Prof. Dr. Robert Mendelsohn, published in *Economics of Disasters and Climate Change*.

distributional implications of weather and climate in rural India. While inequality implications of climate change across countries have been studied extensively (Burke *et al.*, 2015b; Kalkuhl and Wenz, 2020; Mendelsohn *et al.*, 2006), the within-country effects have received only little attention (Hallegatte and Rozenberg, 2017). Yet, wealth and inequality are important channels through which climate change affects who migrates and who stays (Cattaneo *et al.*, 2019). This evidence helps to explain the mechanisms behind climate migration choices in the chapters that follow. Here, we apply the framework for studying distributional implications of environmental goods by Hsiang *et al.* (2019), where an environmental externality (i.e., damage) is a social cost that can be expressed as a function of i) the level of exposure to environmental conditions and ii) socio-economic attributes. Both of these factors interact with each other and are potential sources of vulnerability, i.e., the rate at which exposure to environmental conditions generates harm given some initial conditions. We focus on the environmental damages resulting from changes in seasonal temperature and precipitation to study whether in rural India households living below the poverty line and those above react differently to climate-related events and if so, why.

For the empirical analysis, we merge ERA5 reanalysis weather data with the representative India Human Development Survey (IHDS) household panel (Desai *et al.*, 2005, 2015) and climate projections provided by the Inter-Sectoral Impact Model Intercomparison Project (Warszawski *et al.*, 2013). Applying a first difference approach, we show that climate change already aggravates inequality in rural India, particularly by reducing consumption of farming households living below the poverty line. Future global warming predicted under RCP8.5 (business as usual) is expected to exacerbate these effects, reducing consumption of poor farming households by one third by the end of the century. As hypothesized, the differences in responses of households living below and above the poverty line to climate-related damages can be explained by i) historical climate, as the poor largely inhabit areas with historically more adverse climatic conditions and ii) by socio-economic factors, as the poor have less access to adaptation technologies and insurance.

Chapter 2: Who Are the Climate Migrants and Where do They Go? Evidence from Rural India[3] The second article of this thesis (chapter 2, Šedová and Kalkuhl (2020)) further explores the case of rural India and builds on findings from the previous article. Here, we examine heterogeneous effects of climatic shocks on migration to derive more clarity on socio-economic characteristics and destination choices of climate migrants. From a policy perspective, this is of particular importance as it enables receiving communities to better prepare for the future influx of migrants under climate change. The analysis draws on the canonical Roy-Borjas model of self-selection into migration which suggests that the driving force behind the selection process is the relative

[3] Joint work with Prof. Dr. Matthias Kalkuhl, published in *World Development*.

inequality between the origin and the destination (Borjas, 1987, 1991; Roy, 1951). Higher inequality at the destination signalizes that the more educated segment of population receives higher wages at the destination and drives migration of individuals drawn from the top end of the skill distribution at the origin, and *vice versa*. The Roy-Borjas model, combined with empirical evidence of extreme poverty and inequality in rural India and findings that climate change further aggravates both (Šedová *et al.*, 2019), enables us to hypothesize that climate migrants are likely to be i) drawn from the lower end of the skill distribution and ii) primarily from agricultural households, as these are the most susceptible to income drops in response to adverse weather shocks.

For the econometric analyses, we draw on the dataset that has already been built for the analysis in chapter 1 and combines ERA5 reanalysis weather data with the IHDS household panel. We model weather shocks as total monthly positive and absolute total monthly negative temperature and precipitation anomalies accumulated over longer periods of time and conduct a series of first difference regression analyses applying linear probability and multinomial logit models. We show that, in contrast to other migrants, climate migrants are less educated and more likely to be from agricultural households, which is in line with our assumptions. Overall, climate change shapes mechanisms of self-selection into migration through its distributional impacts. We also find that the destination choices of climate migrants are determined by both, a households' ability to bear the upfront costs of moving that — in this context — is strongly determined by local weather and the economic opportunities at the destination. Finally, we show that climate change drives migration into cities and thus significantly accelerates urbanization in India.

Chapter 3: A Meta-Analysis of Climate Migration Literature[4] With the original econometric research from the previous chapters, we contribute new evidence of the contextual effects of weather and climate. In contrast, in the third chapter (chapter 3, Šedová *et al.* (2021)), we undertake a systematic summary of the econometric climate migration literature. We particularly draw on a meta-regression analysis (MRA), which provides a statistically rigorous methodology to systematically integrate conflicting evidence (Stanley and Doucouliagos, 2012). MRAs are an essential tool to maintain objective discussions of a particular topic and resulting policy implications. Given that the number of studies trying to establish a direct association between climatic events and migration increased over the past decades and delivered highly mixed findings, this effort is an important step forward, not only for the academic but also the broader policy discourse.

The overall aim of this MRA is to i) summarize direct links between adverse climatic events and human migration, ii) map patterns of climate migration, and iii) explain the variation in outcomes. We meta-analyze the most comprehensive sample thus

[4]Joint work with Lucia Čizmaziová and Athene Cook.

far of 3,625 estimates retrieved from 116 original econometric studies. Because of the heterogeneity in research designs and contexts typical for the empirical climate migration literature (Berlemann and Steinhardt, 2017), we classify the estimated effects by statistical significance, and direction and statistical significance to estimate probit and multinational probit models, respectively. We establish a common understanding of the circumstances in which climate migration emerges to make it more predictable. We show that slow-onset events — in particular temperature extremes and drying conditions — are more likely to increase migration than sudden-onset events. We further summarize the general climate migration patterns, showing that climate migration likely originates in rural areas and takes place internally, to cities. At the same time, our results emphasize that while migration may serve as an adaptation to climate change, particularly socio-economically vulnerable segments of the population might lack the means to afford it. We show that the likelihood of becoming trapped in affected areas is particularly high for women and in low-income countries, especially on the African continent. We draw attention to the lack of common ground in terms of methodology across econometric climate migration studies and quantify existing biases in the evidence that, among other things, stem from pitfalls typical for the climate impact literature (e.g., not addressing spatial correlation of climatic events and correlation among climatic events, over-controlling, or not applying causal inference techniques (Auffhammer *et al.*, 2013; Berlemann and Steinhardt, 2017; Dell *et al.*, 2014)). In addition, we find evidence of a general publication bias, as well as publication biases related to effects of specific climatic events, and the gender and discipline of lead authors.

This MRA also identifies avenues for future research of pressing importance. It narrows down topical (e.g., lack of evidence on urban out-migration) and geographical (e.g., lack of evidence from Europe or small islands in the Pacific Ocean) gaps, which might systematically influence climate migration debates. It further emphasizes the need to establish a unified best practice for future empirical climate migration studies. Such a framework would facilitate estimation of an effect size of climate change impacts on migration in a future meta-analytic study and improve the learning experience of expected future climate change impacts on migration.

Chapter 4: Improving the Evidence Base on Climate Migration: Methodological Insights from Two Meta-Analyses[5] The fourth chapter (chapter 4, Hoffmann *et al.* (2021)) addresses this gap and establishes a common ground on how such an interdisciplinary topic as climate migration should ideally be analyzed empirically. Since the authors of climate migration literature come from various disciplines, they pursue very divergent research strategies in their original studies. We present a detailed analysis of how these different concepts and methods shape our understanding of climate migration and identify best practices to avoid typical methodological pitfalls. Our study is based on

[5]Joint work with Dr. Roman Hoffmann and Dr. Kira Vinke, published in *Global Environmental Change*.

insights from two recently completed meta-analyses of climate migration — i.e., Šedová *et al.* (2021) (chapter 3 of this dissertation) and Hoffmann *et al.* (2020) — together with an in-depth review of state-of-the-art data sources and relevant approaches from across disciplines of, among others, climate sciences, econometrics, migration studies and economics. We identify five challenges which relate to the i) measurement of migration and of ii) climatic events, iii) integration and aggregation of data, iv) identification of causal relationships, and v) exploration of contextual factors and mechanisms. Advances in research and modeling relevant for these critical areas are then presented together with best cases to guide future scientific efforts to study the climate-migration nexus. A stronger integration of the different perspectives and approaches across different areas could prove very beneficial for the development of the climate migration research field in the future.

Overall, this review is meant to help researchers from across disciplines to better recognize and understand inter-dependencies and complexities in the modeling of climate migration and provide them with an overview of the best available tools that can enable them to address some of the pertinent challenges. Simultaneously, we aim to inform policy makers about the tremendous complexity of assessing the link between climatic effects and human migration and emphasize the need for careful interpretation of evidence that can be shaped by contextual influences and methodological choices.

Chapter 5: Global Food Prices, Local Weather and Migration in Sub-Saharan Africa[6] In the fifth chapter of my dissertation (chapter 5, Ludolph and Šedová (2021)), we complement the literature by another original climate migration study. We analyze implications of climatic shocks transmitted via international commodity prices. This study is rooted in the topical gaps identified in chapter 3, which suggest that the climate migration literature thus far has primarily focused on implications of geographically localized climatic events. Yet, the increased number of local climatic shocks have also led to large fluctuations of international commodity prices through their effect on the aggregate output. Due to the increasing global interconnectivity of economic and ecological systems, these shocks then reverberate through international markets (Bren d'Amour *et al.*, 2016; Puma *et al.*, 2015) and can affect real incomes of households in distant countries and thus their ability to migrate (Cattaneo and Peri, 2016; Clemens, 2014).

This paper has two main objectives. First, it aims to provide a full picture of climatic effects on human migration in Sub-Saharan Africa during the decade of the 2007/08 global food price crisis, by i) studying the implications of exogenous global food price changes on the probability of households sending one of their members as a labor migrant, and ii) complementing the analysis by comparing the effects of global prices to those of local weather conditions. Second, it aims to shed light on the heterogeneous

[6]Joint work with Lars Ludolph.

effects of these climate-related factors on the migration decision along the household wealth distribution, arguing that both global crop prices and the quantity of agricultural produce importantly determine household incomes. We hypothesize that income shocks have an *a priori* ambiguous impact on migration as the aggregate effect is determined by household wealth through an interplay of two opposing forces: the ability to bear the up-front costs of migration on the one hand, and the opportunity costs of migration that increase with rising income levels on the other (Bazzi, 2017; Cattaneo and Peri, 2016).

We find that, similar to the effect of positive local weather shocks, the effect of locally-relevant global crop price changes on household out-migration depends on the initial household wealth. Higher international producer prices relax the budget constraint of poor agricultural households and facilitate migration. The effect on richer households is the opposite. The order of magnitude of a standardized price effect is approximately one third of the standardized effect of a local weather shock. We show that migration patterns in response to price changes differ from the ones induced by local weather events. Unlike positive local weather shocks, which mostly facilitate internal rural-urban migration, positive income shocks through rising producer prices only increase migration to neighboring African countries, likely due to the simultaneous decrease in real income in nearby urban areas. Finally, we analyze whether conflict induced by higher producer prices could have been an additional mechanism at play, explaining the association of global crop prices and migration. Yet, we find that while crop prices are indeed associated with conflict, conflict does not play a role for the household decision to send a member as a labor migrant.

All of the essays presented above constitute my dissertation and are further detailed in the chapters that follow. The dissertation then concludes by synthesizing the findings, and outlining resulting policy implications and avenues for future research on climate migration.

Chapter 1

Distributional Impacts of Weather and Climate in Rural India[1]

Barbora Šedová
Matthias Kalkuhl
Robert Mendelsohn

[1]The authors are grateful for helpful suggestions and constructive comments from Leonie Wenz. We also benefited from the suggestions by the participants in the Venice Summer Institute 2019 (Poverty, Inequality and their Associations with Disasters and Climate Change), EAERE-FEEM-VIU European Summer School 2019 and the Conference of the European Association of Environmental and Resource Economists 2019.

Chapter Abstract

Climate-related costs and benefits may not be evenly distributed across the population. We study distributional implications of seasonal weather and climate on within-country inequality in rural India. Utilizing a first difference approach, we find that the poor are more sensitive to weather variations than the non-poor. The poor respond more strongly to (seasonal) temperature changes: negatively in the (warm) spring season, more positively in the (cold) rabi season. Less precipitation is harmful to the poor in the monsoon kharif season and beneficial in the winter and spring seasons. We show that adverse weather aggravates inequality by reducing consumption of the poor farming households. Future global warming predicted under RCP8.5 is likely to exacerbate these effects, reducing consumption of poor farming households by one third until the year 2100. We also find inequality in consumption across seasons with higher consumption during the harvest and lower consumption during the sowing seasons.

1.1 Introduction

Inequality has far-reaching detrimental impacts on economic prosperity (Easterly, 2007) and its reduction has become one of the defining challenges of the 21st century (UNDP, 2018b). Economists have long understood that climate change, manifested through changing average climatic conditions and extreme weather events, threatens to further exacerbate inequality (Hsiang *et al.*, 2019). For instance, climate change-related weather shocks already aggravate the North-South economic divide (Burke *et al.*, 2015b; Diffenbaugh and Burke, 2019; Kalkuhl and Wenz, 2020; Mendelsohn *et al.*, 2006) and are projected to affect the poorest countries the hardest (King and Harrington, 2018; Schleussner *et al.*, 2016). While the inequality implications of climate change across countries have been studied extensively, the within-country implications have received only little attention (Hallegatte and Rozenberg, 2017; Islam and Winkel, 2017; Karim and Noy, 2016). Because the poor represent a small fraction of national income, climate-related effects on the poor may have a negligible impact on the income at the national level. Therefore, studies providing aggregate perspectives may be missing an important part of the story (Hallegatte and Rozenberg, 2017). A better understanding of the inequality implications of climate-related risks within countries is essential to minimize losses and enhance well-being in a changing climate. We contribute with this study and analyze the distributional implications of weather and climate in rural India. We address the following research questions: *How do adverse weather events affect different wealth groups in rural India? What are the sources of households' vulnerabilities to adverse weather events?* Further, we examine the effects of temperature and precipitation changes on poor and non-poor households under RCP8.5.

The empirical literature on inequality implications of climate-related events is just emerging and provides mixed insights. While some studies find that climate-related risks increase inequality within countries (Bui *et al.*, 2014; Narloch and Bangalore, 2018; Warr and Aung, 2019), there are studies that find a negative association (Abdullah *et al.*, 2016; Keerthiratne and Tol, 2018) or no significant effect (Feng *et al.*). Moreover, the evidence on India emerges only indirectly as a by-product of studies with a different focus and suggests that disadvantaged groups might suffer disproportionately from adverse weather effects (Burgess *et al.*, 2014; Carleton, 2017). With this research, we address this existing gap by explicitly studying the distributional implications of climate-related events in rural India.

Almost 70% of the Indian population lives in rural areas. Despite a decrease in rural employment in agriculture to 62% in 2015-16 (ILO, 2016), the rural population is still strongly reliant on agricultural production (Krishna Kumar *et al.*, 2004). Since formal insurance to buffer against adverse weather events is rare (Munshi and Rosenzweig, 2016) and agricultural production is still heavily dependent on weather, Indian agriculture is particularly vulnerable to yield damage under adverse weather shocks (Auffhammer and Carleton, 2018; Carleton, 2017; Fishman, 2016). Already, climate change has affected the monsoon patterns in India in two important ways; the rainfall in the monsoon season has decreased (Auffhammer *et al.*, 2012; Dash *et al.*, 2007; Ramanathan *et al.*, 2005) and the distribution of the rainfall has become more extreme (Goswami *et al.*, 2006). Moreover, surface temperature increases have accelerated over time (Padma Kumari *et al.*, 2007). Since the rural poor have generally less access to credit, adaptation technologies and/or inhabit locations that have less favorable climatic conditions (Hsiang *et al.*, 2019), we hypothesize that they are particularly vulnerable to adverse weather events. Therefore, we expect climate change to aggravate inequality in rural India in the future.

In this study, we draw on the India Human Development Survey (IHDS) collected in 2004-2005 and in 2011-2012, ERA5 reanalysis data and climate projections provided by the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP). We conduct a first difference panel data analysis. First, we analyze the distributional implications of changes in seasonal temperature and precipitation on households' consumption. Second, we interact the weather variables with a set of household-specific characteristics and historical climate to explore the source of households' vulnerabilities to weather variations. Third, we predict the distributional implications in rural India under a high global warming scenario (RCP8.5).

Our results suggest that the poor are more sensitive to weather variations than the non-poor. They respond more strongly to (seasonal) temperature changes: negatively in the warm spring season, more positively in the cold rabi season. Less precipitation is harmful to the poor in the monsoon kharif season and beneficial in the winter and spring seasons. The effects are largely, but not solely channeled via agriculture. We show that adverse weather aggravates inequality, particularly by reducing consumption of the poor farming households. Climate change predicted under RCP8.5 scenario is likely to exacerbate these effects. We also find inequality in consumption across seasons with higher consumption during the harvest and lower consumption during the sowing seasons. Food consumption is more protected from shocks than non-food consumption. Economic factors (bank account ownership, land ownership or access to adaptation technology) and historical climate explain the heterogeneity in weather responses. Households that are able to smooth their consumption (e.g., by having access to financial institutions, wealth) or can afford avoidance technology face lower marginal damages from adverse weather events. Households that live in less favorable climates (e.g., hotter climates), on the other hand, face higher marginal damages. Therefore, policies that improve access to financial institutions and adaptation technologies would reduce the consumption losses under adverse weather events, faced particularly by the poor farming households.

The next section presents the theoretical framework and methodological approaches. In section 1.3, we provide an overview of the data and constructed variables. Findings are presented in sections 1.4 and 1.5 and projections in section 1.6. The last section provides concluding remarks.

1.2 Theoretical and methodological approaches

1.2.1 Theoretical framework

We apply the framework presented by Hsiang *et al.* (2019) for studying the distributional implications of environmental goods. According to this framework, an environmental externality (i.e., damage) is a social cost that can be expressed as a function of two factors: the level of *exposure* to environmental conditions and the *socio-economic attributes* that may affect the implications of exposure for economic well-being. Formally, this function is captured by the following equation:

$$D = f(e, x) \tag{1.1}$$

Here, D is environmental damage, e is level of exposure and x captures socio-economic attributes. Exposure refers to the state of the environment at a given time in a given space, such as air pollution, deforestation, or temperature. Socio-economic variables interact with exposure. They are the potential sources of vulnerability, whereby vulnerability is here defined as the rate at which exposure to environmental conditions generates harm given some initial conditions. This framework assumes that, conditional on the same levels of exposure and socio-economic attributes, the damage function is constant across individuals. A change in the environmental exposure might have important distributional implications for two reasons. First, if the change in environmental exposure differs across individuals, the change in environmental damages is likely to differ as well, regardless of the initial level of exposure or the structure of the damage function. Second, even if the change in exposure is relatively uniform across individuals, the different vulnerability of each individual may lead to distributional consequences (Hsiang *et al.*, 2019).

As this study focuses on the distributional implications of weather and climate, we further focus on the environmental damages resulting from change in temperature and precipitation. Hsiang *et al.* (2019) argue that the two main origins of vulnerabilities to climate-related events are: i) economic (e.g., less access to credit or technology) and ii) a nonlinear damage function (i.e., poorer people generally inhabit locations whose baseline climates are less favorable, which may correspond with the steeper portions of damage functions). In this study, we build on the insights from Hsiang *et al.* (2019) to understand whether poor and non-poor households in rural India react differently to climate-related events, and if so why. We specifically explore a model where the historical climate and the socio-economic variables interact with exposure, i.e., temperature and precipitation. It is not clear whether the exposure of poor and rich to future climate change is comparable. However, if the poor are more sensitive to temperature and precipitation changes than the rich, there can still be distributional consequences.

1.2.2 Methodological approaches

We apply a first difference approach (Griliches and Hausman, 1986; Hahn *et al.*, 2007) to study the distributional implications of changes in seasonal weather and to analyze leading causes of the heterogeneity in weather vulnerability across households. Since taking first differences leads to the dropping out of household-specific (h), time-invariant fixed-effects (λ_h), this approach addresses the problem of omitted variables with panel data. Thus, it enables us to identify a causal relationship between seasonal temperature (T) and precipitation (P) at the district-level (d), and a variable approximating households' consumption (C).

To explore the heterogeneity in responses to changing weather, we draw on historical climate (i.e., district-specific seasonal historical average temperature $\bar{T}$ and precipitation $\bar{P}$) and household characteristics (X) and interact them with seasonal temperature and precipitation changes. We use the initial levels of household characteristics from IHDS-I, because they are exogenous to the weather change that will follow. Additionally, we employ a constant β_0 controlling for an unobserved trend common to the whole rural India, 12 month dummies summarized as M_h capturing whether households were interviewed in a given month in one of the two IHDS rounds and two year dummies capturing the interview years in one of the rounds summarized by Y_{h1} and Y_{h2}. The standard errors are clustered at the district level, given that there is some spatial correlation in our treatment.

We estimate two equations. First, to understand the distributional implications, we interact the weather changes with a binary variable Z (where $Z \in X$) indicating whether households live below the poverty line and estimate the following equation:

$$\Delta C_{hd} = \beta_0 + \beta_1 \Delta T_d + \beta_2 \Delta T_d Z_{hd1} + \beta_3 \Delta P_d + \beta_4 \Delta P_d Z_{hd1} + \beta_5 M_{hd} + \beta_6 Y_{hd1} + \beta_7 Y_{hd2} + \Delta\epsilon_{hd} \tag{1.2}$$

Second, we interact the weather variables with all household-specific characteristics as well as with historical climate and estimate the following equation:

$$\begin{aligned}\Delta C_{hd} = \beta_0 + \beta_1 \Delta T_d + \beta_2 \Delta T_d X_{hd1} + \beta_3 \Delta T_d \bar{T}_d + \beta_4 \Delta P_d + \beta_5 \Delta P_d X_{hd1} + \beta_6 \Delta P_d \bar{P}_d + \\ \beta_7 M_{hd} + \beta_8 Y_{hd1} + \beta_9 Y_{hd2} + \Delta\epsilon_{hd}\end{aligned} \tag{1.3}$$

Equation 1.3 enables us to shed more light on the leading causes of the heterogeneity in households' vulnerabilities to changes in seasonal weather.

1.3 Data

To build our sample, we combine household panel data from the India Human Development Survey (IHDS) produced by the University of Maryland and the National Council of Applied Economic Research, New Delhi (Desai *et al.*, 2005, 2015) with ERA5 reanalysis data produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) (C3S, 2017)[2] and climate projections provided by the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) from Potsdam Institute for Climate Impact Research and the International Institute for Applied Systems Analysis (Warszawski *et al.*, 2013).

1.3.1 Household data

IHDS has collected nationally representative data from 41,554 households in 1,503 villages and 971 urban neighborhoods across India in two rounds; 2004-2005 (IHDS-I) and 2011-2012 (IHDS-II) (Desai *et al.*, 2005, 2015). IHDS has much lower attrition rate in rural (approximately 9%) than in urban India (approximately 26%). Since our analysis only considers rural India, the attrition problem is minimized and according to the standards of Alderman *et al.* (2001) considered relatively low. Our final sample contains approximately 25,500 rural households in 260 districts that were interviewed in both rounds.[3] The sample consists of approximately 15,000 farming and approximately 10,500 non-farming households. We categorize households as farming households, if they are involved in crop production on land that they either own or rent, using information from IHDS-I.

Using the information on households' consumption, we construct three main dependent variables that aim to approximate households' economic well-being: i) change in logarithms of a household's total monthly consumption expenditures per adult equivalent household member in Indian rupees between the two IHDS rounds (Δ*Consumption*), ii) change in logarithms of a household's total monthly food consumption expenditures per adult equivalent household member in Indian rupees between the two IHDS rounds (Δ*Food consumption*), and iii) change in logarithms of a household's total monthly non-food consumption expenditures per adult equivalent household member in Indian rupees between the two IHDS rounds (Δ*Non-food consumption*). In both rounds, IHDS asks households a set of questions to estimate their total consumption expenditures. Questions about consumption of frequently purchased items (mostly food) apply a

[2]This publication Contains modified Copernicus Climate Change Service Information [2019]. Neither the European Commission nor ECMWF is responsible for any use that may be made of the Copernicus Information or Data it contains.

[3]Observations with missing values relevant for the analysis were dropped from the sample. Observations, where rural/urban categorization changes between the two IHDS rounds were dropped, likewise.

monthly framework (i.e., *how much of these items have been consumed in the past 30 days?*) and questions on the remaining items (e.g., medical items, transportation etc.) apply a yearly framework (i.e., *how much did you spend in the last 365 days on ...?*). Based on this information, we create a measure of monthly consumption per adult equivalent household member for both IHDS rounds. We convert the values from IHDS-I to 2012 price levels to make the values in both rounds comparable. To produce a measure comparable across households and account for households' economies of scale, we follow Keerthiratne and Tol (2018) and utilize the modified equivalence scale by the Organisation for Economic Co-operation and Development (OECD). This scale assigns a value of one to the household head, of 0.5 to each additional adult household member and of 0.3 to each child. This scale accounts for the size and the age of the household members. However, its drawback is that it does not take into account other characteristics that might affect households' needs, such as the number of disabled or sick household members. For the robustness analysis, we utilize a change in logarithms of a households' number of valuable assets per adult equivalent households member ($\Delta Assets$) between the two IHDS rounds. In contrast to consumption expenditures, assets reflect rather the long-term economic level.

To analyze the distributional implications (see section 1.2), we employ a binary variable *Poor* from IHDS-I that captures whether a household is below the poverty line.[4] We interact this variable with the change in weather between the IHDS rounds. This enables us to examine heterogeneous implications of weather for consumption by wealth groups. We assume that values from IHDS-I are exogenous to the changes in consumption and changes in weather between the two IHDS rounds. Even though we are aware that the exogeneity assumption might not perfectly hold, this approach minimizes reversed causality and over-controlling problems (Angrist and Pischke, 2009) and allows for examination of distributional effects.

To study households' sources of vulnerability to weather-related damages, we utilize a set of variables from IHDS-I capturing households' socio-economic status (e.g., access to credit or technology), as suggested by Hsiang *et al.* (2019) (see section 1.2.1). Again, we assume that the values from IHDS-I are exogenous to the changes in the consumption and weather between the two IHDS rounds. To capture households' access to credit, we employ a binary variable *Bank account* that takes on a value of one if a household owns a bank account, and zero otherwise. Further, we employ a binary variable *Land* that takes on a value of one if a household owns land and zero otherwise. We perceive land ownership as a form of economic security/insurance. To capture households' access to adaptive technologies. We employ a binary variable *Air cooler* that takes on a value of one if a household owns an air cooler, we also employ a binary variable *Irrigation* that takes on a value of one if a household has access to irrigation of any type.

[4]The poverty line is a nation-wide set poverty line that is adjusted for rural/urban and state-specific purchasing power.

Lastly, we employ 12 monthly dummy variables indicating whether a household was interviewed in a specific month in one of the two IHDS rounds. We also employ two year dummy variables indicating i) whether a household was interviewed in 2004 (1) or 2005 (0) during IHDS-I and ii) whether a household was interviewed in 2011 (1) or 2012 (0) during IHDS-II.

The summary statistics presented in Table 1.1 indicate that the overall monthly consumption of an adult equivalent household member in rural India increased by 26%, food consumption decreased by 1%, non-food consumption increased by 48% and number of assets per adult equivalent household member increased by almost 30%. Moreover, in IHDS-I approximately 23% of rural Indian households live below the poverty line, 64% of rural households own land, 25% have a bank account, 7% own an air cooler and 34% have access to irrigation.

Additionally, in Appendix A.1, Table A.1, we present a correlation matrix of the explanatory variables from IHDS-I used in our regression models. The evidence suggests that the variables are not strongly correlated. The highest correlation coefficient with magnitude of almost 0.5 is between the variables land ownership and access to irrigation. Hence, we believe that multicollinearity is not a problem in our analysis.

Table 1.1: *Summary statistics: Household-specific variables (IHDS data)*

Variable	Mean	Std. Dev.	Min.	Max.	Units
Dependent variables					
ΔConsumption	0.262	0.643	-3.191	4.613	change in log of monthly cons.
ΔFood consumption	-0.013	0.601	-3.719	3.553	change in log of monthly food cons.
ΔNon-food consumption	0.474	1.076	-8.553	8.122	change in log of monthly non-food cons.
ΔAssets	0.295	0.448	-2.079	2.773	change in log of assets owned
Control variables					
Poor	0.228	0.419	0	1	binary: hh. is below poverty line (1)
Land	0.635	0.481	0	1	binary: hh. owns land (1)
Bank account	0.246	0.431	0	1	binary: hh. has bank account (1)
Air cooler	0.074	0.262	0	1	binary: hh. has air cooler (1)
Irrigation	0.336	0.472	0	1	binary: hh. access to irrigation (1)
N					25482

Dependent variables use information from both IHDS rounds. Consumption and assets are expressed as "per adult equivalent household member" using the OECD equivalence scale. Control variables use information from IHDS-I.

1.3.2 Weather data

ERA5 is the fifth generation of ECMWF atmospheric reanalyses of the global climate. It is a high-quality reanalysis dataset, which relies on information from weather stations, satellites, and sondes. ERA5 provides data at a geographical resolution of 31km and has been regridded to a 0.25×0.25 degrees latitude-longitude grid. Currently, the weather data is available from January 1979 onward, with a temporal resolution of up to one hour (Copernicus Climate Change Service, 2017). Reanalysis data solves for endogeneity problem resulting from the weather stations placement, variation in the quality of data collection, and variation in the quantity of collected data and produces a consistent best estimate of atmospheric parameters over time and space (Auffhammer *et al.*, 2013; Colmer, 2018; Donaldson and Storeygard, 2016). This is of particular importantce in India, where the spatial and temporal coverage of weather stations has deteriorated over time (Colmer, 2018). We draw on monthly temperature averages and precipitation totals and aggregate them at the district level. Districts are the finest geographical level at which we are able to identify IHDS households.

In order to understand climate-related impacts it is important to distinguish between seasons. Coefficients between seasons might be significantly different and the annual temperature and precipitation might not capture important effects that happen over a year (Massetti *et al.*, 2016; Sanghi and Mendelsohn, 2008). Hence, in our analysis we draw on levels of temperature and precipitation and distinguish between four different seasons: winter (January-February), spring (March-May), kharif (June-September) and rabi (October-December) (Sanghi and Mendelsohn, 2008). Kharif and rabi are the two major cropping seasons in India. Rainfall at the end of the kharif season provides moisture to the soil and in this way determines irrigation for the rabi crop. Hence, kharif monsoon is essential for both, kharif and rabi yields (Auffhammer and Carleton, 2018; Carleton, 2017; Guiteras, 2009). Although the timing of planting varies by a few weeks within India starting in the south and going north, we define the planting seasons as fixed. This is a standard practice in the economic panel literature (Auffhammer and Carleton, 2018; Schlenker and Roberts, 2009).

We generate variables capturing the change in the district-specific winter, spring, kharif and rabi averages of monthly mean temperature and total monthly precipitation between the two IHDS rounds. To do this, we consider households' interview months and years.[5] For both IHDS rounds we construct variables capturing the weather of the four seasons preceding the interview. For a household interviewed in a month during a specific season, we consider conditions of this season from the preceding year as these are more likely to have determined households' consumption over the past 365 days.[6] For demonstration, if during IHDS-I a household was interviewed in March 2004, we generate variables capturing winter conditions in 2004 and conditions of the other seasons in 2003. Then we do a similar exercise for IHDS-II and calculate the changes in seasonal temperature and precipitation between the two IHDS rounds. These changes serve as the main source of identification, as described in section 1.2.2. Because temperature and precipitation are correlated and they both have an effect on the outcome variables, we include them both in the regressions (Auffhammer *et al.*, 2013). Table 1.2

[5]During IHDS-I households were interviewed either in 2004 or 2005 and in IHDS-II either in 2011 or 2012 in one of the 12 months.

[6]As mentioned in section 1.3.1, IHDS collected data on consumption using information from the last 30 days and from the last 365 days.

presents summary statistics of the changes in seasonal weather used in this study. It shows that between the two IHDS rounds, Indian households were exposed to lower winter, spring and kharif and higher rabi temperatures. Moreover, winter, spring and rabi precipitation decreased and kharif precipitation increased between the two IHDS rounds.

Table 1.2: *Summary statistics: Climate-related variables (ERA5 data)*

Variable	Mean	Std. Dev.	Min.	Max.	Units
ΔTemp. winter	-0.598	0.808	-2.498	1.808	°C
ΔTemp. spring	-0.748	0.885	-2.81	1.23	°C
ΔTemp. kharif	-0.166	0.499	-1.548	0.994	°C
ΔTemp. rabi	1.146	1.714	-0.542	6.863	°C
ΔPrecip. winter	-0.063	0.197	-1.014	0.701	100mm
ΔPrecip. spring	-0.065	0.263	-1.617	0.723	100mm
ΔPrecip. kharif	0.635	0.578	-1.106	3.294	100mm
ΔPrecip. rabi	-0.086	0.272	-1.576	0.784	100mm
N			25482		

All variables are generated using ERA5 reanalysis data. Changes in seasonal weather capture changes in winter (January-February), spring (March-May), kharif (June-September) and rabi (October-December) seasons that households were exposed to preceding both of their IHDS interviews.

Additionally, we create historical district-specific averages of winter, spring, kharif and rabi temperature and precipitation between 1979 and the month/year of a household's IHDS-I interview. These variables capture district-specific climate (as opposed to the variables capturing weather, discussed in the previous paragraph) that households have been exposed to until the time of their first IHDS interview. By interacting the weather variables with the historical district-specific averages, we distinguish the effects of temperature and precipitation changes in warmer/cooler and in drier/wetter climates, respectively (see section 1.2.2). These interactions enable us to test whether the response to damages is non-linear and depends on long-term climatic conditions. Weather is expected to have a different effect across different climates (see section 1.2.1). Figure 1.1 displays the historical, season-specific means for temperature and precipitation.

In Appendix A.1, Table A.2, we present a correlation matrix of the weather and climate variables used in our regression models. The evidence suggests that changes in the seasonal weather are not strongly correlated. The highest correlation coefficient with magnitude of 0.6 is between change in spring temperature and precipitation. The correlation among historical conditions, especially among variables capturing historical temperatures, is however much larger. We estimated equation 1.3 also without including the historical conditions and the results were approximately the same. Hence, we believe that controlling for them does not affect the efficiency of other estimators and provides a good orientation for understanding the differences in weather effects across different climates.

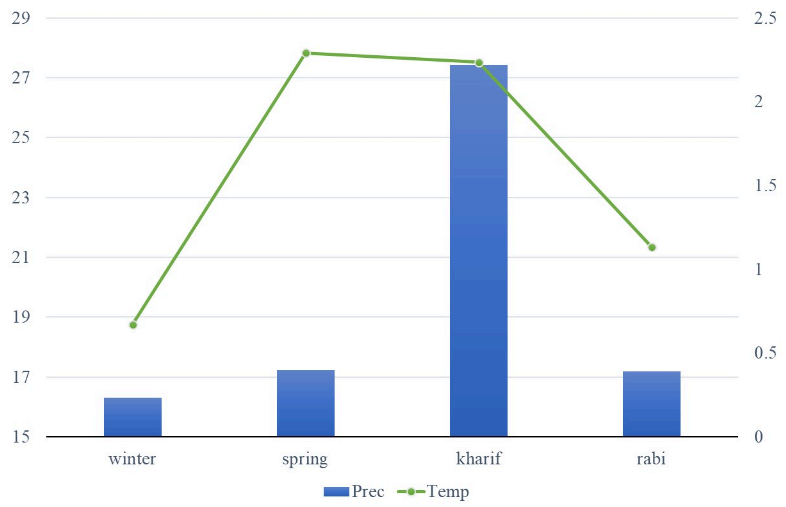


Figure 1.1: *Historical climate by season (y-axis, left: °C; y-axis, right: 100mm)*

1.3.3 Climate projections data

We derive temperature and precipitation projections from ISIMIP (Warszawski *et al.*, 2013). ISIMIP provides climate data until 2099 that are in line with five major climate models (Warszawski *et al.*, 2013). We utilize data with 0.5 degree resolution that originate from the Princeton Earth System Model of the Geophysical Fluid Dynamics Laboratory (GDFL-ESM2M, (Dunne *et al.*, 2012)) and include a bias-correction technique (Hempel *et al.*, 2013) ensuring long-term statistical agreement of the projections with observational data from the WATCH database (Weedon *et al.*, 2011). We draw on projections corresponding to Representative Concentration Pathway 8.5 (RCP8.5) scenario. RCP8.5 is one of the four greenhouse gas concentration scenarios adopted by the Intergovernmental Panel on Climate Change for the fifth Assessment Report. It is a "business as usual" case, based on forecasts corresponding to low income, high population and high energy demand that results from only modest improvements in energy intensity. RCP8.5 thus represents the pathway with the highest greenhouse gas emissions (Riahi *et al.*, 2011). We generate district-specific changes in long-term seasonal (winter, spring, kharif and rabi) temperature and precipitation, comparing the averages for time spans 2006–2030 and 2070–2099. Using long-run averages is appropriate to capture climate change as climate is usually defined as a pattern of weather in a particular area taken over a longer term (usually at least 30 years) (Auffhammer *et al.*, 2013).

Table 1.3 presents the corresponding summary statistics. Under the RCP8.5, average temperature is predicted to increase by 1.5 °C in winter, by 2 °C in spring, by 1.8 °C in kharif and by 1.7 °C in rabi season between 2006–2030 and 2070–2099. Moreover, average spring and winter precipitation is predicted to decrease by approximately 3mm and rabi precipitation by 5mm. Kharif precipitation is not predicted to change substantially on average.

Table 1.3: *Summary statistics: Climate change between 2006–2030 and 2070–2099 projected under RCP8.5 (ISIMIP data)*

Variable	Mean	Std. Dev.	Min.	Max.	Units
Δ Temperature winter	1.471	0.435	0.332	2.387	°C
Δ Temperature spring	2.029	0.341	0.997	2.848	°C
Δ Temperature kharif	1.777	0.43	1.042	2.87	°C
Δ Temperature rabi	1.682	0.429	0.92	2.642	°C
Δ Precipitation winter	-0.031	0.04	-0.164	0.067	100mm
Δ Precipitation spring	-0.034	0.086	-0.263	0.365	100mm
Δ Precipitation kharif	0.004	0.399	-0.635	1.727	100mm
Δ Precipitation rabi	-0.048	0.146	-0.456	0.786	100mm
N			25482		

The sample size for the predicted temperature changes is lower (only 25009 observations), as there are more missing values. The changes in temperature and precipitation capture differences in the long-run seasonal averages for the time spans 2006-2030 and 2070-2099 predicted under RCP8.5. The data originates from the GFDL-ESM2M.

1.4 Results: Distributional effects

Here, we present the evidence of the distributional implications of changes in seasonal weather. Section 1.4.1 displays the main outcomes, i.e., implications for households' overall consumption. To disentangle the effects, in section 1.4.2 we show implications for households' food and non-food consumption. Further, in section 1.4.3 we discuss seasonal effects and in section 1.4.4 we conduct a series of robustness analyses. In every table are three models. The sample in model 1 consists of all, in model 2 of farming and in model 3 of non-farming households in rural India. The first two columns of every model display marginal effects of seasonal weather separately for poor and non-poor households and the third column presents the same results differently, by showing the difference in their responses. The bottom part of the tables indicate the aggregate (annual) effect of temperature and precipitation.

1.4.1 Main outcomes: Overall consumption

Results on implications of changes in seasonal weather for the overall consumption of the poor and non-poor are presented in Table 1.4. Warmer spring temperatures increase overall consumption of non-poor and decrease consumption of poor households in all three regression models. According to model 1, an increase in spring temperature by 1 °C increases consumption of the non-poor by 6% and reduces consumption of the poor by almost 22%. The positive response coefficients of the non-poor are larger for non-farming (6%/°C) than farming (5%/°C) households. In contrast, the magnitudes of the negative response coefficients are larger for the poor farming (26%/°C) than the non-farming households (19%/°C), suggesting that the effects are strongly, but not solely, channeled by agriculture. This outcome is in line with Sanghi and Mendelsohn (2008), who show that spring temperatures in India are particularly harmful for farmers. Only the poor non-farming households react significantly to kharif temperatures. A 1 °C increase in temperature raises their overall consumption by almost 12%. Rabi temperatures are positively associated with overall consumption of the poor households. The magnitude of the effect is only slightly larger for the farming (8%/°C) than the non-farming (7%/°C) households. This is in line with Sanghi and Mendelsohn (2008), who find that higher fall temperatures are beneficial to the Indian farmers as they allow for a longer growing season and help ripen the crops.

We show that for all rural poor, overall consumption is negatively and significantly associated with winter precipitation. With -40%/100mm, the magnitude of the effect is larger for non-farming than farming (-29%/100mm) households. Further, we find a negative association between spring precipitation and overall consumption of poor and no significant effect for the non-poor. With 88%/100mm, the magnitude of the effect is almost twice as large for the poor farming than non-farming households, suggesting that it is strongly channeled via agriculture. This outcome is in line with Sanghi and Mendelsohn (2008), who show that wetter springs are particularly harmful for Indian farmers. Thus, the trend of decreasing spring precipitation (see sections 1.3.2 and 1.3.3) might be beneficial for the overall consumption of the poor. Kharif precipitation is significantly and negatively associated with overall consumption of the non-poor and positively associated with overall consumption of the poor in all three models. Even though the coefficients are much smaller (e.g., in model 1, the coefficient is -8%/100mm for non-poor and 15%/100mm for poor) than coefficients of winter and spring precipitation, the overall magnitudes of the effects might be larger since the summary statistics in section 1.3.2 show that the changes in kharif precipitation over time are much larger than in other seasons. The direction of the effect of the poor is in line with the broader literature that indicates that lower rainfall during the monsoon season decreases yields in India (Auffhammer *et al.*, 2012; Kumar *et al.*, 2004; Selvaraju, 2003; Webster *et al.*, 1998). Rabi precipitation is positively associated with overall consumption of the non-poor in all three models and the magnitude of the effect is larger for the farming households. This is in line with Sanghi and Mendelsohn (2008), who write that wetter falls are beneficial as they enable cropping to extend beyond just the post-monsoon period. Even though we do not find a significant response of the poor, model 2 shows that the effect on consumption of poor farmers is significantly different and lower from the one of non-poor farmers.

The bottom part of Table 1.4 presents the annual (seasonal aggregate) temperature and precipitation coefficients in India for the poor and non-poor. Overall, consumption of the non-poor is not significantly affected by annual temperature and precipitation changes. However, we find evidence that in response to an annual temperature increase, the consumption of the poor farming households changes significantly with a 15% decrease per 1 °C increase in temperature. This outcome indicates that temperature increases predicted under future climate change might exacerbate inequality in rural India. Moreover all poor households react significantly and negatively (e.g., in model 1, the effect is 77%/100mm) to changes in annual precipitation. The magnitude of the effect is the largest for farming households. The extent of the distributional implications will depend on the relative magnitudes of the climate-related seasonal changes in precipitation. For the overall distributional implications of future climate change, see section 1.6.

We also conduct the analysis at the district level, comparing consumption implications of weather changes between districts with higher and lower concentrations of the poor. The outcomes on the seasonal weather effects are in line with our main analysis and suggest that poorer districts are likely to suffer larger consumption losses from adverse weather events. This implies that adverse weather events might exacerbate inequality between the districts. Jayachandran (2006) provides a plausible explanation, suggesting that equilibrium effects are likely to amplify the impacts of productivity shocks on wages in poorer areas, where labor is more inelastic. Such equilibrium wage effects hurt the poor workers, however they act as an insurance for landowners.[7]

1.4.2 Food and non-food consumption

To better understand what type of consumption households adjust in response to changes in weather, we discuss the evidence on the implications for food and non-food consumption (see Appendix A.2, Tables A.3 and A.4, respectively). The positive response of the non-poor to spring temperatures in Table 1.4 is driven by an increase in both food and non-food consumption. All types of the poor reduce their food and non-food consumption if spring temperature increases. The outcomes on overall consumption are driven more strongly by reduction in non-food consumption. Further, warmer rabi months increase food consumption of all poor households and non-food consumption especially of the poor farming households. Hence, both effects drive the outcomes in Table 1.4. The negative effect of winter precipitation on the poor in Table 1.4 is driven by a decrease in non-food consumption. Further, we find a negative effect of spring precipitation on food and non-food consumption of the poor, with much larger magnitudes for non-food consumption, which drives the outcomes in Table 1.4. We show that too much kharif precipitation is bad for food and non-food consumption of the non-poor, whereby decrease in non-food consumption seems to drive the main outcomes more strongly. However, non-food consumption of the poor is positively associated with

[7] These regression results are available upon the request.

Table 1.4: *Effects of seasonal weather on households' consumption by wealth group (results from equation 1.3)*

	ΔConsumption								
	All (1)			*Farming* (2)			*Non-farming* (3)		
	Non-poor	*Poor*	*Diff.*	*Non-poor*	*Poor*	*Diff.*	*Non-poor*	*Poor*	*Diff.*
Temperature									
ΔTemp. winter	-0.024	0.018	0.042	-0.022	0.024	0.046	-0.021	0.008	0.029
	(0.018)	(0.031)	(0.033)	(0.020)	(0.032)	(0.034)	(0.021)	(0.037)	(0.039)
ΔTemp. spring	0.063***	-0.215***	-0.278***	0.045*	-0.256***	-0.301***	0.057*	-0.193***	-0.250***
	(0.024)	(0.038)	(0.038)	(0.026)	(0.042)	(0.042)	(0.030)	(0.045)	(0.044)
ΔTemp. kharif	-0.030	0.052	0.082	-0.036	0.002	0.038	-0.009	0.117*	0.126*
	(0.032)	(0.059)	(0.065)	(0.033)	(0.074)	(0.081)	(0.040)	(0.061)	(0.068)
ΔTemp. rabi	0.024	0.074***	0.050***	0.027	0.081***	0.054***	0.028	0.068**	0.040***
	(0.026)	(0.028)	(0.013)	(0.027)	(0.028)	(0.014)	(0.032)	(0.034)	(0.015)
Precipitation									
ΔPrecip. winter	-0.016	-0.321***	-0.305***	-0.090	-0.287**	-0.198	0.115	-0.401***	-0.516***
	(0.063)	(0.110)	(0.117)	(0.064)	(0.120)	(0.124)	(0.076)	(0.133)	(0.146)
ΔPrecip. spring	0.009	-0.634***	-0.643***	0.034	-0.884***	-0.918***	-0.026	-0.443***	-0.417***
	(0.056)	(0.108)	(0.126)	(0.063)	(0.155)	(0.179)	(0.061)	(0.099)	(0.107)
ΔPrecip. kharif	-0.080***	0.153***	0.234***	-0.073***	0.128***	0.201***	-0.091***	0.189***	0.279***
	(0.024)	(0.030)	(0.030)	(0.023)	(0.032)	(0.032)	(0.030)	(0.036)	(0.038)
ΔPrecip. rabi	0.175***	0.037	-0.138	0.212***	-0.056	-0.268*	0.155***	0.121	-0.034
	(0.048)	(0.107)	(0.123)	(0.046)	(0.134)	(0.139)	(0.055)	(0.096)	(0.108)
N		25482			15060			10422	
R^2		0.114			0.112			0.125	
ΔAnnual temperature	0.034	-0.070	-0.104	0.014	-0.150	-0.163	0.055	0.000	-0.055
	(0.041)	(0.064)	(0.060)	(0.042)	(0.069)	(0.066)	(0.050)	(0.069)	(0.067)
ΔAnnual precipitation	0.087	-0.765	-0.852	0.084	-1.099	-1.182	0.154	-0.534	-0.688
	(0.104)	(0.195)	(0.216)	(0.109)	(0.227)	(0.240)	(0.117)	(0.190)	(0.207)

All models are estimated using first-difference approach that eliminates the time invariant, direct effects. The sample in model 1 consists of all, in model 2 of farming and in model 3 of non-farming households in rural India. The dependent variable is constructed using data from IHDS-I and II. It captures the change in logarithms of consumption per adult equivalent household member between the two IHDS rounds. The binary variable Poor is derived from IHDS-I and takes on a value of one if a household lives below the poverty line and zero otherwise (Non-poor). All weather variables are constructed using ERA5 data and capture the change in households' exposure to seasonal temperature (in °C) and precipitation (in 100mm) between the two IHDS rounds. Four seasons are distinguished: winter (January-February), spring (March-May), kharif (June-September) and rabi (October-December). We also include a time trend and control for months and years of the interviews (see Appendix A.3, Table A.5). The first two columns of every model display the marginal effects of weather variables separately for poor and non-poor and the third column presents the same results differently, by showing the difference in their responses. The bottom part of the table presents the aggregate (annual) effect of temperature and precipitation. Standard errors clustered at the district-level are in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

kharif precipitation and drives the outcomes in the main analysis. Rabi precipitation is good for food and non-food consumption of the non-poor and food consumption of the poor non-farming households. We show that the negative effect of an increase in annual temperature on the overall consumption of the poor farmers is driven by a decrease in non-food consumption. The negative effect of an increase in annual precipitation on the overall consumption of the poor households is driven by a reduction in non-food consumption. Overall, our findings are in line with the literature that suggests that food consumption is more protected from shocks than non-food consumption (Duflo and Udry, 2004; Skoufias and Quisumbing, 2005; Skoufias *et al.*, 2011).

1.4.3 Seasonal effects

In Appendix A.3, we present the coefficients of the remaining controls from the main analysis, i.e., interview month and year dummies. The evidence in Table A.5 shows that farming households had higher overall consumption in 2004 compared to 2005. Non-farming households had lower overall consumption in 2004 compared to 2005 and in 2011 compared to 2012. Further, we observe seasonal fluctuations in overall consumption. The results suggest that all types of households have higher overall consumption in months April, June and September and farming households also in August. These months coincide with harvesting of the rabi and kharif crops, respectively. Moreover, farming households have lower consumption in October, which coincides with the start of rabi sowing season. These results therefore suggests that households cannot smooth consumption well over the year; they consume less in the lean season and more in the harvest season when they are less cash-constrained. This finding is in line with the literature on seasonal fluctuations in consumption in rural economies in the low- and middle-income countries (Brune *et al.*, 2011; Bryan *et al.*, 2014; Chaudhuri and Paxson, 2002; Dercon and Krishnan, 2000). In addition, non-farming households have also higher consumption in November and December. Further, Table A.6 suggests that all types of households had lower food consumption in 2011. We only find evidence of seasonal fluctuations in food consumption of non-farming households, with higher food consumption in April, June October and November. Table A.7 indicates that the increase in overall consumption during the harvest months as suggested by outcomes in Table A.5 is mainly driven by an increase in non-food consumption.

1.4.4 Sensitivity analyses

The outcomes of the sensitivity analyses are presented in Appendix A.4. In Table A.8 we use ($\Delta Assets$) as an alternative dependent variable and analyze the distributional effects of changes in seasonal weather. Overall, fewer coefficients are significant than in Table 1.4, indicating that households' longer-term wealth fluctuates less in response to weather variations than monthly consumption. We find further evidence of a positive effect of spring temperatures for all non-poor, a negative effect of winter precipitation for poor farmers, a negative effect of kharif precipitation for non-poor farmers and a positive effect of rabi precipitation for non-poor non-farmers as suggested by the main analysis. In Table A.9, we only interact the seasonal temperature changes with the Poor/Non-poor dummy to see how much the results change if precipitation variables are not included. We find further evidence of a negative effect of spring temperature, a positive effect of rabi temperature on all types of poor households and a positive effect of spring temperature on all non-poor as suggested by the main analysis. Lastly, in Table A.10 we include interactions between changes in temperature and precipitation into the main regressions. Almost all interactions are insignificant and the main results remain largely unchanged.

1.5 Results: Sources of vulnerability

Here, we present the evidence from estimating equation 1.3 on the underlying causes of households' vulnerabilities to weather changes. We run the regressions on the full sample of rural households (model 1), on farming households (model 2) and on non-farming households (model 3). We split the results into three parts: in section 1.5.1 we discuss whether response to damages is non-linear and depends on long-term climatic conditions; in section 1.5.2 we focus on the heterogeneity in households' socio-economic attributes; and in section 1.5.3 we discuss the implications for consumption inequality, when including these additional controls.

1.5.1 Non-linear damages

Here, we shed more light on whether the marginal effect of seasonal weather depends on the long-term climatic conditions (see table 1.5). We find a significantly negative effect of the interactions between changes in winter temperatures and the corresponding historical conditions in all three models. This means that a decline in winter temperature decreases consumption stronger in regions that are already cold - while consumption in warmer areas is less affected. The effect is larger for the non-farming than for the farming households suggesting that agriculture is not the primary channel of this effect. Further, the coefficient on the interaction of kharif temperature with the historical conditions is significantly negative in models 1 and 3. Thus, if the kharif temperatures increase in historically warmer regions consumption of non-farming households decreases. This evidence also suggests that the effects are not primarily channeled via agriculture.

We find a negative effect of the interaction between spring precipitation and the historical conditions in all three models. Hence, more spring precipitation in historically

Table 1.5: *Effects of seasonal weather on households' cons. by historical climate (results from equation 1.3)*

	ΔConsumption		
	All	*Farming*	*Non-farming*
	(1)	*(2)*	*(3)*
Temperature			
ΔTemp. winter x Temp. winter hist.	-0.013***	-0.009**	-0.019***
	(0.004)	(0.004)	(0.004)
ΔTemp. spring x Temp. spring hist.	0.003	0.001	0.012***
	(0.003)	(0.003)	(0.004)
ΔTemp. kharif x Temp. kharif hist.	-0.024**	-0.012	-0.045***
	(0.011)	(0.012)	(0.015)
ΔTemp. rabi x Temp. rabi hist.	0.004	0.002	0.012*
	(0.004)	(0.004)	(0.006)
Precipitation			
ΔPrecip. winter x Precip. winter hist.	0.036	-0.009	0.090
	(0.101)	(0.103)	(0.154)
ΔPrecip. spring x Precip. spring hist.	-0.172***	-0.134*	-0.225***
	(0.060)	(0.072)	(0.068)
ΔPrecip. kharif x Precip. kharif hist.	-0.004	-0.006	-0.001
	(0.011)	(0.011)	(0.012)
ΔPrecip. rabi x Precip. rabi hist.	0.155**	0.210**	0.047
	(0.073)	(0.096)	(0.077)
N	25482	15060	10422
R^2	0.124	0.122	0.140
Time trend	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes

This table presents results from equation 1.3. Coefficients of further controls are displayed in figures 1.2 and 1.3 as well as in Table A.12. All models are estimated using first-difference approach that eliminates the time invariant, direct effects (e.g., the direct effect of hist. temp. or precipitation). The sample in model 1 consists of all, in model 2 of farming and in model 3 of non-farming households in rural India. The dependent variable is constructed using data from IHDS-I and II. It captures the change in logarithms of consumption per adult equivalent household member between the two IHDS rounds. All weather and climate variables are constructed using ERA5 data and capture the interactions between change in households' exposure to seasonal weather between the two IHDS rounds and corresponding historical district-specific climate. Four seasons are distinguished: winter (January-February), spring (March-May), kharif (June-September) and rabi (October-December). We also include a time trend and control for months and years of the interviews. Standard errors clustered at the district-level are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

wetter climates is bad for consumption. The effect is stronger for the non-farming households suggesting that agriculture is not the main channel. A potential explanation could be an occurrence of floods. Lastly, we show that more precipitation during the rabi season is good in regions with historically more precipitation and the effect is mainly driven by agriculture.

In Table A.11, Appendix A.5, we show a formal t-test of differences in climates inhabited by poor and non-poor. We find that on average, the poor live in climates that are significantly warmer in all seasons and have more precipitation in kharif and less precipitation in the remaining seasons. Hence, as for historical temperature in particular, the poor seem to inhabit regions with more adverse conditions than the non-poor. This gives a part of explanation why the poor are more affected by weather, as it interacts with the climate.[8]

[8] We also conducted a correlation analysis between the binary variable Poor and the district-specific climates. The absolute values of all correlation coefficients are lower than 0.15, which signalizes that the distribution of rural poor is only partially conditioned by climate.

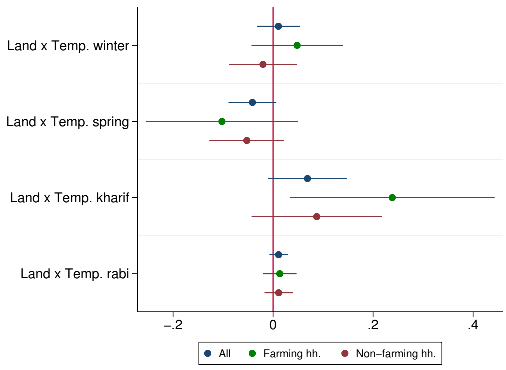
1.5.2 Socio-economic characteristics

In this section, we explore whether households' socio-economic characteristics further explain the heterogeneity in responses to weather changes. We present the coefficients of the interactions of changes in weather with access to credit in Figure 1.2 and with access to technology in Figure 1.3.

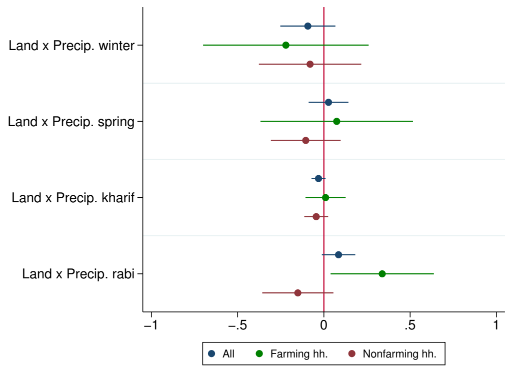
The estimated outcomes indicate that land ownership is particularly important in interacting with weather changes for farming households since the coefficients are only significant in model 2. Land-owning farming households respond much stronger to hotter temperatures in kharif and rainfall in rabi than non-land-owners. If the temperature in kharif season and precipitation in dry rabi season increase (which is a good thing), consumption of the land-owning farming households increases. Potential explanation is that land-owning farmers benefit from higher harvests/revenues as they sell a lot of their produce. Non-land owners who are farmers might also sell their harvest, but as they have no land, they probably work more in non-farming or in other farms where they benefit less from good weather conditions.

We find evidence that bank account ownership mitigates adverse effects of weather. The significantly positive interaction (model 2) with kharif temperature suggests that farming households with a bank account have higher consumption if summer temperature increases compared to households without a bank account. We also find a positive effect of the interaction term with winter precipitation for all and non-farming households. It shows that if winter precipitation increases (which is a bad thing as suggested in section 1.4.1) households that own a bank account have higher consumption. Further, the interaction term of bank account ownership and rabi precipitation is significantly negative in model 1. It indicates that if households face lower precipitation during the dry rabi season, they have higher consumption if they have a bank account. Thus, access to banks and bank account ownership enable households to smooth their consumption by saving up or borrowing money and make them less vulnerable to the adverse weather events. Our results are in line with Burgess *et al.* (2017) and Jayachandran (2006), who show that access to formal financial institutions in rural India mitigates adverse weather impacts.

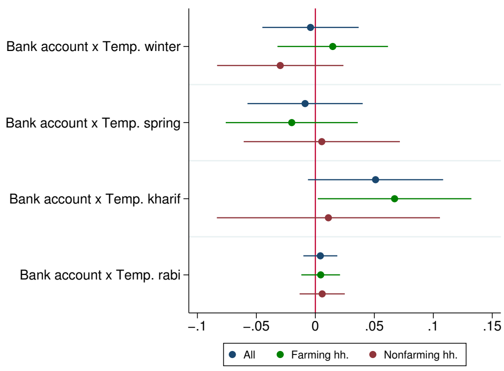
Figure 1.3 indicates that farming households, which own an air cooler have significantly higher consumption if the winter precipitation increases. A potential explanation is that air cooler ownership captures a wealth effect, i.e., richer households live in better houses and are therefore less adversely affected by precipitation in winter. Further, we find significantly negative interaction terms of irrigation with the summer and rabi temperatures for farming households. These outcomes presumably capture that farmers with access to irrigation tend to plant crops that are more heat-sensitive. For example, the data show that farming households with access to irrigation tend to grow comparatively



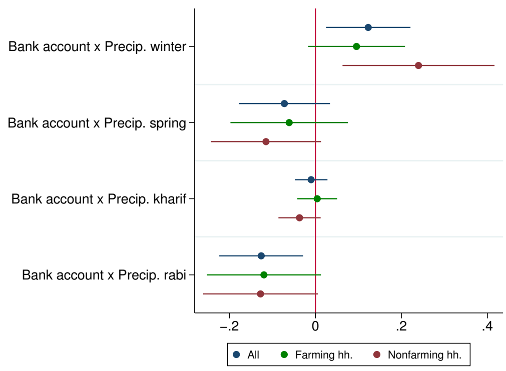
(a) Δ *Temp.* $\times$ *Land ownership*



(b) Δ *Precip.* $\times$ *Land ownership*

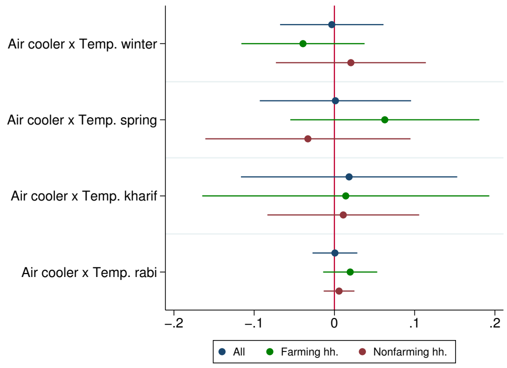


(c) Δ *Temp.* $\times$ *Bank account*

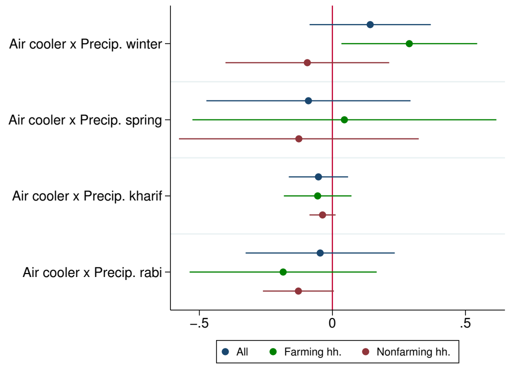


(d) Δ *Precip.* $\times$ *Bank account*

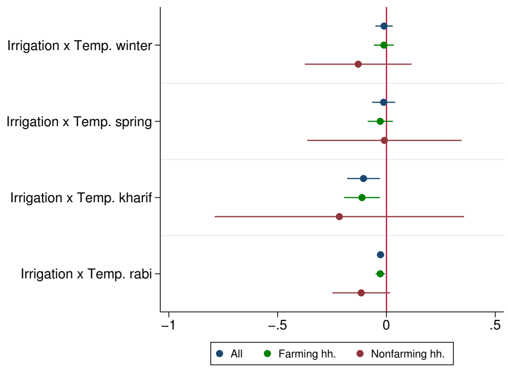
Figure 1.2: *Effects of seasonal weather on households' cons. by access to credit (results from equation 1.3)*



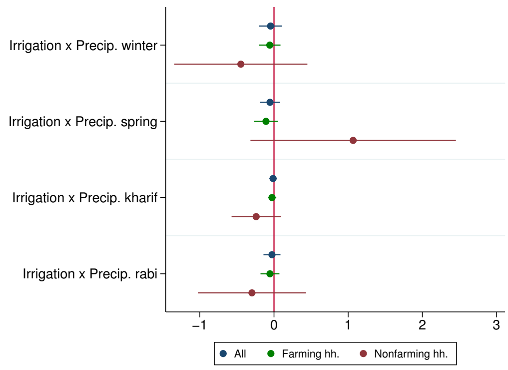
(a) Δ *Temp.*×*Air cooler*



(b) Δ *Precip.*×*Air cooler*



(c) Δ *Temp.*×*Irrigation*



(d) Δ *Precip.*×*Irrigation*

Figure 1.3: *Effects of seasonal weather on households' cons. by access to technology (results from equation 1.3)*

more wheat which is highly sensitive to heat stress (Lobell *et al.*, 2012; Tashiro and Wardlaw, 1989).

1.5.3 Implications

Here, we briefly discuss how controlling for historical climate and access to credit and technology affects the responses of poor and non-poor households to changes in weather. To do this exercise, we compare the interactions of changes in seasonal weather and the variable Poor from estimating equation 1.3 (see Table A.12 in Appendix A.5) with the coefficients from the main analysis of the distributional implications of a changing weather, as presented in Table 1.4. We find that after controlling for historical climate, access to credit and technology, the poor and the non-poor have more similar responses to temperature. Thus, historical climate and socio-economic characteristics explain the difference in responses to changes in seasonal temperature. However, the poor still remain more sensitive to precipitation.

Table 1.6: *Predicted change in cons. of the farming households in rural India from the climate change between 2006–2099 under the RCP8.5*

	ΔConsumption	
ΔClimate (RCP 8.5)	*Poor*	*Non-poor*
Temperature		
Δ Temp. winter	0.037	-0.033
Δ Temp. spring	-0.554	0.09
Δ Temp. kharif	0.003	-0.064
Δ Temp. rabi	0.133	0.046
Precipitation		
Δ Precip. winter	0.014	0.002
Δ Precip. spring	0.026	-0.001
Δ Precip. kharif	-0.013	0.000
Δ Precip. rabi	0.005	-0.008
Total future Δ	*-0.349*	*0.032*

Changes in future (2006–2099) consumption under RCP8.5 are calculated by multiplying the estimated coefficients from Table 1.4, model 2 with the predicted changes in temperature and precipitation from Table 1.3 for poor and non-poor farming households separately.

1.6 Climate change example

To illustrate how future climate change might affect households' consumption, we use all estimated coefficients from Table 1.4, model 2 on farming households. We focus on farming households, since in section 1.4.1 we show that climate change might aggravate inequality particularly through the adverse effect of increasing temperature on the poor farming households (the implications of changing precipitation is clarified below). We draw on the changes in temperature and precipitation from today to 2100 predicted under RCP8.5, as suggested in section 1.3.3, Table 1.3. We multiply the climate change variables with the estimated response coefficients by season for the poor and non-poor farming households separately. Then, we sum up the effects to get the final climate change consequence for the poor and non-poor. The outcomes are presented in Table 1.6. They suggest that under RCP8.5, consumption of the poor farming households decreases by almost 35% and consumption of the non-poor farming households increases by approximately 3% as a consequence of long-term changes in average seasonal temperature and precipitation. Hence, climate change predicted under RCP8.5 is likely to aggravate inequality in rural India by the end of the century, whereby poor farmers are expected to face substantial consumption losses. It is important to note, that these predictions are ceteris paribus. They might exaggerate the responses to temperature and precipitation changes as the estimated coefficients are based on econometric analysis using historical data and are applied to a future climate change scenario, not taking into account the possibility of further adaptation.

1.7 Conclusion

In this study, we analyze the inequality implications of climate change in rural India. We contribute to the emerging literature on the inequality implications of climate-related events within countries (Abdullah *et al.*, 2016; Keerthiratne and Tol, 2018; Warr and Aung, 2019), to the literature on the heterogeneous effects of weather on various socio-economic outcomes in India (Burgess *et al.*, 2014; Carleton, 2017; Taraz, 2018; Zaveri and Lobell, 2019) and to the literature on the seasonal variations in consumption in the low- and middle-income countries (Brune *et al.*, 2011; Chaudhuri and Paxson, 2002; Dercon and Krishnan, 2000) in several ways. First, we conduct a comprehensive analysis of attributing weather variations to within-country and seasonal consumption distribution at the household level. Second, by merging several recent datasets, we provide evidence representative for the whole of rural India. Third, we predict the distributional implications under a high global warming scenario (RCP8.5). Fourth, we provide evidence-based policy recommendations centered around reduction of climate-related vulnerabilities of the rural poor.

The main limitation of our study is that the data only enable us to analyze short-run weather variations. Our predictions of climate change impacts are based on short-run responses to weather and may fail to consider households' adaptation in the long-run. Moreover, we are only able to assign weather to households at the district-level. A longer period of time (e.g., 30 years) with weather assigned to households at a finer resolution would be an ideal setting to approximate the climate change experiment. Despite these shortcomings and given the data, this is the best possible approximation of the climate-related implications on within-country inequality.

Our results show that climate change already aggravates inequality in rural India, whereby poor farming households suffer the largest percentage losses. The differences in responses of the poor and the non-poor to climate-related damages can be explained by historical climate as the poor largely inhabit climates with historically more adverse conditions, and by socio-economic factors as the poor have less access to technology and insurance. These findings are in line with Hsiang *et al.* (2019). The key recommendation for policy makers is to improve access to financial institutions and adaptation technologies especially for the rural poor in India as improved accessibility would reduce the consumption losses under adverse weather events. The key recommendation for future research is to gather more evidence on within-country distributional implications of climate-related events since the adverse effects on the poor might often be overlooked in more aggregated analyses.

Chapter 2

Who Are the Climate Migrants and Where do They Go? Evidence from Rural India[1]

Barbora Šedová
Matthias Kalkuhl

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Chapter Abstract

In this paper, we move from the large strand of research that looks at evidence of climate migration to the questions: *who are the climate migrants?* and *where do they go?* Understanding these effects is crucial to design policies that mitigate welfare losses of migration choices due to climate change. We study the direct and heterogeneous associations between weather extremes and migration in rural India. We combine ERA5 reanalysis data with the India Human Development Survey household panel and conduct a regression analysis by applying linear probability and multinomial logit models. This enables us to establish a causal relationship between temperature and precipitation anomalies and overall migration as well as migration by destination. We show that adverse weather shocks decrease rural-rural and international migration and push people into cities in different, presumably more prosperous states. A series of positive weather shocks, however, facilitates international migration and migration to cities within the same state. Further, our results indicate that in contrast to other migrants, climate migrants are likely to be from the lower end of the skill distribution and from households strongly dependent on agricultural production. We estimate that approximately 8% of all rural-urban moves between 2005 and 2012 can be attributed to weather. This figure might increase as a consequence of climate change. Thus, a key policy recommendation is to take steps to facilitate integration of less educated migrants into the urban labor market.

2.1 Introduction

It is well established that climate-related events affect the patterns of human migration (IPCC, 2014). Since 2008, an average of 26.4 million people have been displaced annually by natural disasters (Yonetani *et al.*, 2015). This figure does not even consider displacement in response to slow changes such as sea level rise, desertification or long-term climate change. At the same time, the empirical evidence of climate migration is ambiguous due to the multidimensional nature of the migration decision in response to climate-related events. This makes generalizations difficult (Berlemann and Steinhardt, 2017; Cattaneo *et al.*, 2019; Millock, 2015). The existing literature suggests that temperature variations generally induce migration (Bohra-Mishra *et al.*, 2014; Mastrorillo *et al.*, 2016; Missirian and Schlenker, 2017; Mueller *et al.*, 2014). However, the evidence on the impacts of rainfall variations is more mixed. Some studies show that migration increases with droughts (Abel *et al.*, 2019; Baez *et al.*, 2017a; Barrios *et al.*, 2006; Dallmann and Millock, 2017; Gray and Mueller, 2012a). There are also studies that do not find any significant impact (Abu *et al.*, 2014; Mueller *et al.*, 2014; Owain and Maslin, 2018). Thus, while migration may serve as a coping strategy in response to weather events, this causality is not universal.

In recent years, a more nuanced perspective has emerged. It acknowledges that weather is one of the drivers affecting migration directly and indirectly by interacting with other factors. This literature is still limited and mostly provides evidence of the heterogeneous effects related to gender (Dillon *et al.*, 2011; Gray and Mueller, 2012b,a; Thiede and Gray, 2017), wealth (Beine and Parsons, 2014; Gray and Mueller, 2012b; Gröschl and Steinwachs, 2017; Mastrorillo *et al.*, 2016) or age (Baez *et al.*, 2017a; Mastrorillo *et al.*, 2016). Despite these developments, it still remains unclear who is migrating in response to weather events and to which destinations. Yet a better understanding of these heterogeneous implications is essential to design policies that mitigate welfare losses of migration choices due to climate change. In particular, refining the destination choices and characteristics of climate migrants enables policy makers to evaluate the potential social and economic consequences of the migration streams predicted under climate change.

With this study, we aim to shed more light on the research questions *who are the climate migrants?* and *where do they go?* In our analysis, we draw on the India Human Development Survey (IHDS) panel collected in 2004-2005 and 2011-2012 and ERA5 reanalysis data. We first use linear probability and multinomial logit models to establish a causal relationship between weather extremes and overall migration as well as migration by destination. Then, we interact the weather extremes with household-specific characteristics (i.e. literacy and dependence on agriculture) to refine the characteristics of climate migrants. To approximate weather extremes, we use district-specific positive and absolute negative temperature and precipitation anomalies accumulated over longer periods of time.

We show that adverse weather shocks decrease rural-rural migration within the same state as well as international migration. A potential explanation is that migration to nearby rural areas becomes less attractive because of the high geographical correlation of weather shocks, while international migration decreases due to stricter financial constraints. We further show that adverse weather shocks (i.e. negative precipitation anomalies) push people into cities in different, presumably more prosperous states, where weather is less likely to be correlated with the adverse conditions at the origin. This finding is in line with the broader literature suggesting that a lack of rain drives migration to urban areas (Barrios *et al.*, 2006; Brückner, 2012; Henderson *et al.*, 2017; Nawrotzki *et al.*, 2017). We provide evidence that a series of positive weather shocks (i.e. more precipitation) facilitates international migration and migration to cities within the same state. Further, our results indicate that in contrast to other migrants, climate migrants are likely to be from the lower end of the skill distribution and from households strongly dependent on agricultural production. We estimate that approximately 8% of all rural-urban moves between 2005 and 2012 can be attributed to weather. This corresponds to 1.5 million climate migrants from rural to urban areas in India. Overall, our outcomes suggest that weather shocks disturb migration mechanisms and change the profile of rural migrants.

Our work contributes to the existing literature examining how weather affects migration in India (Bhattacharya and Innes, 2008; Dallmann and Millock, 2017; Viswanathan and Kumar, 2015) and to the emerging stream of literature explaining the heterogeneous weather implications (discussed above) in multiple ways. First, we draw on ERA5 high-quality reanalysis data and IHDS data and apply them uniquely to study climate migration. In this way, we provide the most up-to-date evidence representative for rural India. Second, we contribute to the novel literature utilizing the Roy-Borjas model to analyze how weather affects the self-selection into migration (Cattaneo and Peri, 2016; Benonnier *et al.*, 2019). To the best of our knowledge, we are the first to focus on the skill distribution among the climate migrants. Third, we quantify past rural-urban climate migration. In this way, we show how climate migration contributes to urbanization in India. Fourth, we provide evidence-based policy recommendations resulting from the approximation of the the profiles and destination choices of climate migrants. These recommendations have important welfare implications under the threat of climate change.

The next section presents the study context. In section 2.3, we provide an overview of the data and constructed variables. In section 2.4, we discuss the methods. Findings are presented in sections 2.5 and 2.6. The last section provides concluding remarks.

2.2 Study context

2.2.1 The case of India

Despite India's significant economic growth since the mid-1990s, the agricultural sector continues to play an important role for the country's economy in terms of both GDP and employment. Even though the contribution of the agricultural sector to the national GDP has declined from 29% in 1990 to 17% in 2016, it accounts for approximately 47% of the national (Ministry of Labour and Employment, 2016; OECD, 2018) and 62% of the rural employment (ILO, 2016). Thanks to the better access to inputs such as fertilisers and seeds, as well as improved irrigation and credit coverage, agricultural production has been increasing on average by 3.6% per year since 2011 (OECD, 2018). As a result of evolving demographics, urbanization and changing demand patterns in particular, the agricultural sector has been diversifying from grains towards pulses, fruits, vegetables and livestock products (Gulati, 2009; Gulati and Saini, 2017). India has further become a major exporter of several key agricultural commodities and is currently the largest exporter of rice and the second largest exporter of cotton globally (OECD, 2018).

Despite these positive trends, there are still important challenges that India faces. The large fraction of employment in the agricultural sector relatively to its GDP share reflects the slow structural change as well as relatively low labor productivity. India's structural transformation has been rather atypical, characterized by fast growth of the service sector, slight growth of the manufacturing sector and no substantial transformation in the occupational structure of the economy (OECD, 2018; Rada and von Arnim). The labor productivity is almost four times higher in the service sector and two times higher in manufacturing compared to the agricultural sector. While the differences in the labor productivity and the corresponding wage rates drive rural workers away from the agriculture, their low levels of education and skills make their integration in the non-agricultural sector difficult. This contributes also to the relatively low urbanization rates, as the job creation outside of the agricultural sector takes predominantly place in urban and peri-urban areas (OECD, 2017, 2018). Specifically, 21% of urban population growth in 1991-2001 and for 22% in 2001-11 can be attributed to the rural to urban migration (OECD, 2018).

Climate change is another major factor challenging the Indian economy. Since agriculture is still heavily rain-fed, yields in India are strongly determined by the weather (Krishna Kumar *et al.*, 2004). As a result of climate change, the rainfall in the monsoon season has decreased (Auffhammer *et al.*, 2012; Dash *et al.*, 2007; Ramanathan *et al.*, 2005) and the distribution of the rainfall has become more extreme (Goswami *et al.*, 2006). Moreover, surface temperature increases have accelerated over time (Padma Kumari *et al.*, 2007). Hari *et al.* (2018) find that the adverse effects of temperature and rainfall variations on Indian crop yields are non-linear and are mostly felt in the extremes.

Further evidence suggests that adverse weather shocks reduce agricultural incomes and increase poverty (Burgess *et al.*, 2014; Hari *et al.*, 2018) and inequality (Šedová *et al.*, 2019) in rural India. However there is no evidence of weather-induced income drops in Indian cities (Burgess *et al.*, 2014).

2.2.2 Theoretical framework

We draw on the canonical Roy-Borjas model to study how the changes in weather distribution affect migration in rural India to shed more light on the main research questions: *who are the climate migrants?* and *where do they go?* Borjas (1987, 1991) adjusted the Roy (1951) model of occupational choice to determine the factors that characterize the self-selection of migrants (Roy-Borjas model). According to the model, the selection process is determined by relative inequality at the origin and the destination. Higher inequality at the destination signalizes that the more educated individuals receive higher wages at the destination and drives migration of individuals drawn from the top end of the skill distribution at the origin. If the destination is comparatively more equal, however, migrants are drawn from the bottom end of the skill distribution.

Recent studies of climate migration utilize the Roy-Borjas model to investigate the effects of the adverse weather impacts on the probability of emigration. These studies are conducted at the macro level and focus primarily on the liquidity constraints imposed by the adverse weather and their heterogeneous migration implications depending on countries' wealth (Cattaneo and Peri, 2016; Benonnier *et al.*, 2019) and access to irrigation (Benonnier *et al.*, 2019). We contribute to this literature and apply the Roy-Borjas model to analyze how weather affects self-selection into migration of individuals in rural India. In our analysis, we focus on the skill distribution among the climate migrants and their destination choices.

To built our hypotheses, we use IHDS data (see section 2.3.2) to analyze the inequality and poverty in rural and urban India. The analysis suggests that inequality and poverty are more substantial in rural than in urban areas (see Appendix B.1, Table B.1). While in the first round approximately 25% and in the second round approximately 21% of rural households lived below the poverty line, these figures were 22% and 11% in urban areas respectively.[2] Moreover, we calculate the standard deviation of income in rural and urban areas for both IHDS rounds to measure inequality.[3] In both rounds, the figure is smaller for urban areas indicating higher equality than in rural areas. Further, the

[2]The poverty line used in the IHDS data is a nation-wide set poverty line that is adjusted for rural/urban and state-specific purchasing power.

[3]To compare the income distribution in rural and urban areas, we apply survey weights and calculate the standard deviation of the logarithm of income per adult equivalent household member. We use the OECD equivalence scale. This scale assigns a value of one to the household head, of 0.5 to each additional adult household member and of 0.3 to each child.

evidence presented in Section 2.2.1 shows that adverse weather shocks decrease income from agriculture and increase poverty and inequality in rural India. In their literature review, Karim and Noy (2016) also highlight that poorer households disproportionately bear the damages of adverse climate-related shocks.

Based on this evidence and the intuition from the Roy-Borjas model we hypothesize that climate migrants are from the lower end of the skill distribution. We further expect climate migrants to be primarily from agricultural households as they are the most susceptible to income drops in response to adverse weather shocks. We further assume that climate migrants go to destinations, where the susceptibility to weather shocks is lower i.e. to urban areas and richer countries with higher probability of finding a low skill job outside the agricultural sector. These hypotheses are tested empirically. Given the character of our data (see section 2.3.2), the timing of migration is not known. Hence, it is not possible to say whether households utilize migration as an *ex-ante* risk management strategy (Stark and Bloom, 1985) or as an ex-post risk coping strategy (Kleemans, 2015).

2.3 Data

To build our sample we combine ERA5 reanalysis data produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) (C3S, 2017)[4] with household panel data from the India Human Development Survey (IHDS) produced by the University of Maryland and the National Council of Applied Economic Research, New Delhi (Desai *et al.*, 2005, 2015).

2.3.1 Weather data

In India, the spatial and temporal coverage of weather stations has deteriorated over time and the available datasets have many missing observations. Data assimilation, producing reanalysis data, is one way climate scientists deal with missing observations. This approach combines observational data from weather stations and remote sensing with a physics-based model. The model then increases information from regions with existing observations to regions with sparse observations. Reanalysis data solves for the endogeneity problem resulting from the weather stations placement, variation in the quality of data collection, and variation in the quantity of collected data and produces a consistent best estimate of atmospheric parameters over time and space (Auffhammer *et al.*, 2013; Donaldson and Storeygard, 2016). Applied economists increasingly utilize

[4] This publication Contains modified Copernicus Climate Change Service Information [2019]. Neither the European Commission nor ECMWF is responsible for any use that may be made of the Copernicus Information or Data it contains.

reanalysis data to study especially the low- and middle-income countries, where the coverage of weather stations over time and space is limited (Burgess *et al.*, 2014; Harari and Ferrara, 2018; Schlenker and Lobell, 2010).

Following this practice, we draw on ERA5, i.e. the fifth generation of ECMWF atmospheric reanalyses of the global climate. ERA5 relies on the information from weather stations, satellites, and sondes. The data has geographical resolution of 31km and has been regridded to a regular latitude-longitude grid of 0.25 degrees. Currently, it is available from January 1979 onward, with a temporal resolution of up to one hour (C3S, 2017). We make use of the monthly means of average temperature two meters above the surface and precipitation.

Our intention is to analyze the migration implications of weather extremes that are expected to become more frequent and more severe as a consequence of climate change. The difference between weather and climate is determined mainly by time. While weather is a short-term (e.g., days or months) condition of the atmosphere, climate is defined as the probability distribution that creates weather events. Long-term averages (i.e. over decades) or higher moments are used to characterize this distribution and possible changes in climate conditions (Auffhammer *et al.*, 2013). To account for weather extremes, we create variables that capture the total monthly positive and absolute total monthly negative temperature and precipitation anomalies accumulated over longer periods of time before each of the two IHDS interviews (see section 2.3.2). The length of each period is defined by the number of months between the two months/years when each of the IHDS interviews was conducted and hence differs by household. The choice of the anomalies is based on the assumption that the deviation from normal conditions can impose adverse effects in any month. A weather anomaly is calculated as a district-specific level difference in mean temperature or precipitation in a given month from its historical mean for 1979 to 1998, divided by its historical standard deviation for 1979 to 1998 (Dell *et al.*, 2014). The definitions of weather anomalies are summarized in Table 2.1. For the exact construction of the variables, see Appendix B.2. The main source of identification in the regression analysis comes from the change in households' exposure to the weather extremes over time (i.e. between the two IHDS rounds). Because of their high correlation and effect on migration, we simultaneously employ temperature and precipitation anomalies into the regression models (Auffhammer *et al.*, 2013).

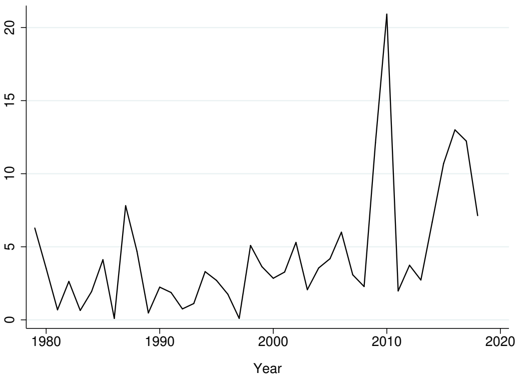
Table 2.2 presents summary statistics of the constructed variables for each IHDS round separately as well as their change over time. It shows that between the two IHDS rounds the exposure to extremely high temperatures has increased on average by almost 26 anomalies and the exposure to extremely low temperatures has decreased on average by almost eight anomalies. Moreover, the exposure to extremely high precipitation has increased on average by almost ten anomalies and the exposure to extremely low precipitation has decreased on average by one anomaly.

Table 2.1: *Definitions of positive and negative weather anomalies*

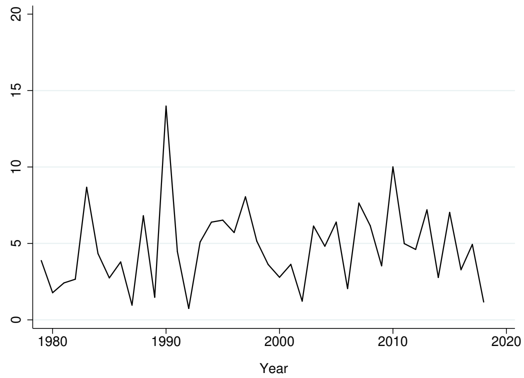
Weather anomalies	Definition
Positive anomaly	District's positive deviation of weather (temperature or precipitation) in a given month from its long-run mean, divided by district's month-specific standard deviation of weather.
Negative anomaly	District's absolute negative deviation of weather in a given month from its long-run mean, divided by district's month-specific standard deviation of weather.

Table 2.2: *Descriptive statistics: Climate-related variables at the district-level (ERA5 data)*

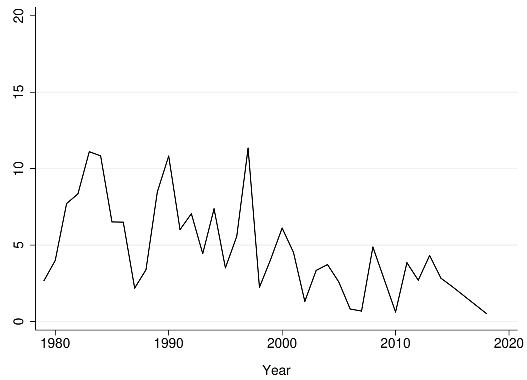
Variable	Mean	Std. Dev.	Min.	Max.	Units
Temperature	24.6125	3.5082	2.3439	29.0195	Historical temp. (1979-1998), °C
Temp. anom. (+) Round 1	42.0680	8.7366	18.4442	64.4016	total monthly anom.
Temp. anom. (+) Round 2	67.9271	17.0027	31.975	141.2042	total monthly anom.
ΔTemp. anom. (+)	25.8591	16.2436	-23.5595	89.3623	total monthly anom.
Temp. anom. (-) Round 1	25.2664	5.0746	13.2326	43.8605	abs. total monthly anom.
Temp. anom. (-) Round 2	17.6921	5.5742	3.2121	39.9299	abs. total monthly anom.
ΔTemp. anom. (-)	-7.5743	6.3207	-27.4704	9.8649	abs. total monthly anom.
Precipitation	0.0331	0.0179	0.0068	0.1241	Historical precip. (1979-1998), mm
Precip. anom. (+) Round 1	30.3394	5.6461	14.9987	47.3527	total monthly anom.
Precip. anom. (+) Round 2	40.0617	15.8764	13.5125	101.6415	total monthly anom.
ΔPrecip. anom. (+)	9.7223	16.1462	-20.1704	73.1488	total monthly anom.
Precip. anom. (-) Round 1	32.3257	4.2845	23.5651	48.4073	abs. total monthly anom.
Precip. anom. (-) round 2	31.1254	6.9039	15.2638	49.977	abs. total monthly anom.
ΔPrecip. anom. (-)	-1.2004	5.7784	-18.1401	14.2227	abs. total monthly anom.
N				24845	



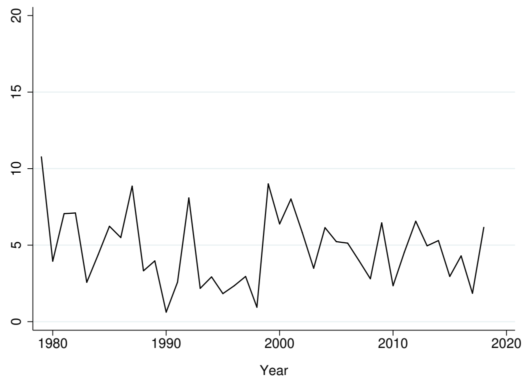
(a) *Total positive temperature anomalies*



(b) *Total positive precipitation anomalies*



(c) *Total negative temperature anomalies*



(d) *Total negative precipitation anomalies*

Figure 2.1: *Historical total temperature and precipitation anomalies in India, 1979–2018 (ERA5)*

To better understand the long-run trend in the weather extremes, in Figure 2.1 we show the yearly total positive and negative temperature and precipitation anomalies since 1979, constructed for the whole of India. The data shows a clear trend for the temperature anomalies; an increasing for positive and a decreasing for negative temperature anomalies. The precipitation anomalies show yearly fluctuations without any clear trend.

When deciding on weather data, we compared ERA5 with the Climatic Research Unit Timeseries (CRU) data from the University of East Anglia on monthly estimates of average temperature and total precipitation gridded to 0.5 longitude by 0.5 latitude degree resolution (Harris *et al.*, 2014). Gridded datasets apply another approach to deal with missing weather observations for observationally sparse regions, namely interpolation of the existing weather information across space and time over a grid. For areas with a sparse station coverage, weather data is interpolated from stations further away. This is problematic as the weather events that identify the response coefficient might vary according to the interpolation scheme and hence across datasets. In fact, most gridded datasets seem to agree on the average values of weather variables across space. However, they are not fully consistent when it comes to the timing or magnitude of the deviations from the mean, which serve as the source of identification in a panel data analysis. Gridded data might fail to capture a lot of weather variation appropriately. For instance, extreme events on station sparse locations might not be accounted for at all (Auffhammer *et al.*, 2013; Dell *et al.*, 2014). The reanalysis data is therefore the preferred choice for our panel analysis focusing on local changes in weather.

In Appendix B.3, we provide a comparative analysis of ERA5 and CRU data. Table B.2 shows descriptive statistics of the state-specific standard deviations of the first differences of the weather anomalies generated using CRU and ERA5 data. These first differences serve as the main source of identification in our analysis (see section 2.4). Apart of the negative precipitation anomalies, the mean values of the standard deviations are substantially larger when using ERA5. This suggests that the interpolation applied to generate the CRU data might have averaged out some of the weather variation. The mean values of standard deviations of the change in negative precipitation anomalies are only slightly larger when using CRU data. In Table B.3, we show the correlation coefficients across datasets of the first differences of weather extremes as well as the historical temperature and precipitation means. The coefficients are high when looking at the historical average temperature and precipitation (e.g., correlation coefficient of average historical temperatures is 0.98). However, the coefficients decrease when looking at their first differences (e.g., correlation coefficient of change in positive temperature anomalies is 0.39). We further compare the geographical variation across the datasets using maps, as presented in Appendix B.3. In order to obtain comprehensive maps for the whole of India (and not for the IHDS districts only), we generate district-specific first differences in the total positive and negative precipitation anomalies for 5-year periods before each of the two IHDS-rounds (i.e. 1999-2003 for IHDS-I and 2006-2010 for IHDS-II). Hence, even though we loose the variation provided by the IHDS interview dates, this variable still enables us to approximate geographical distribution of the treatment variables. The maps also suggest larger geographical variation when using ERA5.

2.3.2 Household data

IHDS collected nationally representative data from 41,554 households in 1,503 villages and 971 urban neighborhoods across India in two rounds; 2004-2005 (IHDS-I) and 2011-2012 (IHDS-II). Our final sample contains approximately 25,000 rural households that were interviewed in both rounds.[5] The attrition rate in the IHDS is much lower in rural India (about 9%) compared to urban India (approximately 26%). By focusing only on

[5]All observations with missing values for the relevant variables are deleted from the sample. Moreover, we also drop households, where information on their rural/urban residence differs between the two IHDS rounds.

rural households, we minimize the attrition problem, which according to the standards of Alderman *et al.* (2001) is relatively low. Additionally, in Appendix B.4 we conduct an attrition analysis. We examine whether the household characteristics from IHDS-I utilized in our main model significantly affect the probability that households drop out from the survey in the second round. However, attrition seems to appear at random in our model. Number of household members is the only significant coefficient that we find. However, it is only significant at the 10% significance level and its magnitude is relatively small.

Using the IHDS data, we construct our dependent variable as well as a set of independent variables. All independent variables are drawn from IHDS-I. In our analysis, they represent time-invariant household-specific characteristics.

The data structure allows migration to be measured at the household-level only. In both rounds, IHDS reports the household-specific number of non-resident members. Non-resident members are classified as migrants if they live outside of their village of origin and out-migrated permanently for reasons other than studies.[6] The non-resident members do not cover migration for marriage. Instead, they capture for instance wives or husbands of household members that live elsewhere and might be sending remittances. Hence, by using information on non-resident members, in the analysis we consider economic migration only. Following the practice in migration literature, we focus on migration of women and men in a productive age (15-65 years). IHDS does not indicate the timing of migration. Instead, it provides the household-specific total number of permanent migrants at the point in time in which the data was collected. From this information, we construct two main dependent variables (Δy). First, we construct a binary dependent variable (Δ *Migration*) that takes on a value of zero if the household-specific number of permanent migrants has decreased or remained the same and of one if a household has increased its number of permanent migrants between the two IHDS rounds.[7] Second, we create a categorical variable (Δ *Migration Destination*) that takes on a value of zero if the household-specific number of permanent migrants has decreased or remained the same between the two IHDS rounds. The positive values of the variable indicate, whether households have sent out migrants to other rural (one), urban (two) or international (three) destinations. This distinction is essential as migration to different

[6]The literature classifies migrants as permanent if they have no intention to return (McLeman and Hunter, 2010). IHDS contains separate information on temporary migrants and non-resident household members. We handle the non-resident household members as permanent migrants even though their intentions of returning are not explicitly known. We do so because these individuals left their households of origin to live at the destinations.

[7]Only approximately 4% of rural households decreased their number of migrants between the two IHDS rounds. We group them together with the households whose migration behavior remained unchanged because we are mainly interested in studying households' decision to engage into migration. Because majority of households that engaged into migration (94%) increased their number of migrants from zero, we group them together with the small fraction of households that increased their number of migrants from a positive number.

destinations is related to different migration costs and employment opportunities (see section 2.2).

The descriptive statistics in Table 2.3 show that in IHDS-I, approximately seven percent of households report having an out-migrant, in IHDS-II this figure increased to almost 17%. Moreover, 14.5% of rural households report an increase in out-migrants between the two IHDS rounds. In comparison, in its 64th nationally representative survey National Sample Survey Organisation (2010) indicates that approximately 12.8% households in rural India reported out-migration in 2007-2008. When split according to gender, this figure was approximately 9% for male out-migration and almost 17% for female. The relatively high out-migration of females is driven by marriage. Further, according to the summary statistics, almost 11% of households have increased out-migration to urban destinations, four percent to other rural destinations and only one percent of rural out-migrants have migrated abroad. The focus on the economic migrants explains the dominance of the migration to urban destinations (NSSO, 2010).[8] Generally, in India permanent migration is considered to be low compared to other countries of similar economic development and size. In particular, the rural-urban migration rates remain low despite the prevailing large wage differentials (section 2.2) (Munshi and Rosenzweig, 2016; Topalova, 2010). Using population censuses of India, Munshi and Rosenzweig (2016) show that among males aged 15–24 rural-urban migration has remained low for decades in the second half of the last century, reaching a maximum of 5.4 percent in the earlier periods and falling to below 4 percent in the more recent periods. Indicating a substantial increase in rural out-migration over time, IHDS data suggest that the trend is changing.

Additionally, we employ a set of demographic and economic household-specific controls that are typically included in the models to predict migration (Gray and Mueller, 2012b; Gray and Bilsborrow, 2013; Thiede *et al.*, 2016). The household-level of the analysis (as opposed to an individual-level) as well as the data availability limit our choice of controls. Nevertheless, we do our best to be as comprehensive as possible. To capture households' demographic composition, we control for the dependency ratio (i.e. number of children younger than 15 years relative to the number of adults)[9], sex ratio (number of males relative to the number of all households' females), married females fraction (number of married females as a fraction of all households' females), married males fraction, number of household members as well as the age, gender and literacy of the household head. To approximate households' economic status, we control for the number of valuable assets owned, land ownership, bank account ownership, dependency

[8]Female migration in India is strongly driven by migration for marriage. From rural areas, these migration streams are dominated by migration to other rural destinations (NSSO, 2010).

[9]In the context of rural India, it is not clear in which age the adults stop contributing (if at all) to the consumption-generating activities of the household. Therefore, to calculate the dependency ration, we relate the number of children to the number of all adults.

on agriculture (i.e. if households report agriculture as their main source of income) and access to irrigation (which also approximates households' ability to adapt). For the purpose of exogeneity, all of the controls are taken from IHDS-I and hence are time invariant. Table 2.3 shows the corresponding descriptive statistics.

Table 2.3: *Descriptive statistics: Household characteristics (IHDS data)*

Variable	Mean	Std. Dev.	Min.	Max.	Units
Migration variables					
Migration	0.2099	0.4073	0	1	binary: has out-migr. in any of IHDS rounds (1)
Migration Round 1	0.0737	0.2613	0	1	binary: has out-migrants (1)
Migration Round 2	0.1672	0.3732	0	1	binary: has out-migrants (1)
ΔMigration	0.1445	0.3516	0	1	binary: increase (1)
ΔMigration Destination	0.2793	0.6912	0	3	categorical: increase rural (1), urban (2), international (3)
ΔMigration Rural	0.0377	0.1905	0	1	binary: increase (1)
ΔMigration Urban	0.1052	0.3068	0	1	binary: increase (1)
ΔMigration International	0.0105	0.1018	0	1	binary: increase (1)
Household head					
Age	48.265	13.4416	12	100	years
Female	0.0736	0.2612	0	1	binary: female (1)
Literate	0.5693	0.4952	0	1	binary: literate (1)
Household characteristics					
Dependency ratio	0.6013	0.5956	0	6	ratio: children to hh. members
Sex ratio	1.3164	0.8781	0.1111	9	ratio: male to female
Married females	0.5721	0.2884	0	1	fraction: married fem. to fem.
Married males	0.4998	0.266	0	1	fraction: married male to male
Members	6.1387	3.1507	2	38	nr. of hh. members
Assets	9.9169	5.1657	0	29	nr. of valuable assets
Land	0.6341	0.4817	0	1	binary: owns land (1)
Bank account	0.2513	0.4338	0	1	binary: has bank account (1)
Agriculture	0.6022	0.4895	0	1	binary: agr. dependent (1)
Irrigation	0.3379	0.473	0	1	binary: access to irrigation (1)
N					24845

Migration captures whether households have an out-migrant at least in one of the IHDS rounds. *Migration Round 1, Round 2* capture whether households report having an out-migrant in the specific IHDS rounds. The remaining migration variables indicate the change between IHDS-I and IHDS-II. The sum of the means of migration rural, urban and international is slightly larger as the mean of the variable Migration, as some of the households increased migration to several destinations. The remaining variables draw on IHDS-I.

2.4 Empirical strategy

There are two main approaches to estimate agents' responses to the changing climate (Burke and Emerick, 2016; Dell *et al.*, 2014). The first is a cross-sectional approach utilizing spatial variation at a point of time, comparing outcomes in hot and cold areas (Mendelsohn *et al.*, 1994; Schlenker *et al.*, 2005). An important econometric challenge when estimating response coefficients of the climate-related variable, β, from cross-sectional models is the assumption that climate is not correlated with other unobservable factors. This assumption leads to an omitted variables problem, increasing the risk of the estimates of β to be biased. The second approach addresses these omitted variable concerns by using longitudinal data and location-specific fixed-effects, absorbing the time-invariant factors (Deschênes and Greenstone, 2007; Lobell *et al.*, 2011; Schlenker and Roberts, 2009). Identification comes via deviation from the mean over time comparing a given spatial entity under colder and warmer conditions. The estimated effect can be interpreted causally. However, it is derived from short-run weather responses which are not necessarily representative for agents' responses to the changing climate in the longer term (e.g., due to possible adaptation). While the second approach solves the identification problem, it does not perform as well in approximating the climate change experiment under slow-onset changes in climate conditions.

Burke and Emerick (2016) address the shortcomings of both the cross-sectional and the longitudinal methods by utilizing the long-differences approach. We follow this approach and focus on estimating the causal effects of weather extremes (i.e. positive and absolute negative temperature and precipitation anomalies) accumulated over longer periods of time on households' decision to migrate. However, we acknowledge that due to the relatively short time span of the IHDS dataset, we are limited in our ability to approximate the climate change experiment. We conservatively refer to the estimated effects as weather effects. Moreover, given the nature of the data (i.e. two waves of household data) and how the equations are specified (see below), the estimated coefficients are in fact first-difference estimators (for more details, see Griliches and Hausman (1986) and Hahn *et al.* (2007)).

In our analysis, we first focus on the estimation of the direct effects of weather extremes accumulated over longer periods of time on migration. We examine the impact of changes in total temperature and precipitation anomalies (denoted by A) at the district-level (d) on a household's (i) migration engagement (y), accounting for household-specific time-invariant fixed effects (λ_i). IHDS provides information on the total number of non-resident members at the time the data was collected. However, it does not provide information about the timing of migration. Therefore, in contrast to Burke and Emerick (2016), we cannot capture the long-term averages for the dependent variable. Rather, we consider the household-specific total number of migrants at the point of each of the two IHDS rounds (y_{i1} for IHDS-I and y_{i2} for IHDS-II). Regarding the weather variables, we consider two longer term periods a and b, each spanning over a number of months before each of the two IHDS rounds. This length is defined by the number of months between the two months/years when the IHDS interviews were conducted (for more details, see 2.3.1) and varies by households. We construct total positive and absolute negative temperature and precipitation anomalies a household was exposed to (see Appendix B.2) during each of the periods. Consequently, our equation for the IHDS-I is defined as follows:

$$y_{id1} = \beta_0 + \beta_1 A_{ida} + \lambda_i + \epsilon_{id1} \tag{2.1}$$

The equation for IHDS-II is defined in the same manner, enabling us to apply the long difference approach as follows:

$$y_{id2} - y_{id1} = \beta_1(A_{idb} - A_{ida}) + (\lambda_i - \lambda_i) + (\epsilon_{id2} - \epsilon_{id1}) \tag{2.2}$$

This leads to dropping out of the household-specific fixed effects. We obtain the following equation:

$$\Delta y_{id} = \beta_1 \Delta A_{id} + \Delta\epsilon_{id} \tag{2.3}$$

Lastly, by following Burke and Emerick (2016), we employ state fixed effects α_s that control for unobserved state-level trends. In addition, we control for household-specific characteristics (X) that take on values from IHDS-I and obtain:

$$\Delta y_{id} = \beta_1 \Delta A_{id} + \beta_2 X_{id1} + \alpha_s + \Delta\epsilon_{id} \tag{2.4}$$

Next, we analyze the heterogeneous effects of the weather extremes to determine the profile of climate migrants. To do this, we examine a variation of equation 2.4 by interacting the weather anomalies with households' level of education or agricultural dependence (summarized by Z, where $Z \in X$):

$$\Delta y_{id} = \beta_1 \Delta A_{id} + \beta_2 \Delta A_{id} Z_{id1} + \beta_3 X_{id1} + \alpha_s + \Delta\epsilon_{id} \tag{2.5}$$

We estimate the equations 2.4 and 2.5 by applying two different approaches. First, we translate Δy_{id} into a binary variable that takes on a value of zero if the household-specific number of permanent migrants has decreased or remained the same and one if the number of permanent migrants has increased (see section 2.3). Following the recent work on climate migration by Baez *et al.* (2017b) and Chen *et al.* (2017) we use a linear probability model. We choose the model based on the convenience of interpretation, especially when using interaction terms and because it is less prone to bias compared to binary response nonlinear models that impose strong assumptions on the error term (homoscedasticity) (Angrist and Pischke, 2009; Ai and Norton, 2003; Wooldridge, 2010). Nevertheless, we test the robustness of our results by utilizing a logistic regression (see Appendix B.7, Table B.8). This enables us to understand the effects of weather extremes on households' decision to migrate. Second, we disentangle the dependent variable by destination and apply the multinomial logit model. In this setting, the dependent variable is a categorical variable that takes on a value of zero if the household-specific number of permanent migrants has decreased or remained the same between the two IHDS rounds, one if the number of rural-rural migrants increased, two if the number of rural-urban migrants increased and three if the number of international migrants increased. The standard errors are clustered at the district-level.

2.5 Results

In section 2.5.1, we present evidence of the direct effects of weather extremes on migration. In sections 2.5.2 and 2.5.3, we present evidence of heterogeneous effects conditional on agricultural dependence and education, respectively.

2.5.1 Direct effects

Table 2.4 displays the results from three different regression models. In model 1, we utilize a cross-sectional analysis to examine how differences in average climate affect households' average migration strategy (i.e. average migration over both IHDS rounds). This regression enables us to understand, which migration implications can be expected from long-run changes in the average temperature and precipitation (for more information on the cross-sectional analysis, see Appendix B.5). Models 2 and 3 represent our preferred specification according to equation 2.4, whereby in model 2 the outcome variable captures the probability of overall migration and in model 3, we distinguish between the destinations of migration.

The estimated coefficient on average temperature in model 1 shows that if the long-run average conditions deteriorate (i.e. the average level of temperature increases), the likelihood of out-migration from rural areas increases. A one degree Celsius increase in the average temperature increases the likelihood of migration by two percentage points. The coefficient on average precipitation is not significant. The results on the other co-variates are mostly consistent with the literature (the direction of the coefficient on Sex ratio is an exception) but should be taken with caution due to potential omitted variable bias.

The coefficient on positive temperature anomalies in model 2 is not significant. Model 3, however, shows that extremely high temperatures are negatively associated with the probability of migration to rural areas and with international migration. To better understand the result on rural-rural migration, in Table B.5, Appendix B.6, we present outcomes from a multinomial logit model, where we further distinguish between rural-rural and rural-urban migration within the same state and to different states (further referred to as five destination model). The negative effect is driven by migration to same-state rural destinations. This suggests that migration within the same state to more distant rural areas becomes less attractive probably because of the high geographical correlation of weather shocks. This finding is in line with findings from the study by Thiede *et al.* (2016) on inter-provincial migration in South America. A potential explanation of the negative coefficient with respect to international migration could be that positive temperature extremes impose stricter financial constraints on households and households' ability to afford international migration decreases. This finding is consistent with the outcomes by Cattaneo and Peri (2016), who show that in poor countries higher temperatures decrease the probability of international moves. We further find a significantly negative coefficient on absolute negative temperature anomalies in model 2. Moreover, model 3 indicates that this effect is mainly driven by the significantly negative effect on international migration.

The evidence from model 2 further suggests that positive and absolute negative precipitation anomalies significantly drive migration. Model 3 further shows that while positive precipitation anomalies drive migration into cities and internationally, absolute negative anomalies significantly drive migration only to cities. Using the example of Indonesia, Kleemans (2015) demonstrates that a sequence of positive precipitation shocks can help households to accumulate wealth, a sequence of negative precipitation shocks, however, has just the opposite effect. Moreover, Jayachandran (2006) and Duflo and Pande (2007) show that positive rainfall shocks are beneficial also in the context of India. Given this evidence, we believe that the explanation for an increase in migration after a series of positive and negative precipitation shocks differs. Urban and international migration after accumulated positive shocks become more affordable and can be perceived as an investment migration (Kleemans, 2015). After accumulated negative shocks, migration can serve as a survival strategy (Kleemans, 2015). This finding contributes to the broader literature showing that negative rainfall anomalies induce migration to urban areas (Barrios *et al.*, 2006; Brückner, 2012; Henderson *et al.*, 2017; Nawrotzki *et al.*, 2017). Further, the five destination model (Appendix B.6, Table B.5) shows that in response to negative precipitation shocks, households are likely to send out migrants to distant cities, in presumably more prosperous regions, where weather is less correlated with the weather at the origin. In response to a positive precipitation shock, (apart of international migration) migration to urban areas within the same state takes place.

We pursue a series of robustness tests to analyze whether the main results are sensitive to the choice of model, alternative levels of error clustering or to exclusion of the state-specific time trends. Largely, the results correspond to the outcomes of the main analysis (see section B.7 in the Appendix).[10]

Finally, the effects of the household controls are mostly significant and they are by large consistent with the findings from previous studies. More precisely, model 2

[10]In section B.7 of the Appendix, we test the sensitivity of the results from section 2.5.1. When using a logit model to test the outcomes from model 2, the results are approximately the same. In Table B.9, we cluster the standard errors at the state level. The results are not sensitive to this change either. Lastly, in Table B.10, we estimate the models without state effects. Models 2 and 3 are instead estimated with a country-wide overall time trend. The results are the most sensitive to this modification. We find support for the results from the main analysis only in model 3 on positive temperature anomalies and absolute negative precipitation anomalies. However, we believe that these results might be a subject to an omitted variable bias. For instance, power in India is divided between union government and state government. Hence, a lot of institutional changes in India happen at the level of states.

suggests that migration increases with education. The five destination model (Appendix B.6, Table B.5) further shows that education is primarily essential when migrating to cities. We also find evidence that migration increases with the household head's age, sex ratio, and that it decreases with the dependency ratio. The results further show that wealthier households are likely to send migrants to cities and internationally. More precisely, migration to cities and international migration increase with ownership of assets. Migration to cities increases with land ownership. Households strongly dependent on agriculture, on the contrary, are less likely to send migrants, this effect is driven by a negative association with migration to urban areas. Moreover, households that have access to irrigation are less likely to move, as they can adapt at the origin. Additionally, we find that the female marriage ratio drives international moves, however in the remaining regressions female and male marriage ratios have a negative effect on migration.

2.5.2 Heterogeneous effects: Agriculture

In this section, we test whether the effects of weather extremes on households' engagement into migration differ depending on their dependence on agricultural production. To do this exercise, we interact extreme temperature and precipitation variables with the binary variable Agriculture. The outcomes from a multinomial logit model, where we distinguish between rural-rural, rural-urban and international migration, are presented in Table 2.5. The reported coefficients can be interpreted as the rate of change in probability of sending out a migrant to one of the three destinations separately for agricultural and non-agricultural households. We also report p-values indicating whether the effects are significantly different for the two types of households. Further, we control for other household-specific characteristics, but we do not report them.

The main result that emerges from this analysis is that the migration implications of precipitation anomalies are strongly channeled via agriculture, which is in line with the broader literature (Coniglio and Pesce, 2015; Marchiori *et al.*, 2012, 2017). In response to positive as well as negative precipitation shocks (dry spells), Indian cities are likely to receive an inflow of migrants from agricultural households. Hence, weather shocks disturb the usual migration mechanisms, where agricultural households are less likely to send out migrants (see section 2.5.1).

Specifically, we find evidence that positive precipitation anomalies have significantly different implications for the agricultural and non-agricultural households. They are likely to reduce rural-rural migration of the individuals from agricultural households. They further lead to stronger rural-urban moves of the individuals from agricultural households, with agricultural households being almost twice as likely to send migrants to cities as non-agricultural households. This effect is driven by migration to urban

Table 2.4: *Direct effects of weather extremes on the probability of out-migration*

	(1)	(2)	(3)		
	Migration	*ΔMigration*	*ΔMigration*		
			Rural	Urban	International
Weather & climate					
Temperature	0.0225**				
	(0.0105)				
Precipitation	1.028				
	(0.870)				
ΔTemp. anomaly (+)		0.0000934	-0.000707***	0.000650	-0.000263**
		(0.000684)	(0.000191)	(0.000575)	(0.000115)
ΔTemp. anomaly (-)		-0.00241*	-0.000617	-0.00154	-0.00158***
		(0.00131)	(0.000533)	(0.00131)	(0.000415)
ΔPrecip. anomaly (+)		0.00184***	-0.00000574	0.00163***	0.000436**
		(0.000562)	(0.000185)	(0.000554)	(0.000178)
ΔPrecip. anomaly (-)		0.00277*	-0.000316	0.00290*	0.000342
		(0.00166)	(0.000563)	(0.00157)	(0.000454)
Household head					
Age	0.00275***	0.00167***	0.000284**	0.00128***	0.0000108
	(0.000254)	(0.000289)	(0.000112)	(0.000171)	(0.0000602)
Female	0.112***	0.00821	-0.000854	0.00598	0.00269
	(0.0160)	(0.0120)	(0.00512)	(0.00855)	(0.00376)
Head literate	0.00916	0.0120**	0.00126	0.00792	0.000937
	(0.00689)	(0.00611)	(0.00290)	(0.00501)	(0.00190)
Household characteristics					
Dependency ratio	-0.00377	-0.0163**	-0.00631**	-0.0118**	-0.00256
	(0.00620)	(0.00726)	(0.00287)	(0.00498)	(0.00168)
Sex ratio	-0.0447***	0.0207***	0.00295	0.00457	-0.00203
	(0.00909)	(0.00724)	(0.00213)	(0.00399)	(0.00166)
Married females	0.139***	-0.0327**	-0.0163**	0.00608	0.0105***
	(0.0272)	(0.0157)	(0.00666)	(0.0123)	(0.00394)
Married males	-0.224***	-0.0646***	-0.00637	-0.0922***	-0.0162***
	(0.0239)	(0.0200)	(0.00674)	(0.0132)	(0.00489)
Members	-0.00526***	-0.00209**	-0.000657	-0.00246***	0.000483*
	(0.00136)	(0.00104)	(0.000413)	(0.000867)	(0.000273)
Assets	0.00548***	0.00360***	0.000245	0.00182***	0.000973***
	(0.000890)	(0.000851)	(0.000336)	(0.000641)	(0.000194)
Land	0.0483***	0.0268***	0.00180	0.0262***	-0.000752
	(0.00810)	(0.00732)	(0.00320)	(0.00594)	(0.00226)
Bank account	0.00577	0.00107	-0.00381	0.00408	0.00149
	(0.00748)	(0.00619)	(0.00293)	(0.00544)	(0.00145)
Agricultural	-0.0300***	-0.0135*	-0.00459	-0.0164***	0.00151
	(0.00844)	(0.00698)	(0.00287)	(0.00603)	(0.00190)
Irrigation	-0.0267***	-0.0243***	-0.00380	-0.0170***	-0.00170
	(0.00863)	(0.00799)	(0.00315)	(0.00618)	(0.00191)
N	24845	24845	24845	24845	24845
R^2	0.103	0.189			
Fixed effects	Yes	Yes		Yes	
Clustering	District	District		District	

Model 1 corresponds to a linear probability model. It is a cross-sectional regression of households' average engagement into migration over time on district-level historical temperature, precipitations and geographic variables and household-level controls. The dependent variable is binary and takes on a value of one if a household has sent at least one migrant in any of the two IHDS rounds. The geographic variables capture distance to city, coast and river, latitude, elevation and soil characteristics. The coefficients of these variables are not reported. Model 2 corresponds to a linear probability model. The dependent variable is a binary variable that indicates an increase in households' migration between the two IHDS rounds. The weather variables capture the change in households' exposure to total positive and negative temperature and precipitation anomalies between the two IHDS rounds. Model 3 corresponds to a multinomial logit model, where the dependent variable indicates an increase in households' migration by destination (rural, urban, international) between the two IHDS rounds. All weather variables are constructed using ERA5 data. Dependent variables use information from both IHDS rounds. Household-level controls use information from IHDS-I. The sample is composed of rural households in India. Reported fixed effects are at the state-level. Clustered standard errors are displayed in parentheses.* p<0.10, ** p<0.05, *** p<0.01.

areas within the same state (Appendix B.6, Table B.6). A possible explanation for this evidence is that positive shocks relax the liquidity constraint of individuals who would not be able to afford migration otherwise (Kleemans, 2015). However, the rural areas still remain poorer and more unequal than the urban as suggested in section 2.2.2 and therefore individuals from the lower end of the skill distribution self-select into migration. Moreover, the evidence suggests that negative precipitation extremes seem to only significantly affect agricultural households, driving migration to cities in other, presumably more prosperous states (Appendix B.6, Table B.6).

To examine the robustness of these outcomes, we conduct several tests that are presented in section B.8, Appendix. These include alternative levels of error clustering or exclusion of the state-specific time trends. The outcomes of the main analysis remain largely unchanged.[11]

2.5.3 Heterogeneous effects: Education

In this section, we present results on heterogeneous effects of weather extremes conditional on the level of education approximated by literacy of the household head. Similarly to the previous section, we interact the weather extremes with the variable Literate and estimate a multinomial logit model distinguishing three potential migration destination: rural, urban and international. The main results are presented in Table 2.6. The reported coefficients can be interpreted as the rate of change in probability of sending out a migrant to one of the three destinations separately for households with a literate and illiterate head. Further, a p-value is reported indicating whether the effects significantly differ between these two types of households. We also control for other household-specific characteristics, these are, however, not reported.

The key message emerging from this analysis is that if climate change increases the intensity and frequency of dry spells, Indian cities are likely to experience an inflow of migrants with lower levels of education. This is a further indication that climate change is expected to distort the migration mechanisms, since education usually drives migration (see section 2.5.1). Similar evidence is provided by Carvajal and Pereira (2010), who show that if hit by an adverse weather shock (more intense rain during Hurricane Mitch), households in Nicaragua with higher levels of education were less likely to move.

[11] In section B.8 of the Appendix, we test the significance of the results from section 2.5.2. In Table B.11, we cluster the errors at the state-level. However, the positive effect of positive precipitation extremes on rural-urban migration of non-agricultural households and the coefficient of difference in responses loose their significance. In Table B.12, we estimate the model with a country-wide overall time trend, i.e. without state trends. We find support for the results from the main analysis regarding the positive effect of positive and negative precipitation anomalies on rural-urban migration of agricultural households as well as the significantly different responses of agricultural and non-agricultural households to positive precipitation anomalies.

Table 2.5: *Heterogeneous effects of weather extremes on the probability of out-migration conditional on agricultural dependence*

	Δ*Migration*		
	Rural	Urban	International
ΔTemp. anomaly (+) $\times$ Non-agricultural	-0.000683***	0.000727	-0.000212*
	(0.000264)	(0.000729)	(0.000111)
ΔTemp. anomaly (+) $\times$ Agricultural	-0.000719***	0.000641	-0.000314**
	(0.000203)	(0.000540)	(0.000136)
p diff.	0.8893	0.8512	0.3464
ΔTemp. anomaly (-) $\times$ Non-agricultural	-0.000567	-0.00120	-0.00134***
	(0.000671)	(0.00152)	(0.000392)
ΔTemp. anomaly (-) $\times$ Agricultural	-0.000590	-0.00173	-0.00177***
	(0.000530)	(0.00128)	(0.000503)
p diff.	0.9644	0.5617	0.2759
ΔPrecip. anomaly (+) $\times$ Non-agricultural	0.000269	0.00110*	0.000440**
	(0.000239)	(0.000650)	(0.000199)
ΔPrecip. anomaly (+) $\times$ Agricultural	-0.000170	0.00194***	0.000479**
	(0.000201)	(0.000557)	(0.000200)
p diff.	0.0579	0.0789	0.8146
ΔPrecip. anomaly (-) $\times$ Non-agricultural	0.000404	0.00151	0.0000450
	(0.000733)	(0.00181)	(0.000444)
ΔPrecip. anomaly (-) $\times$ Agricultural	-0.000746	0.00375**	0.000707
	(0.000630)	(0.00163)	(0.000552)
p diff.	0.1223	0.1184	0.1141
N		24796	
Fixed effects		Yes	
Clustering		District	

The outcomes correspond to a multinomial logit model, where the dependent variable indicates an increase in households' migration by destination (rural, urban, international) between the two IHDS rounds. The coefficients can be interpreted as the rate of change in probability of sending out a migrant separately for agricultural and non-agricultural households. The p-values indicate significant difference in the effects. Other household-specific characteristics are controlled for, but are not reported. The weather variables are constructed using ERA5 data. Dependent variable uses information from both IHDS rounds. Household-level controls use information from IHDS-I. The sample is composed of rural households in India. Reported fixed effects are at the state-level. Clustered standard errors are displayed in parentheses.* p<0.10, ** p<0.05, *** p<0.01.

More precisely, we show that there is a significant difference in how illiterate and literate households react to negative precipitation anomalies. While the illiterate households are likely to send out migrants to cities in response to dry spells, the literate households do not react significantly. Moreover, the five destination model in Table B.6, Appendix B.6 suggests that the rural-urban moves usually take place to different, presumably more prosperous states (see Appendix B.6, Table B.7).

Additionally, we conduct several robustness tests, presented in Appendix, section B.9 to analyze the sensitivity of the main outcomes to the alternative measurement of education, alternative levels of error clustering or to exclusion of the state-specific time trends. We find evidence for most of the results of the main analysis.[12]

2.6 Projected rural-urban climate migration

We utilize the estimated coefficients to quantify the magnitude of the rural-urban climate migration in India that took place between the two IHDS rounds as suggested by model 3, Table 2.4. The focus is on migration to urban areas, since our results show that this type of migration is most likely to increase in response to weather extremes. The coefficients on positive and negative precipitation anomalies are significant. Hence, for quantifying the magnitude of past climate migration, we focus on these outcomes only. The results discussed below are presented in Table 2.7.

After estimating the model, we calculate the mean predicted probability of an increase in urban migration, by applying survey weights from IHDS-I. By multiplying the predicted probability (11.2%) with the number of rural households (approximately 126 million), we find that approximately 14.11 million households engaged into rural-urban migration between the two IHDS rounds. As a next step, we set the positive precipitation anomalies to zero and calculate the predicted probability of the same model for a scenario of past zero positive precipitation anomalies. By multiplying the predicted probability (10.6%) with the overall number of rural households, we estimate that approximately 13.36 million households would have engaged into migration if there had not been any positive precipitation anomalies. The difference between the number of migrant households predicted by the main model and under the scenario of zero positive precipitation anomalies indicates that 0.75 million households have engaged into migration in response to the positive precipitation anomalies. With an average increase

[12] Here, we discuss the outcomes of the sensitivity analyses of the results from section 2.5.3. They are presented in section B.9 of the Appendix. We use an alternative measure of education indicating whether households' head ever attended school (Table B.13). The evidence supports our main findings. We run our main model while clustering the standard errors at the state-level (Table B.14). Also in this case, we find evidence for the results from the main analysis. Last, instead of using state trends, we only use an overall trend (Table B.15). The results react sensitively to this change. We find additional evidence for the positive effect of rural-urban migration in response to negative precipitation anomalies for illiterate households, however the p-value suggests that the effect is not different from the one for the literate households.

Table 2.6: *Heterogeneous effects of weather extremes on the probability of out-migration conditional on education*

	Δ *Migration*		
	Rural	Urban	International
ΔTemp. anomaly (+) × Illiterate	-0.000892***	0.000341	-0.000319**
	(0.000224)	(0.000664)	(0.000129)
ΔTemp. anomaly (+) × Literate	-0.000566**	0.000798	-0.000237*
	(0.000222)	(0.000572)	(0.000122)
p diff.	0.1618	0.2827	0.4075
ΔTemp. anomaly (-) × Illiterate	-0.000624	-0.000967	-0.00180***
	(0.000593)	(0.00137)	(0.000469)
ΔTemp. anomaly (-) × Literate	-0.000650	-0.00187	-0.00147***
	(0.000594)	(0.00136)	(0.000444)
p diff.	0.9618	0.2892	0.3086
ΔPrecip. anomaly (+) × Illiterate	0.0000751	0.00177***	0.000422**
	(0.000227)	(0.000634)	(0.000212)
ΔPrecip. anomaly (+) × Literate	-0.0000897	0.00148***	0.000451**
	(0.000205)	(0.000552)	(0.000204)
p diff.	0.4619	0.4392	0.8915
ΔPrecip. anomaly (-) × Illiterate	-0.000140	0.00516***	0.000330
	(0.000713)	(0.00171)	(0.000518)
ΔPrecip. anomaly (-) × Literate	-0.000489	0.00141	0.000320
	(0.000620)	(0.00165)	(0.000500)
p diff.	0.6289	0.0024	0.9823
N		24845	
Fixed effects		Yes	
Clustering		District	

The outcomes correspond to a multinomial logit model, where the dependent variable indicates an increase in households' migration by destination (rural, urban, international) between the two IHDS rounds. The coefficients can be interpreted as the rate of change in probability of sending out a migrant separately for literate and illiterate households. The p-values indicate significant difference in the effects. Other household-specific characteristics are controlled for, but are not reported. The weather variables are constructed using ERA5 data. Dependent variable uses information from both IHDS rounds. Household-level controls use information from IHDS-I. The sample is composed of rural households in India. Reported fixed effects are at the state-level. Clustered standard errors are displayed in parentheses.* p<0.10, ** p<0.05, *** p<0.01.

in migration of 1.34 individuals per rural migrant household in India, this corresponds to approximately 1 million migrants in response to the positive precipitation anomalies. We do the same calculations for the negative precipitation anomalies. We find that between the two IHDS rounds there were approximately 1.5 million rural-urban climate migrants in India. This corresponds to almost 8% of all rural-urban moves.

Table 2.7: *Magnitude of past rural-urban migration in response to weather*

Scenario	Migration probability	Predicted nr. of migrant hh.	Δ in nr. of migrant hh.	Δ in nr. of migrants
Main model	11.20%	14.11 million		
Past zero precip. anomalies (+)	10.60%	13.36 million	0.75 million	+1 million
Past zero precip. anomalies (-)	10.93%	13.77 million	0.34 million	+0.46 million
Total nr. of urban climate migrants			1.46 million	
Climate migrants as % of all urban migrants			7.77%	
Total nr. of rural urban migrants			18.9 million	
Total nr. of rural hh. in IHDS-I			126 million	
Average increase in nr. of migrants per migrant hh.			1.34	

Migration probabilities represent the predicted probability of rural-urban migration from the multinomial logit model 3 in Table 2.4. They correspond to the probabilities from the main model and two different scenarios, i.e., past zero positive and negative precipitation anomalies. The predicted number of migrant households shows the number of households that engaged into rural-urban migration according to a given scenario. The change in the number of migrant households and migrants, represents the change compared to the respective figures predicted by the main model (all figures are rounded to millions). The estimations were conducted by applying survey weights.

2.7 Discussion and concluding remarks

In this study, we examine the direct and heterogeneous implications of temperature and precipitation extremes on rural out-migration in India to shed more light on the questions *who are the climate migrants?* and *where do they go?* Our work contributes to the existing literature examining weather effects on migration in India and to the emerging stream of literature explaining the heterogeneous weather implications (section 2.1). We construct a unique panel dataset combining novel high quality reanalysis data ERA5 with IHDS household panel. We analyze the direct and heterogeneous effects of weather extremes on households' decision to send out migrants to various destinations and predict how weather affects urbanization in India.

The data structure used within this study enables us to examine migration only at the household-level. We are only able to examine weather within a relatively short period of time and to match it to households only at the district-level. These aspects are limitations to our analysis. Migration would ideally be studied at the individual-level, matching weather variables with individuals at a finer resolution. To approximate the climate change experiment, a longer time span of at least 30 years would be ideal. Despite these shortcomings, we provide the first comprehensive analysis of attributing migration decisions to weather shocks accumulated over longer time to identify the profiles and destination choices of climate migrants in rural India. Given the character of the data this is the best possible approximation of the climate change experiment and its implications for migration.

We show that adverse weather shocks decrease same-state rural-rural and international migration and push people into cities. Potential explanation is that while migration to nearby rural areas becomes less attractive because of the high geographical correlation of weather shocks, international migration decreases due to stricter financial constraints. A series of positive weather shocks (i.e., more precipitation), however, facilitates international migration and migration to cities within the same state. Further, our results indicate that in contrast to other migrants, climate migrants are likely to be from the lower end of the skill distribution and from households strongly dependent on agricultural production. They are likely to migrate to distant cities in presumably more prosperous states, where weather is less likely to be correlated with the adverse conditions at the origin. We estimate that so far climate migration has only contributed little to urbanization (approximately 8%). This might however, change in the future as a result of climate change. Overall, our outcomes indicate that weather shocks disturb migration mechanisms and change the profile of rural migrants.

As suggested in section 2.2.1, one of the reasons for the slow structural change in India is that the urban destinations do not have sufficient capacity to absorb rural migrants because of their lower levels of education (OECD, 2017, 2018). This is potentially problematic, since we show that as a consequence of climate change, the inflow of rural migrants from the lower end of the skill distribution to Indian cities is likely to increase. Thus, a key policy recommendation is to take steps to facilitate integration of less educated migrants into urban labor markets to mitigate potential welfare losses under the climate change. Even though migration is costly, if it is undertaken in a sensitive manner, it may be an effective adaptation strategy (IPCC, 2014; Gemenne and Blocher, 2017). *To facilitate orderly, safe, regular and responsible migration and mobility of people, including through the implementation of planned and well-managed migration policies* is also stressed under the Sustainable Development Goal number 10.7.[13]

[13] 17 Sustainable Development Goals set by the United Nations General Assembly in 2015, define the global priorities for 2030 with the overarching goal to end poverty and put the world on a sustainable path (UNDP, 2018b).

There is still a lack of research on the migration flows under future global warming (IPCC, 2018). In the light of the above, a better understanding of the magnitudes of future climate migration as well as the destination choices and profiles of climate migrants is crucial to design targeted policies centered on the welfare of the directly and indirectly affected segments of population: the migrants, those left-behind and the receiving community. Therefore, future research should aim to provide more evidence in this direction.

Chapter 3

A Meta-Analysis of Climate Migration Literature[1]

Barbora Šedová
Lucia Čizmaziová
Athene Cook

[1]The authors are grateful for helpful suggestions and constructive comments from Rainald Borck, Max Callaghan, Maik Heinemann, Roman Hoffmann, Matthias Kalkuhl, Nicolas Koch, Katrin Millock, Jan Minx, Anouch Missirian, Nils Ohlendorf, Wolfram Schlenker and Johanna Wehkamp. We also benefited from the suggestions by the participants at the 6th World Congress of Environmental and Resource Economists in Gothenburg and Research Seminar in Economics of the University of Potsdam. Furthermore, we would like to thank Alkis Blanz, Christina Chang and Ana Grulovic for their support in the coding process.

Chapter Abstract

The large literature that aims to find evidence of climate migration delivers mixed findings. This meta-regression analysis i) summarizes direct links between adverse climatic events and migration, ii) maps patterns of climate migration, and iii) explains the variation in outcomes. Using a set of limited dependent variable models, we meta-analyze thus-far the most comprehensive sample of 3,625 estimates from 116 original studies and produce novel insights on climate migration. We find that extremely high temperatures and drying conditions increase migration. We do not find a significant effect of sudden-onset events. Climate migration is most likely to emerge due to contemporaneous events, to originate in rural areas and to take place in middle-income countries, internally, to cities. The likelihood to become trapped in affected areas is higher for women and in low-income countries, particularly in Africa. We uniquely quantify how pitfalls typical for the broader empirical climate impact literature affect climate migration findings. We also find evidence of different publication biases.

3.1 Introduction

Over the past decades, and especially in the context of continued climate change, human migration has increasingly become a matter of vigorous scientific and policy debates. In the assessment reports (AR) by the Intergovernmental Panel on Climate Change (IPCC) for instance, the total number of references with the word *migration* increased from 2 in the AR1 to 185 in the AR5 (Minx *et al.*, 2017). While one of the reasons behind this increased attention are the striking magnitudes of future migration flows predicted by some studies (Rigaud *et al.*, 2018),[2] the evidence suggests that the association between climate change and migration is not strictly positive (Berlemann and Steinhardt, 2017; Millock, 2015). To understand the relationship in its complexity, the scientific community has moved away from studying whether people migrate or not as a direct response to climatic effects and how many will do so in the future, towards studying the heterogeneous impacts (Black *et al.*, 2011a; Cattaneo *et al.*, 2019). Greater understanding of *when* and *how* climate change affects migration today and thus could have an influence in the future can importantly guide design and implementation of policy interventions, to avoid or mitigate any present and future welfare losses from climate change-related migration choices.

We contribute to this literature with the most comprehensive meta-regression analysis (MRA) to date, synthesizing all empirical analyses of climate migration published at least in a working format until October 31st, 2018. The broad range of research contexts and designs across original studies enables us to address the following questions: *How do different adverse climatic events affect migration?*, *What are the existing climate migration patterns?* and *What drives the differences in the existing evidence?* We meta-analyze a new, comprehensive and transparently constructed sample of 3,625 estimates retrieved from 116 original papers that examine the direct association between climatic events and human migration, applying regression analysis. Because of the heterogeneity of data and research designs across original studies, we classify the estimated effects by i) the statistical significance, and ii) the direction and statistical significance to estimate probit and multinational probit models respectively, following the practices, for instance, of Card *et al.* (2010); Waldorf and Byun (2005) or Wehkamp *et al.* (2018). We hypothesize that the variation across findings stems from different migration implications of different climatic events, as well as from factors related to modeling of climatic variables, conceptualizing and modeling of migration, diversity of study contexts and estimation techniques.

This MRA complements several streams of literature. First, we contribute to literature reviews that synthesize direct effects of climatic events on human migration (Berlemann

[2]Rigaud *et al.* (2018) forecast that over 143 million people in Sub-Saharan Africa, South Asia, and Latin America, will be forced to move within their own countries by 2050 as a result of slow-onset climate change alone.

and Steinhardt, 2017; Cattaneo *et al.*, 2019; Hunter *et al.*, 2015; Kaczan and Orgill-Meyer, 2020; Millock, 2015) by providing a quantitative summary with a multivariate regression analysis. We deliver new evidence showing that slow-onset climatic changes, in particular extremely high temperatures and drying conditions (i.e., extreme precipitation decrease or droughts), are more likely to increase migration than sudden-onset events. We also show that sudden-onset events do not significantly affect migration, either because migration is unlikely to serve as an adaptation to these events, or because capturing migration specific to sudden-onset events is challenging.

Second, by synthesizing the evidence from across different contexts, we contribute to the recent efforts to understand heterogeneous implications of climatic events for migration (Cattaneo *et al.*, 2019). This enables us to identify general patterns of and selection into climate migration. We show that climate migration patterns are strongly determined by budget constraints and climate-related sensitivity of livelihoods at the origin and at the destination. We also find systematic gender differences in climate migration, i.e., that women are generally less likely to self-select into migration to adapt to slow-onset climate change. We do not find, however, any gender differences in migration implications of sudden-onset events. This is an important contribution as these differences have thus-far been poorly understood (Cattaneo *et al.*, 2019), but play a crucial role for climate security.

Third, we complement two recent meta-analyses (i.e., Beine and Jeusette (2019) and Hoffmann *et al.* (2020)) of climate migration and close important research gaps. Unlike Hoffmann *et al.* (2020), who focus exclusively on macro studies at the country level to synthesize larger-scale effects of environmental factors on migration, we consider both micro- and macro-level analyses. By zooming into specific contexts, we reveal important nuances that cannot be found at aggregated levels. For instance, we shed more light on the selection into migration, detail specifics of climate migration patterns within countries' borders, or explore temporal dimensions. We further complement Beine and Jeusette (2019), who provide valuable insights into how modeling of migration and climatic variables, econometric approaches or contextual effects impact climate migration evidence, by uniquely studying potential biases from methodological pitfalls typical for the general climate impact literature, as discussed for example by Auffhammer *et al.* (2013), or Dell *et al.* (2014). Among other things, we show that not addressing spatial correlation of climatic events and correlation among climatic events, over-controlling, or not applying causal inference techniques systematically affects the evidence. The quantification of these biases serves also as an important contribution to the general climate impact literature. In addition, the samples of both aforementioned MRAs are substantially smaller compared to our comprehensive sample of 116 studies, which is representative of the whole literature landscape at the time.[3]

[3] The sample by Beine and Jeusette (2019) considers 51 and the sample by Hoffmann *et al.* (2020) has 30

Taken together, this MRA provides key contributions for the policy as well as scientific community, for example by uniquely mapping internal climate migration patterns - the most prevalent climate migration form, addressing longstanding methodological discussions in the climate impact literature, or analyzing biases by authors' disciplines and genders. Our MRA ensures high reliability and quality of the extracted information as every study has been coded by two independent coders. Lastly, we lay the foundation for a best practice of climate migration analysis and highlight important avenues for future research.

In the next section, we detail the construction of the population of original studies. Section 3.3 provides an overview of a conceptual and methodological approaches. Section 3.4 presents the meta-analysis outcomes from the aggregate sample and section 3.5 from sub-samples defined by climatic variables. Lastly, section 3.6 provides concluding remarks and discusses policy and research implications.

3.2 Assembling the sample of original studies

Studies qualify for our sample if they fulfill the following inclusion criteria: i) they are written in the English language, ii) they apply regression analysis to explain migration by climate-related drivers, iii) they perceive climatic events as push factors, iv) they report the minimum information as suggested by Stanley and Doucouliagos (2012) (i.e., regression coefficients, sample size, standard errors and/or t-statistics and/or p-values), and v) they report direct effects of climate-related variables. As for the last criterion, we exclude all estimates with interactions or polynomial terms. We acknowledge that interaction terms and polynomials provide important contextual information. However, because the original studies often only report the conditional effects, it becomes challenging to calculate the overall marginal effect of a climatic event unless the original data is retrieved and reanalyzed. Given the large number of studies and limited resources, we decided to follow recommendations by Stanley and Doucouliagos (2012) and restrict our sample only to direct effects. Nevertheless, the broad range in coding of climatic events and research contexts in our final sample of studies allows us to capture both the non-linear as well as the heterogeneous implications of climatic impacts for migration. Lastly, we did not impose any geographical or temporal inclusion criteria. Moreover, we considered both published studies and gray literature, which enables us to examine the existence of a publication bias.

To ensure that the construction of our sample of original studies is reproducible and transparent, in Appendix C.1 we detail the flow of articles through the searching and screening process. Here, we followed the RepOrting standards for Systematic Evidence

original studies.

Syntheses in environmental research (ROSES) ensuring that all necessary information is present and described in detail (Haddaway *et al.*, 2018). Figure C.1 then depicts an adaptation of the ROSES flow diagram and Table C.1 provides a comprehensive list of the collected papers. Overall, we identified 116 original studies. The main unit of analysis in our study is at the effect-level. One original study may contain several regression models and one regression model may contain more than one estimated effect of climate-related variables on migration. We decided to use all of this information and obtained a comprehensive sample of 3,625 estimated effects.

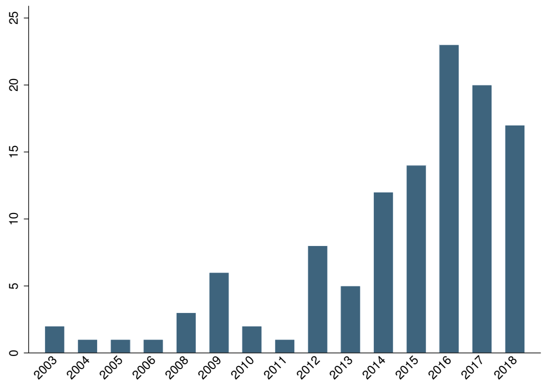


Figure 3.1: *Number of original studies by year*

Figure 3.1 shows that the econometric literature on climate-related migration emerged in the early 2000s and has been growing ever since, with most of the studies published in 2016. Table 3.1 provides descriptive statistics of the sample of original studies. It shows that the literature is dominated by male authors, since approximately 43% of primary authors of the original studies are female. 75% of the studies are published in peer-reviewed journals. An average study in our sample is cited approximately 50 times according to Google Scholar and published in a journal with an impact factor of 2.5.

Table 3.1: *Summary statistics: Sample of original studies*

Variable	Mean	Std. Dev.	Min.	Max.
Year	2014.509	3.427	2003	2018
Author female	0.431	0.497	0	1
Published	0.75	0.435	0	1
Citations	49.5	163.882	0	1659
Impact factor	2.523	5.403	0	41.063
N		116		

Figure 3.2 further displays the distribution of original studies by disciplines of lead authors. It shows that lead authors of 60% of the studies are economists, 13% are geographers, and almost 16% are sociologists, implying that the econometric climate migration literature is strongly dominated by these three disciplines.

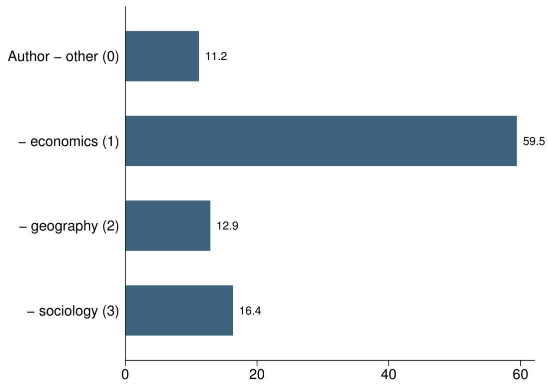


Figure 3.2: *Percent of original studies by discipline of the primary author*

3.3 Conceptual and methodological approach

In section 3.3.1, we illustrate the conceptual underpinning that guided the choice of information that we extracted from original studies. In section 3.3.2, we describe the generated variables. In section 3.3.3, we present the meta-analytic model.

3.3.1 Conceptual framework

The conceptual framework and the resulting choice of specific variables are guided by several streams of literature, namely the technical MRA literature, the climate impact literature, and the empirical climate migration literature.

First, the technical MRA literature suggests that a general meta-regression model can be summarized as follows (Nelson and Kennedy, 2009; Stanley and Doucouliagos, 2012):

$$Y = f(P, X) + e \tag{3.1}$$

where Y is the dependent variable that captures the estimated effect, P is the focal predictor (i.e., the key independent variable of interest), X covers a set of moderator variables recording different research designs, contexts and study characteristics assumed to systematically affect the evidence and lastly, e is the error term. We follow this structure, when coding variables to be applied in this MRA.

Second, the climate impact literature guided the choice and coding of focal predictors, i.e., adverse climatic events. Climate change involves long-run irreversible changes referred to as slow-onset events, as well as changing likelihoods and intensities of different sudden-onset shocks. As for the slow-onset events, warming climate is accompanied by sea-level rise (Levermann *et al.*, 2013), changes in precipitation patterns (Lehmann *et al.*, 2018), or increasing drought durations and intensities particularly over drying areas (Naumann *et al.*, 2018). These long-term changes are unlikely to reverse even if we would stop emitting carbon emissions completely (IPCC, 2013, 2018). In addition, global warming increases intensities and frequencies of sudden-onset shocks such as floods (Hirabayashi *et al.*, 2013; Lehmann *et al.*, 2018), hurricanes (Lin *et al.*, 2012), or tropical cyclones (Knutson *et al.*, 2010). On aggregate, these climatic changes are linked to severe economic damages (Burke *et al.*, 2015b; Dell *et al.*, 2012; Kalkuhl and Wenz, 2020).

Migration may serve as an important risk management strategy for affected populations to cope with adverse climatic events. At the same time, a stricter budgetary constraint resulting from such events may inhibit costly migration and trap populations in the affected areas. Thus, the association between adverse climatic events and migration depends on initial wealth. This has been formalized by i) Cattaneo and Peri (2016) with respect to slow-onset events, where migration may serve as an adaptation strategy, and ii) by Kleemans (2015) with respect to sudden-onset events, where migration may serve as a survival strategy. In this MRA, we draw on this framework to conceptualize the association between specific climatic events linked to economic losses and human migration. In section 3.3.2, we present the coded climatic variables.

Third, the in-depth analysis of both the empirical climate impact and climate migration literature guided our choice of moderator variables. These variables map the broad range in research foci and designs, data quality as well as information about the characteristics of lead authors and original studies across the empirical climate migration literature (Berlemann and Steinhardt, 2017; Cattaneo *et al.*, 2019; Millock, 2015; Neumann and Hermans, 2017; Piguet *et al.*, 2018). They capture factors that could potentially impose systematic biases across the estimated findings. The choice of specific variables is discussed in sections 3.3.2 - 3.3.2.

3.3.2 Sample of coded data

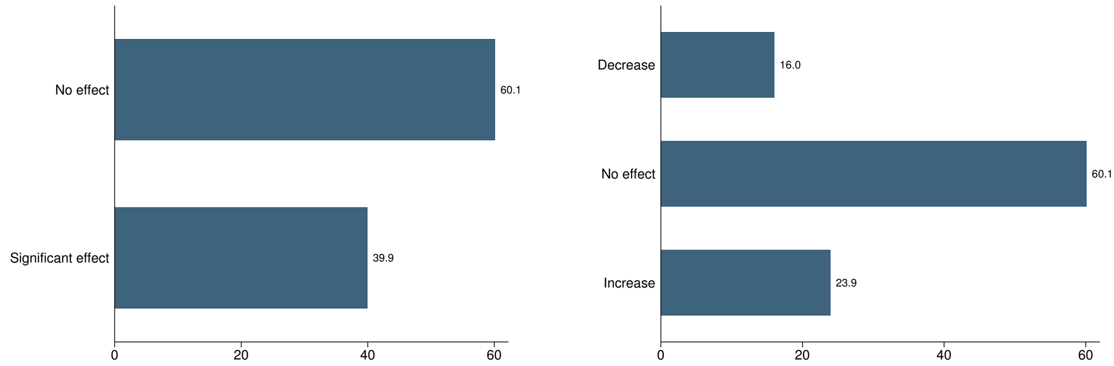
To maintain the highest scientific rigor, information extracted from original studies was double-coded by two independent coders. A third coder reviewed both sets of coding to merge the data and examine potential inconsistencies. Inconsistencies were then discussed among the coders to arrive at a shared understanding and resolution. We code dependent variables and several right hand-side variables categorized into the following five groups: i) climatic variables, ii) study-level variables, iii) sample characteristics, iv) migration-related variables, and v) econometric modeling variables. Appendix C.3, Table C.2 presents the respective summary statistics and Table C.3 the weighted summary statistics. For an overview of the distribution of categories of categorical variables, see Figure C.2 in Appendix C.3.

Dependent variable

Ideally, an MRA would extract impact coefficients from original studies that are immediately comparable to estimate the *true* effect of the focal predictor on the dependent variable. Here, estimating the effect size is not possible because of the substantial heterogeneity in research designs and contexts. First, there are significant differences in measurements of migration across the sample of original studies. The measurements include migration of individuals, movements of whole households, urbanization rates or asylum applications. The studies further differ in the level of the analysis, some providing micro- and some more aggregated perspectives. These varying conceptualizations of migration lead to significant differences in coding of the dependent variables (binary, count, continuous etc.). Second, the original studies employ a broad range of estimation techniques. Third, focal predictors, as well es their coding are also very heterogeneous across but also within different types of climate-related events. For example, temperature can be recorded in degrees Celsius, degree days, anomalies or deviations from the location-specific long-run mean. All of these differences impede the direct comparability of the coded effects (Stanley and Doucouliagos, 2012).

Thus, we follow the literature that utilizes limited dependent variable MRA models (Card *et al.*, 2010; Minviel and Latruffe, 2017; Waldorf and Byun, 2005; Wehkamp *et al.*, 2018). We construct two types of dependent variables. First, a binary variable that takes on a value of one if an adverse climatic event has a significant (at 10% level) effect on migration and zero otherwise. This variable enables us to analyze whether adverse climatic events generally change migration patterns, independent of the effect direction. Second, a categorical variable that takes on a value of one if climate migration significantly decreases, two if there is no significant effect and three if climate migration significantly increases. With this variable, we analyze the direction and the statistical significance of climatic effects on migration. For the distribution of the effects by dependent variable, see Figure 3.3.

An important aspect of our MRA is the coding of effects from two-stage models. In cases where for instance agricultural output is instrumented by several climate-related variables (see e.g., Feng *et al.* (2010); Iqbal and Roy (2015), or Viswanathan and Kumar (2015)) we code the effect of each climatic variable separately. As regards the direction and the statistical significance of each climatic variable, we consider them together with the direction and significance of the instrumented variable. If at least one of the two (i.e., instrumental and instrumented) variables is insignificant, we code an insignificant effect. If one of the two variables has a significantly negative and the other a significantly positive effect on the outcome, we code a negative effect. If both of the two variables have simultaneously a significantly negative or positive effect on the outcome, we code a positive effect.



(a) *Binary* **(b)** *Categorical*

Figure 3.3: *Dependent variable: Distribution of climatic effects on migration (percent)*

Climatic variables

Climate migration is typically studied according to the type of a climate-related driver. Given the discussion in section 3.3.1, we generate a binary variable (*Slow (1)*) only distinguishing between slow- (1) and sudden-onset (0) climatic events, to see whether their effects on migration systematically differ. We further generate a set of moderator variables capturing specific climatic events with a sufficient number of observations that are shown to cause economic losses. As regards the slow-onset events, there is evidence that higher temperatures (Burke *et al.*, 2015b; Dell *et al.*, 2012; Kalkuhl and Wenz, 2020), lower precipitation levels (Duflo and Pande, 2007; Jayachandran, 2006; Kleemans, 2015), droughts (Ding *et al.*, 2011; Meyer *et al.*, 2013) and sea-level rise (McAlpine and Porter, 2018; Sušnik *et al.*, 2015) are linked to economic losses. The effects of changing temperature and precipitation are non-linear and mostly felt at the extremes (Bohra-Mishra *et al.*, 2014; Burke *et al.*, 2015b; Carleton and Hsiang, 2016; Schlenker and Roberts, 2009). Based on this evidence, we code two categorical variables: i) *Temperature increase* and ii) *Precipitation decrease*. Both of them take on three different values: zero if an effect is not related to temperature or precipitation, respectively; one if an effect captures a moderate; and two if it captures an extreme change. We code extreme effects, if models in original studies employ functional forms indicating substantial deviation from normal conditions (i.e., minimum/ maximum levels surpassed, conditions above/below two standard deviations from the long run average, warm/cold or dry/wet spell, degree days above optimal temperature, days below/above min./max. and more). We code moderate effects if climatic variables are expressed in e.g., levels, standard deviations or logarithms. Further, we code two binary variables capturing an effect of a *Drought (1)* and *Sea-level rise (1)*. As for sudden-onset events, there are examples of economic damages as a result of floods (Carrera *et al.*, 2015; Haddad and Teixeira, 2015; Meyer *et al.*, 2013) and hurricanes (Strobl, 2011, 2012). Correspondingly, we code binary variables

Flood (1) and *Hurricane/cyclone/typhoon (1)*.

To account for the source of climate-related data, we employ a binary variable *Self-reported event (1)*. It takes on a value of one if a study uses self-reported climatic events and zero if more objective data from existing weather products (e.g., weather stations, reanalysis or gridded data-sets (Auffhammer *et al.*, 2013; Donaldson and Storeygard, 2016)) is used. Self-reported weather data is often applied in climate impacts studies (e.g., Gray and Mueller (2012a), or Koubi *et al.* (2016c)). Yet, they may be biased, depending on the motivation or ability of surveyed individuals to accurately report a climatic event.

We further construct a variable capturing the temporal dimension of the association between a climatic event and migration. Researchers use different approaches to define climatic events not only in terms of functional forms but also temporal dimensions. For instance, some studies focusing on low-income countries hypothesize that migration takes place at *t+1* after income from agriculture (determined by weather) is realized at the end of the year *t* (Bazzi, 2017; Gray and Mueller, 2012a). However, there are also studies that look at the direct association between migration and weather (Beine and Parsons, 2014; Nawrotzki *et al.*, 2015b). While, these considerations are often guided by a specific theoretical framework, we abstract from their discussion. Rather, we focus on the biases that they cause in practice. We employ a binary variable *Direct event (1)*, which takes on a value of one if a given climatic variable is directly associated with migration and zero if there is a time lag (we do not distinguish between the length of the lag).

Lastly, the coding of specific climatic events varies widely across but also within different event types. We analyze if and how different measures of specific events impact the estimated effects in section 3.5, when conducting MRA of sub-samples defined by specific climatic events. For temperature- and precipitation related MRAs we differentiate between measures capturing variability (e.g., anomalies or deviations), extremes (see above) and levels (e.g., degrees Celsius, millimeters). For drought-related MRA, we differentiate between binary treatments and measures of intensity. For flood-related MRA, we distinguish between binary treatments, measures capturing economic losses or event counts.

Study-level variables

This group of variables records characteristics of the original studies, as partially introduced in section 3.2. Specifically, we employ a binary variable capturing the lead authors' gender (*Author - female (1)*), a categorical variable capturing the lead authors' discipline (*Author - discipline*), a continuous variable accounting for the year of publication or latest draft of the original study (*Year of publication/ latest draft*) and lastly a binary variable that captures whether the original study is published in a peer-reviewed journal or not (*Peer-reviewed (1)*), to potentially detect a general publication bias (a similar approach is taken by e.g., Card *et al.* (2010), or Wehkamp *et al.* (2018)). Publication bias arises when a certain type of result tends to be published in peer-reviewed journals. It is a well-documented phenomenon in social sciences (Franco *et al.*, 2014; Gerber and Malhotra, 2008). Selective reporting of scientific findings increases the likelihood that published evidence reflects type I errors rather than true population parameters. It also inhibits assessment of the state of knowledge since a certain type of outcome is not observable (Franco *et al.*, 2014). As regards climate migration, learning experience impeded by publication bias might directly lead to inefficient resource allocation or programming and thus have direct adverse welfare effects. In addition to the variable *Peer-reviewed (1)*, the remaining study-level variables might detect other forms of a publication bias. For instance, authors of different disciplines, or genders[4] might have different motivations to publish a certain type of results, or due to scientific advances (e.g., in terms of data or methods), newer studies might more accurately capture the true relationship.

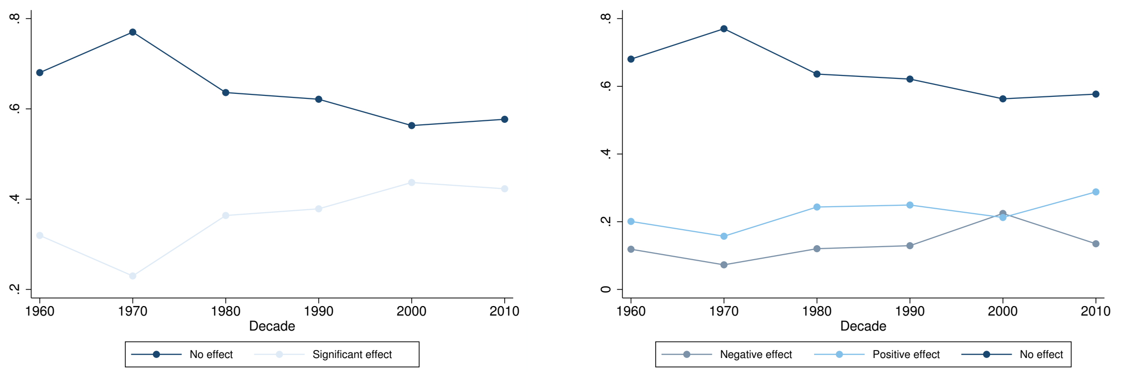
Sample characteristics

These moderator variables record the framework of a model, from which a specific coefficient is derived. One study usually contains several models and these can be applied to various sub-samples of data. The binary variable *Micro-level analysis (1)* takes on a value of one if a coded effect is derived from an analysis conducted at the micro-level and zero for more aggregated analyses. Micro-level analyses provide more detailed information that might get lost in the aggregated perspectives capturing larger-scale trends, and vice versa. Thus, this variable also accounts for any systematic difference in our results compared to Hoffmann *et al.* (2020) exclusively meta-analyzing macro-level studies. We further employ a set of decadal dummies starting from 1960 onward, capturing whether data-sets cover a specific decade. If a model uses data stretching over several decades, the respective decadal dummies take on a value of one.[5] Figure 3.4 shows the distribution of significant and insignificant (3.4a), and significantly positive, significantly negative and insignificant (3.4b) effects over time using these temporal dummies. The increase in the fraction of significant effects over time suggests that change in migration strategy has been increasingly used as a response to adverse climatic events. Yet, when differentiated by effect direction, we do not observe substantial differences in the distribution of significantly positive and negative effects over time.

Similarly, following Hoffmann *et al.* (2020), we further generate three binary variables, namely *Low-income included (1)*, *Lower-middle income included (1)* and *Higher-middle income included (1)*. Each of them takes on a value of one if an effect is derived from a model

[4]For instance, men are shown to be more likely to take risks to achieve higher status and engage in questionable research practices (Fang *et al.*, 2013).

[5]Some of the studies consider data covering periods before 1960. Yet, the number of observations is very small. Thus, we abstract from coding decadal dummies from before 1960.



(a) *In-/significance (%/year)*　　**(b)** *Direction and significance (%/year)*

Figure 3.4: *Temporal distribution of estimated effects of adverse climatic events on migration*

covering a sample of low-income, lower-middle-income and/or upper-middle-income countries, as classified by the World Development Indicators dataset (World Bank, 2020). If a model uses data covering countries from several income categories, all the respective dummies take on a value of one. This enables us to test the established inverted U-shaped relationship between economic development and climate migration, i.e., a climate-related income decline may depress migration of the very poor, but provide incentives to move to the less poor populations (Cattaneo and Peri, 2016). We further code a binary variable *Multiple countries (1)* that takes on a value of one if a given coefficient is derived from a model using a sample covering several countries. Such analyses might reveal completely different trends than country-specific studies. For instance, they might fail to reveal certain patterns if countries from different economic groups are considered.

Lastly, we code a set of continent-specific dummies to map the literature visually. Figure 3.5 displays the number of estimated coefficients by countries and continents as well as their continent-wise distribution among negative, positive and insignificant effects.[6] Most of the evidence covers Asia, Africa and North America. Obvious geographical research gaps are well documented by the country-specific map. For instance, as regards Europe we only have evidence of climate migration from the Netherlands. The stacked bar chart suggests that the likelihood to become immobile (i.e., decrease in migration) in response to adverse climatic events is the largest on the African continent in line with Millock (2015). On the contrary, migration is most likely to be positively associated with adverse climatic events in Asia, North and South America, with 27-28% of significantly positive effects. The chart does not cover Australia, since we only have very few (i.e., 25 effects) respective observations and so the effect distribution could provide a biased picture of climate migration trends.[7]

[6] The figure at the continent-level does not display effects derived from multi-continent models. Similarly,

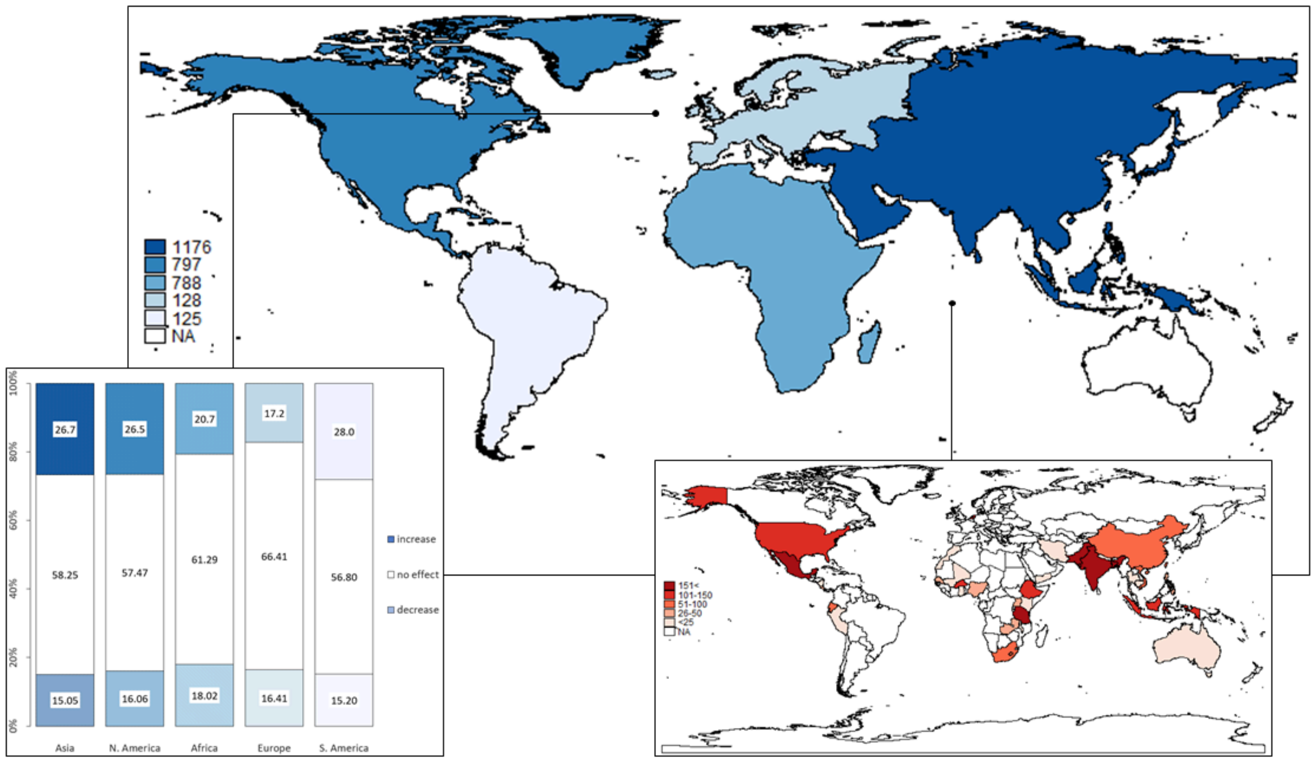


Figure 3.5: *Number and distribution of estimated effects of adverse climatic events on migration (effects from multi-continent or multi-country models are not included)*

Migration-related variables

We code several moderator variables to cover the heterogeneity in modeling migration. We distinguish between temporal, as well as spatial dimensions related to the origin and the destination of migrants. The categorical variable *Origin* records whether the model considers out-migration from rural (0) or urban (1) areas or whether the origin is not defined (2). Figure C.2 in Appendix C.3 suggests that we only have very few observations of climate migration from urban areas. The variable *Destination 1* distinguishes between internal (0), international (1) or undefined (2) destination choices. The variable *Destination 2* captures whether the model considers migration to rural (0) or urban (1) destinations or whether the destination is not defined at this scale (2). The binary variable takes on a value of one, if an original model explicitly considers temporary migration of less than a year. Further, the binary variable *Measurement (1)* indicates whether the migration measure accounts for out-migration only (unilateral (0)), or both out- and in-migration (bilateral (1)). By employing the variable *Migrants*, we also analyze the effect of the migration domain, i.e., what group of potential migrants does the study look at. In the original studies, these different domains are typically captured by using specific sample compositions. We distinguish between migration of women (0), men (1), whole households (2), overall (3) migration and other (4) categories. For all variables, we abstract from the interpretation of these *undefined* effects, but include the categories for the sake of sample completeness.

Econometric modeling variables

Literature points out common mistakes from specific analytic choices, when studying climatic impacts using econometric methods (see e.g., Auffhammer *et al.* (2013); Berlemann and Steinhardt (2017) or Dell *et al.* (2014)). To quantify the resulting biases, we employ a set of moderator variables as presented below.

The categorical variable *Approach* distinguishes between different estimation techniques applied in climate migration literature. It takes a value of zero, if a coefficient is derived from a cross-sectional analysis, where the identification comes from geographical variation in climatic conditions at one point in time (- *cross-section (0)*). The variable takes on a value of one, if the applied econometric approach draws on longitudinal data, as well as time- and unit of observation-specific fixed-effects (- *panel - causal (1)*). Here, the identification of climatic responses comes via deviation from the mean over time, comparing a given entity under different climatic conditions. The estimates can thus be

the figure at the country-level does not display effects derived from multi-country models.

[7] At the time we finalized the literature search for our MRA, we could not identify more studies with this geographical focus, fitting the inclusion criteria. However, recently new evidence from Australia emerged importantly contributing to filling this gap, see for instance Zander and Garnett (2020a,b).

interpreted causally. Further, the variable takes on a value of two if an effect is derived using instrumental variable approach (- *IV (2)*), as explained in section 3.3.2. Lastly, *Approach* takes on a value of three (- *panel-other/pool (3)*), if the coefficient is derived from an analysis that uses pooled data or panel data, where the coefficients might suffer from an omitted variable bias (i.e., models do not simultaneously apply unit of observation- and time-specific fixed effects).

This moderator variable directly addresses longstanding academic debates in the climate impact literature on how to estimate agents' responses to the changing climate (Dell *et al.*, 2014). Notably, panel data analyses are often compared to classical cross-sectional studies. The cross-sectional approach may suffer from an omitted variable bias, because the climatic variable of interest as well as the outcome variable may both be correlated with other factors which cannot always be adequately controlled for. Compared to cross-sectional techniques that typically analyze effects of long-run temperature and/ or precipitation averages, panel studies have been criticized for poorly capturing the effect of climate since the responses are derived from short-term weather variations. Nevertheless, due to omitted variable concerns it has been the preferred approach established as a quality standard in the literature. For instance, other meta-analyses from climate impact literature such as Hoffmann *et al.* (2020), or Hsiang *et al.* (2013) use these standards as inclusion criteria for their sample of original studies. Our intention differs from these efforts. By including analyses using different econometric designs, we aim to examine whether applying causal inference techniques produces systematically different outcomes. We also conduct a sensitivity test only considering sub-sample of studies using causal inference to see whether not applying these quality standards affects our main conclusions (see Appendix Table C.9).

Another recently raised concern by climate impact scholars addressed with the variable *Approach* is the application of climatic variables as instruments to study their effect through a particular intermediary variable (Burke *et al.*, 2015a; Koubi, 2019). Climatic events have been shown to significantly impact a variety of socio-economic outcomes (Carleton and Hsiang, 2016; Dell *et al.*, 2014), which might plausibly also affect the decision to stay or leave (Black *et al.*, 2011a), such as conflict (Hsiang *et al.*, 2013), mortality (Deschênes and Moretti, 2009) or agricultural income (Schlenker and Roberts, 2009). Thus, the exclusion restriction (i.e., climate only affects migration through its effect on the instrumented variable) necessary for the validity of climatic variables as instruments might be violated (Angrist and Pischke, 2009) and systematically bias the evidence.

Spatial correlation of weather is another important issue in the climate impact literature. Unless this spatial correlation is addressed, produced standard errors might be biased. Clustering of standard errors at the level of the geographical aggregation of the treatment is most commonly applied to address this issue (Auffhammer *et al.*, 2013).

Hence, we employ a respective binary moderator variable *Clustered std. errors (1)*.

Further, the specification of econometric models is non-trivial. Climatic events are correlated. If a model only accounts for one climatic variable, this causes an omitted variable bias (Auffhammer *et al.*, 2013; Berlemann and Steinhardt, 2017). Thus, there are good reasons to believe that the number of climatic controls could systematically affect the estimated outcomes. The variable *Nr. of climatic variables*, which captures the model-specific number of additional climatic variables controlled for, allows us to examine these potential biases.

Moreover, econometric models often include controls (e.g., income or conflict), which have been shown to be direct outcomes of climatic events and to also have an impact on the outcome variable (i.e., migration). This causes the *over-controlling* problem (Dell *et al.*, 2014), also referred to as the *bad controls* problem (Angrist and Pischke, 2009). To analyze whether and how these specification choices affect the derived estimates, we employ three moderator variables. The count variable *Nr. of controls* records the total number of controls that an econometric model includes in addition to the considered climatic event. The binary variables *Income-related controls (1)* and *Polit. stability controls (1)* take on a value of one if a given econometric model controls for an income-related variable (e.g., agricultural income, household wealth), and/or a variable capturing political situation, respectively. These are the most common controls included in the climate migration models that contribute to the *over-controlling/bad controls* problems.

Lastly, the binary variable *Main model (1)* takes on a value of one if a derived effect is presented in the main model of the original study and zero otherwise. It shows whether authors have a bias towards publishing a certain type of result in the main model. Thus, similar to the variable *Peer-reviewed*, this variable is typically employed in meta-analyses to detect the presence of a publication bias.

3.3.3 Meta-analytic models

We employ two types of limited dependent variable models. Firstly, we estimate a probit model, whereby the binary dependent variable takes on a value of one if a given climatic variable has a significant effect on migration and zero otherwise. Among other things, this model enables us to understand in which contexts climatic variables have a significant effect on migration. The probability of obtaining a positive outcome is given by (Maddala, 1986; Wooldridge, 2010):

$$P(y_i = 1|x_{ims}, \beta) = \int_{-\infty}^{-x_{ims}\beta} \phi(z)dz \tag{3.2}$$

where $\phi(z)$ denotes the standard normal density and y captures the (in)significance of the estimated effect i. For simplicity, x summarizes the focal predictors, as well as the set of moderator variables at the effect-, model- (m) or study-level (s) and β covers the respective parameters to be estimated.

Secondly, we estimate a series of multinomial probit models (MNPs). MNPs are random utility models with a discrete dependent variable with more than two outcomes that have no natural ordering. We code a categorical dependent variable accounting for the significance and direction of the estimated migration effect. It takes on a value of one if migration decreases, two if there is no significant change in migration and three if migration increases in response to a given climatic variable. Among other things, this model enables us to examine the direction in which specific climatic events affect migration. The dependent variable y_i for the ith effect takes on a value $j = 1, 2$ or 3 and is associated with an underlying latent variable $y^{\star}_{ij}$, such that:

$$y^{\star}_{ij} = x_{ims}\beta + \epsilon_{ij} \tag{3.3}$$

where ϵ_{ij} have independent standard normal distributions. The outcome $y^{\star}_{ia}$ is chosen if $y^{\star}_{ia} > y^{\star}_{ib}$ for $a \neq b$. Hence, the probability of observing, for instance, the first effect category (i.e., $j = 1$) is given as follows:

$$P(y_{i1}) = P[y^{\star}_{i1} > y^{\star}_{i2}] \;\&\; P[y^{\star}_{i1} > y^{\star}_{i3}] \tag{3.4}$$

Similar expressions can be derived for $P(y^{\star}_{i2})$ and $P(y^{\star}_{i3})$. We choose MNP rather than a multinomial logit model (MNL). The MNL model imposes strict assumptions on the error terms as it restricts the correlation between each pair of errors in the model to be zero. This causes the Independence of Irrelevant Alternatives (IIA) problem, i.e., the multinomial logit assumes that the relative probabilities of any two outcomes are unaffected by the addition of another outcome. MNP, on the contrary, allows for all possible correlations among error terms (Maddala, 1986; Hausman and Wise, 1978).

As suggested by Nelson and Kennedy (2009), a complete meta-analysis should address heterogeneity, heteroscedasticity and correlation of the observations. The term heterogeneity implies that the estimates from the original studies do not measure the same effect. To address this issue, we employ a set of moderator variables (X in model 3.1) that capture the potential sources of heterogeneity.

As a result of different primary sample sizes, sample observations and estimation techniques, the estimated effects have non-homogeneous variances, i.e., suffer from heteroscedasticity. As a consequence, some estimates are more reliable (smaller variance, or larger sample size) than the others (larger variance, smaller sample size). Typically, the inverse of variances is used to control for such robustness differences. However, numerous original studies in our sample do not report this information. Alternatively, the sample size can also be used as a weight since it is inversely related to the variance (Waldorf and Byun, 2005). Following the MRA literature (e.g., Horowitz and McConnell

(2002); Waldorf and Byun (2005); Nelson and Kennedy (2009); Wehkamp *et al.* (2018)) we use this approach to maximize the statistical efficiency of the meta-analysis. As regards the functional form of the weights we follow Wehkamp *et al.* (2018) and apply a log of square root of the sample sizes. The square root gives higher weight to the effects from models with more observations, but at a decreasing rate. We utilize the log-transformation, since the wide range of the square root sample size values (min. 6.24; max. 14541.7) could lead to over-correction for robustness differences when weighting.

Further, since we use multiple estimates per primary study, these observations may be correlated within studies. To account for this potential within-study dependence, we follow Nelson and Kennedy (2009); Card *et al.* (2010); Wehkamp *et al.* (2018) and apply robust standard errors clustered at the study-level.

3.4 Results from an aggregate MRA

Here, we report outcomes from MRAs of the full sample of reported effects. Table 3.2 shows average marginal effects from probit (i.e., model (1) according to equation 3.2), and multinomial probit (i.e., model (2) according to equation 3.3) models. In the interest of space, we do not report standard errors (for the comprehensive outcomes, see Appendix C.4, Table C.4). We find that extreme temperatures unlikely reduce migration and the positive, at conventional levels insignificant effect on migration increase is an indication of a generally positive association. This evidence underlines the non-linear impacts of temperature mostly felt in the extremes (Burke *et al.*, 2015b; Schlenker and Roberts, 2009). Moderate precipitation decrease is not likely to reduce migration, but rather suggests to have no effect. While both extreme precipitation reduction and droughts unlikely reduce migration, their positive, yet insignificant effects on migration increase further support broader conclusions from the literature (see e.g., Cattaneo *et al.* (2019)) that drier conditions are linked to departures. Sea-level rise is likely to have an insignificant effect, contradicting conclusions by Perch-Nielsen *et al.* (2008) that sea-level rise is positively associated with migration. A possible explanation of our rather counter-intuitive findings is that the historical sea-level rise has not yet crossed the critical magnitudes that would trigger out-migration. At the same time, our sample only has a very small number of observations (less than 3%) capturing sea-level rise effects. Both of these factors hinder drawing meaningful conclusions and imply that more evidence in this direction is needed. Floods are likely to have an insignificant migration effect as also suggested by Perch-Nielsen *et al.* (2008), who indicate that floods prompt adaptive responses other than moving. We further find that hurricanes are unlikely to reduce migration and an indication (yet the effect is insignificant) that they are likely to have an insignificant effect.

Overall, these patterns have two possible explanations. Firstly, change in migration behavior is more likely to serve as an adaptation to slow-onset events that have irreversible implications possibly by allowing more time to gather resources to migrate. In contrast, sudden-onset events rapidly deplete resources, reducing the ability to move (Kaczan and Orgill-Meyer, 2020). Alternatively, sudden-onset events tend to be associated with a type of moves that are difficult to capture, such as short-distance or irregular migration (Cattaneo *et al.*, 2019; Ponserre and Ginnetti, 2019). To resolve this, more research on migration responses to rapid-onset events and possible mechanisms behind them is needed. We further compare this evidence with conclusions of the other two MRAs of climate migration. Our findings that extreme temperature and precipitation changes induce migration are in line with Hoffmann *et al.* (2020), but contrast Beine and Jeusette (2019), who show that extreme temperatures do not affect mobility. Our conclusions on the implications of floods are in line with Beine and Jeusette (2019), but contrast Hoffmann *et al.* (2020) who suggest that rapid-onset events induce migration. Overall, differences in results can likely be explained by diverging samples considered in the respective MRAs.

Table 3.2 further shows that direct adverse climatic events are by 7 p.p. less likely to decrease migration compared to lagged events. Even though insignificant, the impact on the migration increase further implies that this association might generally be positive. Kleemans (2015) provides a possible explanation suggesting that contemporaneous income decrease triggers survival migration. This contrasts the insignificant effect of a time lag between environment-migration association revealed by Hoffmann *et al.* (2020).

As regards study properties, we find evidence of various biases. Authors from disciplines of economics and geography are likely to report an increase in climate migration. We further reveal that newer studies are likely to find an insignificant effect (2 p.p./year), possibly reflecting advances in data availability and quality or methodological advances, which enable more precise estimations. This finding contrasts Beine and Jeusette (2019), who find no systematic differences based on the year of publication. Moreover, in contrast to Beine and Jeusette (2019) and Hoffmann *et al.* (2020) we find evidence of publication bias in the aggregate climate migration literature, i.e., peer-reviewed journals are likely to report a significant decrease in migration in response to adverse climatic events.

As for sample characteristics, we reveal that in low-income countries climatic events do not significantly affect migration. However, we find an indication of a positive association in lower-middle income countries. We find a clearly positive relationship between climatic events and migration in upper-middle income countries. This evidence is suggestive of the inverted U-shaped relation between economic development and migration as discussed in section 3.3.2 and is in line with findings by Hoffmann *et al.* (2020).

As regards migration-specific moderator variables, studies where the origin of migration is urban are more likely to find an insignificant effect of adverse climatic events on migration compared to studies that analyze rural out-migration. A potential explanation is that in rural contexts, where livelihoods are more dependent on climate-sensitive activities (e.g., agriculture), migration serves as an important adaptation strategy (Cai *et al.*, 2016; Feng *et al.*, 2010; Šedová and Kalkuhl, 2020). Yet, we only have a few observations in the category *Origin - urban* (see Appendix C.3, Figure C.2) and more evidence in this direction is needed to verify the validity of these outcomes. Studies that use a bilateral measure of migration are unlikely to find evidence of climate migration, compared to studies that use a unilateral measure. The explanation is rather intuitive, since migration rates captured by bilateral measures are lower than unilateral measures as they are reduced by the number of in-migrants. Further, females are generally less likely to significantly adapt their migration strategy in response to adverse climatic events, possibly because male household members typically migrate in search of alternative livelihoods (Chindarkar, 2012).

Lastly, we show that differences across estimation techniques and model specifications significantly affect the estimated outcomes. Estimates derived using causal inference are by 9 p.p. less likely to find a significant increase in climate migration compared to cross-sectional analyses. Thus, cross-sectional analyses likely overestimate the positive effect of climatic events on migration, if we assume that causal inference techniques more accurately captures the climate-migration association. Models that control for more climatic variables are less likely to find a significant effect, with a decrease in likelihood by almost 2 p.p. per an additional climatic control included. Because climatic events are correlated, an additional climatic event controls out the variation of already included climatic variables and increase the likelihood of their insignificance. Further, an additional control included reduces the likelihood of finding a decrease in climate migration. Moreover, controlling for variables approximating income or political situation are less likely to find a significantly positive association between migration and adverse climatic events. These outcomes support the conclusions derived by Cattaneo *et al.* (2019) that wealth and political stability are important mechanisms through which climatic events have an effect on migration. Including them in econometric models controls out an important part of the variation of climatic events and causes the over-controlling problem. The remaining residual effect tends to be biased downwards.

In Appendix C.5, we show a series of sensitivity tests examining whether and how the derived conclusions depend on our research design choices. First, in Table C.5, we analyze whether there is generally a difference in implications of slow- and sudden-onset climatic events. Second, in Tables C.6, C.7 and C.8 we employ alternative weighting strategies. Third, in Table C.9 we meta-analyze a sub-sample of effects derived from analyses using causal inference techniques (see section 3.3.2). Fourth, in Table C.10 we meta-analyze a sub-sample of effects with focus on international migration to understand whether there are different climatic drivers of internal and international moves. Overall,

Table 3.2: *Meta-analytic probit (1) and multinomial probit (2) models*

	(1)	(2)		
	Significant effect	Decrease	No effect	Increase
Climatic variables				
Temp. increase - moderate (1) / ref.: no temp. (0)	0.015	-0.050	-0.009	0.059
- extreme (2)	0.037	-0.134***	-0.064	0.198
Precip. decrease - moderate (1) / ref.: no precip. (0)	-0.109	-0.092**	0.111	-0.019
- extreme (2)	-0.048	-0.131***	0.044	0.087
Drought (1)	-0.023	-0.140***	-0.023	0.163
Sea level rise (1)	-0.282***	-0.149***	0.249***	-0.100
Flood (1)	-0.192***	-0.075**	0.208***	-0.133**
Hurricane/cyclone/typhoon (1)	-0.133	-0.092**	0.127	-0.034
Self-reported event (1)	-0.056	-0.001	0.041	-0.040
Direct effect (1)	-0.036	-0.074***	0.034	0.040
Study-level variables				
Author: female (1)	0.026	-0.037	-0.022	0.060
Author - economics (1)/ref.: other (0)	0.085	-0.076	-0.071	0.147***
- geography (2)	-0.042	-0.171***	0.027	0.144**
- sociology (3)	-0.098	-0.083	0.095	-0.012
Year of publication/ latest draft	-0.021**	-0.013***	0.021***	-0.008
Peer-reviewed: yes (1)	-0.002	0.045*	0.009	-0.054
Sample characteristics				
Micro-level analysis (1)	-0.040	0.012	0.045	-0.057
Multiple countries (1)	-0.022	-0.037	0.032	0.005
Low income included (1)	-0.000	-0.014	0.001	0.013
Lower-middle income included (1)	-0.052*	-0.052**	0.049	0.003
Higher-middle income included (1)	0.066**	0.006	-0.065**	0.058**
Migration-related variables				
Origin - urban (1)/ ref.: rural (0)	-0.199**	-0.119***	0.198**	-0.080
- undefined (2)	0.021	-0.000	-0.010	0.011
Dest. 1 - internat. (1)/ ref.: internal (0)	-0.010	-0.021	-0.003	0.023
- undefined (2)	-0.001	-0.000	0.002	-0.002
Dest. 2 - urban (1)/ ref.: rural (0)	-0.069	-0.091	0.081	0.010
- undefined (2)	-0.014	-0.074	0.019	0.055
Temporary (1)	0.097	0.010	-0.088	0.077
Measurement - bilateral (1)	-0.107**	-0.001	0.106**	-0.105***
Migrants - male (1)/ ref.: female (0)	0.057	0.044	-0.056	0.012
- households (2)	0.216***	0.146***	-0.205***	0.059
- overall (3)	0.198***	0.073*	-0.198***	0.125***
- other (4)	0.269***	0.081*	-0.267***	0.186***
Econometric modeling variables				
Approach - panel-causal (1)/ref.: cross-section (0)	-0.076	0.020	0.066	-0.087*
- IV (2)	0.071	0.106	-0.097	-0.009
- panel-other /pool (3)	0.034	0.034	-0.038	0.004
Clustered std. errors (1)	0.033	0.002	-0.019	0.017
Nr. of climatic variables	-0.016**	-0.004	0.015**	-0.011*
Nr. of controls	-0.002	-0.003**	0.002	0.001
Income-related controls (1)	-0.038	0.041*	0.037	-0.078**
Polit. stability-related controls (1)	-0.009	0.072*	0.004	-0.076*
Main model (1)	0.015	0.005	-0.011	0.006
Observations	3625	3625	3625	3625

Coefficients in model 1 capture the rate of change in probability of finding a significant effect of adverse climatic events on migration. Coefficients in model 2 capture the rate of change in probability of finding a significantly negative (1), no (2) or significantly positive (3) effect of adverse climatic events on migration. Std. errors are clustered at the study-level. Both models also control for decade-specific dummies. In the interest of space and because we do not find strong results the coefs. are not reported. For the full model specification with std. errors, see Appendix Table C.4). * p<0.10, ** p<0.05, *** p<0.01.

these tests provide strong support for the outcomes from the main analysis. New, notable evidence is i) a clear positive effect of extremely high temperatures and extremely dry conditions, ii) that when applying an instrumental variable approach, researchers are unlikely to find an insignificant effect, and iii) climate migration mostly takes place internally. For a more detailed discussion, see Appendix C.5.

3.5 Results from MRAs by climatic events

Here, we present outcomes from several MRAs of climate migration direction for sub-samples defined by climatic events with the highest number of reported effects. The outcomes are reported as mean marginal effects of moderator variables and are presented visually in four different sub-sections, by the following four climatic events: temperature increase (section 3.5.1, Figure 3.6), precipitation decrease (section 3.5.2, Figure 3.7), droughts (section 3.5.3, Figure 3.8) and floods (section 3.5.4, Figure 3.9). These analyses enable us to examine systematic biases that may stem from unique approaches to studying implications of specific climatic events (e.g., modeling droughts or floods, discipline-specific biases) and particular migration patterns they induce. The set of moderator variables in each of the following sections might differ from the comprehensive list employed in the main analysis (section 3.4), as some of the variables were causing multicollinearity in these more restricted samples. Differences in model specifications are discussed in Appendix C.6.

3.5.1 Temperature increase

We show that studies drawing on self-reported events are likely to find an insignificant association between higher temperatures and migration. As suggested in section 3.3.2, self-reported data may be biased. Our findings imply that these less objective measures distort the climate migration evidence. We find a clear positive association between direct, as well as extreme effects of temperature and migration, amplifying the weak evidence from the main analysis.

We reveal that female authors are unlikely to report a negative effect of a temperature increase on migration. A plausible explanation is that female authors are less likely to take risks and present new findings that do not match the conventional narrative (Fang *et al.*, 2013) that climatic hazards induce migration. We only find a weak evidence that economists and geographers are likely to report a significant increase in climate migration. We reveal that sociologists tend to find an insignificant effect of temperatures.

We show that studies conducted at the micro-level are likely to find a decrease in migration in response to higher temperatures. This emphasizes the necessity of conducting both micro- and macro-level studies as they seemingly capture different trends in climate migration. It also underlines that this MRA complements Hoffmann *et al.* (2020), who exclusively focus on macro analyses. Moreover, we find additional evidence for the inverted U-shaped relation between economic development and climate migration.

The outcomes further indicate that higher temperatures are unlikely to reduce temporary migration and the insignificant coefficients suggest a generally positive association. This is in line with Call *et al.* (2017), who show that temporary migration is an important adaptation strategy if local yields decrease due to higher temperatures. We find additional evidence that women are generally less likely to respond to climatic stress. These gender effects are reinforced by the new, explicit evidence that men are more likely to significantly respond to temperature-related events by adjusting their migration strategy.

Lastly, our results explicitly suggest that estimates derived from causal inference are likely to find insignificant effect of higher temperatures on migration, validating the suggestive outcomes from the main analysis. We further show that using instrumental variable analyses unlikely produces a decrease in climate migration. This systematic bias reinforces concerns about the validity of using climatic variables as instruments, discussed in section 3.3.2. We also show that accounting for spatial correlation of climatic events by clustering standard errors likely produces a positive coefficient of higher temperature on migration. Finally, we validate the main findings, i.e., that including more climatic controls reduces the likelihood of finding a significant effect.

3.5.2 Precipitation decrease

We reveal that female lead authors are likely to report an increase in migration due to less precipitation. Similarly as in section 3.5.1, possibly this is because female authors might be more likely to present findings that match the conventional narrative that climatic hazards induce migration (Fang *et al.*, 2013). We find additional evidence that newer studies are likely to report insignificant effect of climatic events on migration, as in the main analysis.

As for climate migration patterns, we find further outcomes indicating that it serves as an adaptation primarily in rural areas. We reveal that if precipitation decreases, international migration is less likely to decrease than internal migration. This suggests that i) decrease in precipitation might trap people in the affected areas, who would have migrated internally and ii) engagement into international migration might not be determined by climatic conditions. Migration in response to less precipitation takes place to urban areas, which are less likely to be dependent on climate-sensitive activities such as agriculture. This validates the general notion that climate change accelerates

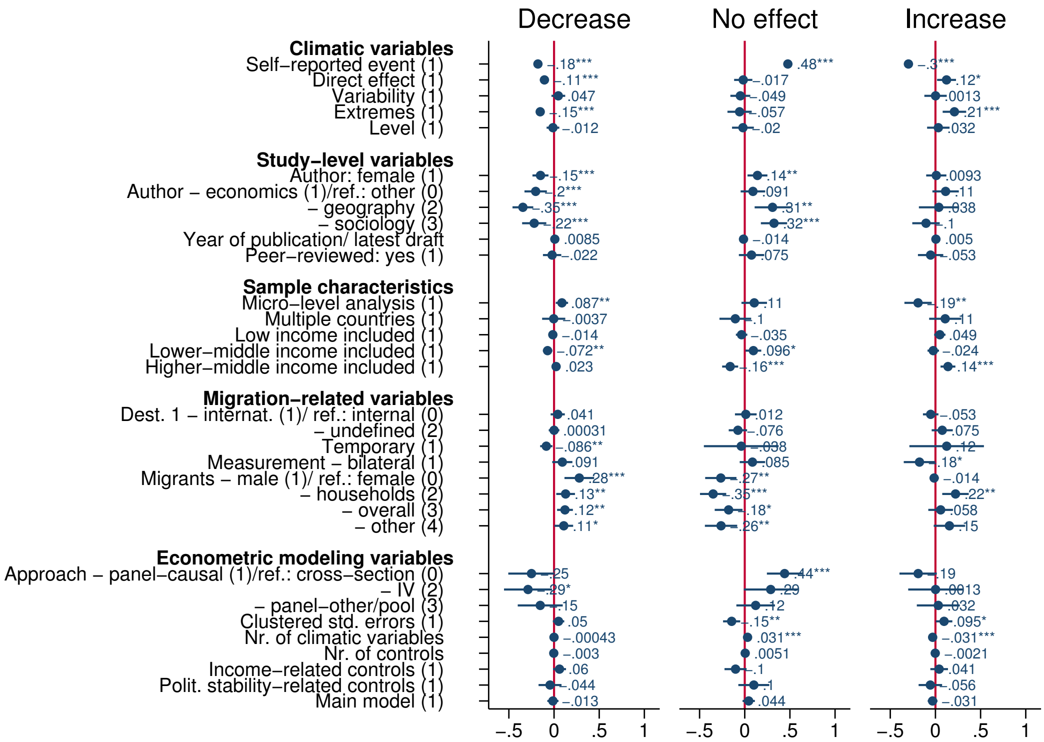


Figure 3.6: *Multinomial probit model for effect direction of temperature increase on migration*

urbanization (Adger *et al.*, 2020). As in the previous sections, we show that women are generally less likely to adapt their migration strategy in response to climatic stress.

We reveal that models using causal inference are less likely to find an insignificant effect of precipitation decrease on migration. This bias goes in the opposite direction compared to the one revealed for the temperature-related sub-sample. Even though directions of these biases are not straightforward to interpret, they ultimately imply that using causal inference techniques produces systematically different outcomes compared to approaches that might suffer from the omitted variable bias. We further show that the number of climatic controls is unlikely to produce a negative effect and an indication (even though insignificant) that it likely produces insignificant coefficients, similar to the main analysis. We find further evidence that models that include income-related controls are not likely to report an increase in climate migration (for intuition, see the main analysis). Lastly, we reveal that authors are more likely to report an increase in migration in response to precipitation decrease in the main model. This contrasts findings by Beine and Jeusette (2019), who largely find no evidence of such a reporting bias.

It is important to note that generally the reliability of precipitation data is perceived to be problematic, which could explain why in this sub-sample analysis, we often do not find further evidence for the main results. Even though weather products tend to agree on long-run averages, particularly in the case of precipitation they do not necessarily agree on anomalies (Auffhammer *et al.*, 2013). Since often deviations from the mean are the main source of identification (especially in causal inference), the choice of weather products is non-trivial and could produce inconsistent evidence. For these and other reasons, recent trend in the climate impact literature is to focus primarily on the implications of temperature demonstrating more consistency across data products, while controlling for precipitation (Burke *et al.*, 2009; Missirian and Schlenker, 2017).

3.5.3 Droughts

We show that in response to self-reported droughts, migration is likely to increase. The bias goes in the opposite direction than in the temperature-related sub-sample, which is not straightforward to interpret. However, it further emphasizes that using subjective measures of climatic events systematically affects the evidence. Consistent with outcomes from other sections, measurement of climatic events matters for what results original analyses produce. If droughts are captured as binary treatments, studies likely find a decrease in migration. Drought intensity measures, however, increases the likelihood of finding a significant effect. This latter outcome is quite intuitive, implying that their intensity rather than mere occurrence enables researchers to better capture droughts' migration implications. It, however, contrasts evidence delivered by Beine and Jeusette (2019), who show just the opposite.

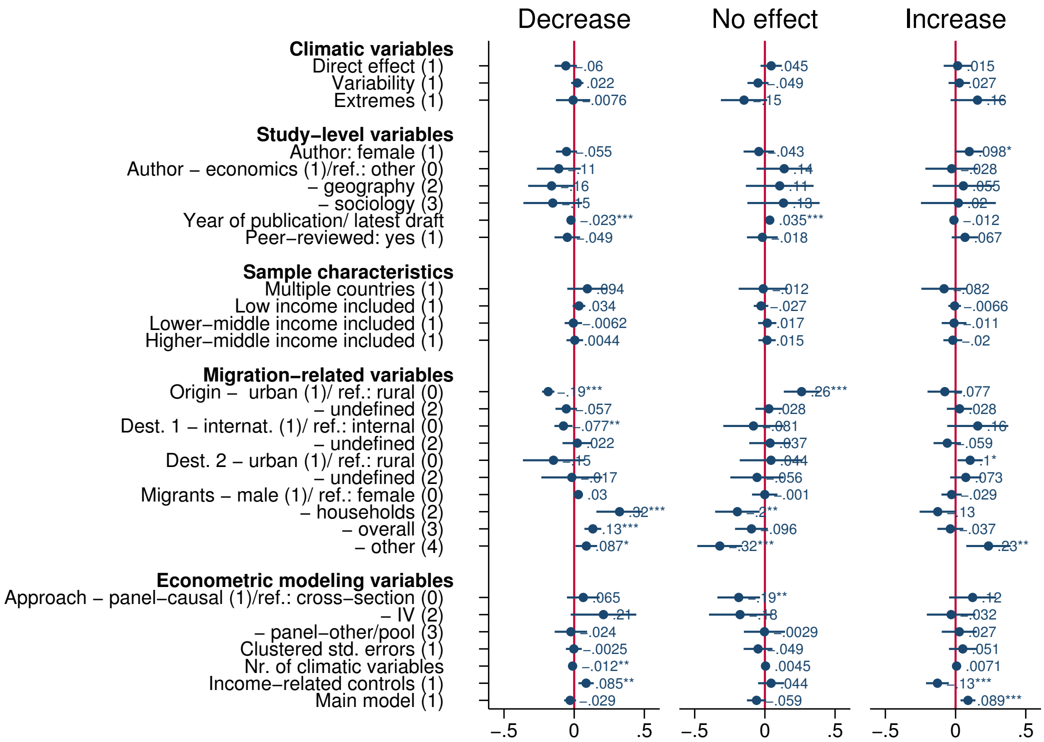


Figure 3.7: *Multinomial probit model for effect direction of precipitation decrease on migration*

Consistent with section 3.5.2, we find that female lead authors are likely to publish an increase in climate migration in line with the more conventional narrative (for intuition, see section 3.5.1). Additionally, we reveal stronger evidence of publication biases suggested by the main analysis; studies led by economists are likely to report an increase and studies published in peer-reviewed journals are likely to report a decrease in climate migration.

We show that analyses conducted at the micro-level are unlikely to find a significant decrease in drought-related migration. This bias goes into an opposite direction as compared to section 3.5.1. Similarly, we reveal that studies covering multiple countries are less likely to report a decrease in climate migration than country-specific analyses. While these bias directions are not straightforward to interpret, they emphasize the importance to consider both i) micro- and macro-level , as well as ii) multi-country and country-specific analyses, because ultimately all of them provide different, likely complementary insights on climate migration dynamics. We further find that lower-middle income countries are less likely to report a decrease in drought-related migration and an indication of a positive association, similar to the main analysis.

We amplify findings from the main analysis, by further showing that migration in response to climatic hazards likely increases from rural areas and is less likely to be undertaken by women.

As for econometric modeling we reveal that studies using causal inference are unlikely to report a decrease in drought-related migration. Even though the bias direction differs from previous sections and it is not straightforward to interpret it, this evidence further emphasizes that the choice of the econometric approach may systematically affect climate migration evidence. Lastly, we show that studies, which apply clustered standard errors are more likely to report a decrease in climate migrations, whereby this bias goes in the opposite direction as the one revealed in section 3.5.1. Also here the bias direction is not easy to interpret. Yet, it suggests that not accounting for spatial correlation of climatic events is important as it systematically produces different evidence.

3.5.4 Floods

Consistent with other sections we find that how climatic events are measured systematically affects the evidence. If floods are captured as losses or binary treatments, researchers are likely to find a positive association with migration.

We reveal that studies led by female authors are likely to report no effect. This contrasts the bias of female lead authors to publish an increase in migration in response to climatic stress as revealed for instance in sections 3.5.2 and 3.5.3. However, since in the main analyses we show that floods are unlikely to induce migration, the explanation for this finding remains as in previous sections. Female lead authors are more likely to

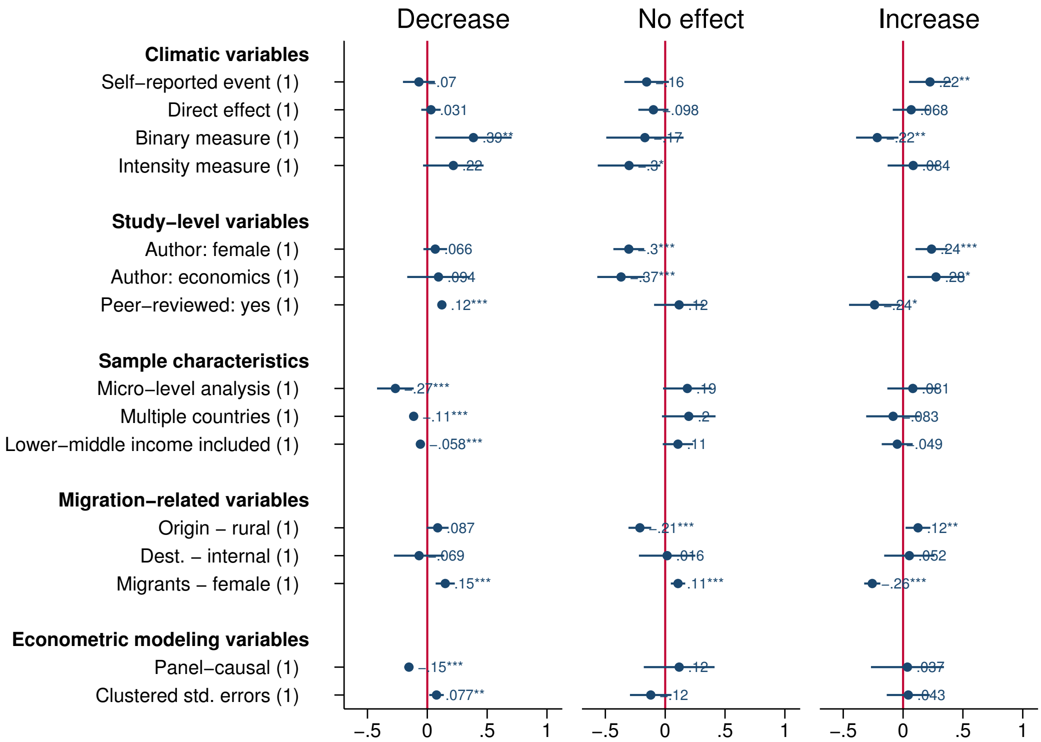


Figure 3.8: *Multinomial probit model for effect direction of drought on migration*

report evidence in line with the conventional narrative. We further show that studies published in peer-reviewed journals are likely to report an insignificant effect and less likely to report a decrease in flood-related migration. This bias differs from the one revealed in the main analysis when pooling all estimates together.

Similarly as in section 3.5.3, samples covering multiple countries are unlikely to report a decrease in flood-related migration than country-specific studies. This further emphasizes that both types of studies are complementary as they reveal different climate migration patterns. We further validate outcomes from the main analysis that low income populations are less likely to significantly respond to climatic hazards, plausibly due to lack of their adaptive capacity.

In contrast to the main outcomes, we fail to find systematic differences in flood-related migration with respect to the migrants' origin. A possible explanation is that floods cause disruptions both in rural areas and cities, in comparison to impacts of slow-onset events that are importantly channeled through agricultural production and thus primarily felt in rural areas. We also find that changes in internal rather than international migration serve as an adaptation to floods as it is less costly (Bazzi, 2017; Cattaneo and Peri, 2016), in line with findings from section 3.5.2. In contrast to the findings form previous sections, we do not find gender-specific differences in flood-related migration. This is in line with Call *et al.* (2017), who show that vulnerable populations such as women are not consistently more/less likely to be displaced by floods. A plausible explanation is that while slow-onset events trigger migration in search of alternative livelihoods, which is more often picked up by men (Chindarkar, 2012), floods are more likely to lead to displacement affecting both genders equally.

In terms of econometric modeling, we further show that applying causal inference techniques systematically affects the evidence, whereby the bias direction is the same as in section 3.5.1. Lastly, outcomes presented in the main models are unlikely to report an increase in flood-related migration.

Taken together, the evidence of the flood-related sub-sample differ the most from the main analysis. This is plausibly because sudden-onset events trigger different adaptive responses than slow-onset events. Thus, the outcomes as found in the main analysis seem to be mainly driven by the slow-onset events, prevalent in our sample.

3.6 Discussion and conclusion

This meta-analysis has considered all relevant econometric studies across multiple disciplines that analyze implications of climate-related events for human migration. By summarizing the mixed outcomes and providing explanations for the sources of heterogeneity in derived conclusions across this rapidly growing literature, we have

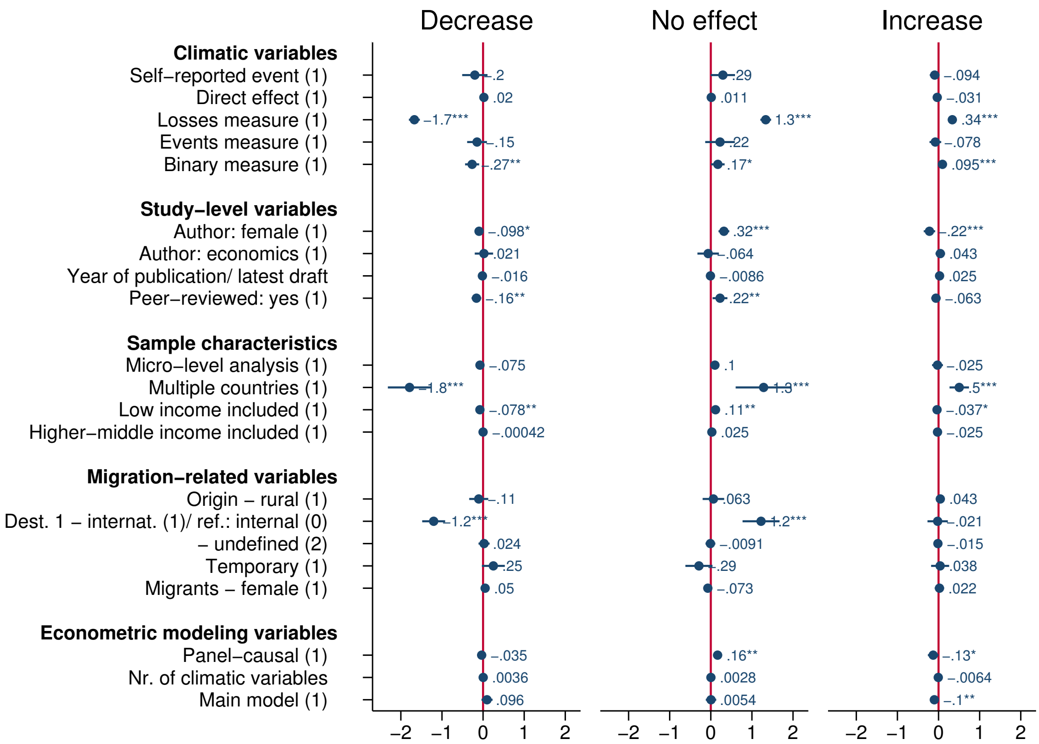


Figure 3.9: *Multinomial probit model for effect direction of flood on migration*

been able to address a number of remaining open questions. The main findings are summarized in Table 3.3.

We show that slow-onset climatic events (particularly temperature extremes and drying conditions) are generally more likely to increase migration than sudden-onset events (i.e., floods and hurricanes). This evidence has two possible explanations. Firstly, migration likely serves as an adaptation to slow-onset events by allowing more time to gather resources to migrate, whereas sudden-onset events hinder people's ability to move by depleting their resources. Alternatively, sudden-onset events tend to be associated with a type of moves that are more difficult to capture. Given the increasing yearly estimates number of people displaced due to natural disasters, the latter explanation seems more plausible.[8] However, to resolve this, future research should aim to improve the understanding of migratory patterns in the aftermath of sudden-onset events.

We find evidence of different biases prevalent in the literature indicating how both the academic and public discourse on climate migration is distorted. For illustration, we show that peer-reviewed journals are likely to report a significant decrease in climate migration. This contrasts findings by Beine and Jeusette (2019) and Hoffmann *et al.* (2020), who do not find evidence of a publication bias in the overall climate migration literature. We also find a publication bias for effects of specific climatic events, as well as gender-, discipline- and time-specific biases. These biases are often a result of researchers or editors making decisions about publishing evidence on the basis of the direction or strength of findings. Yet, they adversely affect our learning experience inhibiting effective policy responses. To combat these practices, an important step for social sciences would entail measures such as pre-registration of studies with journals and incentives to also report insignificant results (Franco *et al.*, 2014). When it comes to policy-making, we recommend to consider the grey literature in addition to peer-reviewed journals in order to amass a more accurate evidence base.

This analysis further enables us to summarize the patterns of climate migration that are seemingly strongly determined by budget constraints and climate-related sensitivity of livelihoods. In line with Hoffmann *et al.* (2020), our findings indicate an inverted U-shaped relationship between countries' income levels and climate migration. We further show that migration responds to slow-onset climatic events particularly in rural areas. Additionally, climate migration is likely to increase in response to contemporaneous rather than lagged adverse climatic events. As regards the destination choices, climate migration likely takes place in middle income countries, internally, and to destinations with lower dependence on the agricultural sector (i.e., cities). The likelihood of becoming trapped in adversely affected areas is higher in low-income countries, on the African continent in particular. Lastly, we show that while women are less likely to adapt to

[8]The estimates show that in 2019 alone, 17.2 million people were displaced due to natural disasters (NRC and IDMC, 2019).

slow-onset climate change by migration, effects of sudden-onset events do not differ by gender. By making migratory responses to climatic events more predictable, this evidence is of high relevance for policy makers. If combined with i) future climate change scenarios indicating which areas are likely to be more severely affected by e.g., temperature extremes (e.g., Xu *et al.* (2020)) or water scarcity (e.g., Schewe *et al.* (2014)), and ii) socio-economic forecasts, our outcomes might enable the identification of hot-spots of future out- and in-migration and locations where people are likely to become immobile. Such information serves as an important entry point for policies, which aim to minimize welfare losses from migration choices in a changing climate.

Lastly, this study also seeks to inspire future research on climate migration and suggests how to move the scientific agenda forward. First, there are some obvious research gaps. Thus-far, research has primarily focused on climate-related out-migration from rural areas, yet we still lack evidence from cities. Further, as presented in Figure 3.5, we need evidence of climate migration from Europe as well as from countries that are likely to be disproportionately affected by climate change such as small island states located in the Pacific Ocean or many land-locked countries on the African continent. More evidence is further needed on migratory responses to sea-level rise, sudden-onset events or in response to distant climatic shocks transmitted e.g., via international commodity prices. Second, as a result of the heterogeneity of estimation techniques as well as approaches to measure migration and climate-related events, this meta-analysis cannot estimate the effect size. This is an important limitation. Yet, this limitation also provides a space to reflect on what the best practices in the climate migration literature are or should be. A methodological guidebook that would bring subsequent studies to a common denominator, would enable a meta-analysis of the effect size of climate change impacts on migration and would hence be an important next step in the field. This would substantially improve the learning experience for policy makers, thus facilitating more efficient policy responses to migration challenges in a changing climate. This is key, as we can ultimately expect that the adverse effects of climate change will be felt across many regions, forcing people in the most affected areas to make the hard decision of whether to stay or to go, with potentially far-reaching implications.

Table 3.3: *Summary of the main findings*

How do different adverse climatic events affect migration?

- Slow-onset events, i.e., temperature extremes, extreme precipitation decrease, and droughts increase migration
- Sudden-onset events, i.e., floods and hurricanes, do not have a significant effect

What are the existing climate migration patterns?

- Climate migration is likely to: originate in rural areas, take place in middle income countries and internally to destinations with low agricultural dependence, and increase in response to contemporaneous rather than lagged adverse climatic events
- The likelihood to become trapped is higher for women and in low-income countries, on the African continent in particular
- Temporary migration likely to increase in response to higher temperatures

What drives the differences in the existing evidence?

- Biases resulting from conceptualization of climatic events
  - Temperature increase: measures of extremes linked to climate migration increase
  - Precipitation decrease: measures of extremes linked to climate migration increase
  - Droughts: measures of intensity linked to significant effects, binary treatments linked to climate migration decrease
  - Floods: measures of losses and binary treatments linked to climate migration increase
- Data quality and sample characteristics:
  - Micro-level analyses: different biases for different sub-samples defined by climatic events
  - Multiple countries: different biases for different sub-samples defined by climatic events
  - Bilateral migration flows: bias towards an insignificant effect
  - Self-reported climatic events: different biases for different sub-samples defined by climatic events
- Biases resulting from attributes at the study-level:
  - Female authors: bias to publish more conventional narratives
  - Authors from Economics and Geography: bias towards reporting an increase in climate migration
  - Newer studies: bias towards an insignificant effect
  - Peer-reviewed journals: bias to report a decrease in climate migration, especially of droughts and insignificant effects of floods
- Biases resulting from econometric modeling:
  - Causal inference: different biases for different sub-samples defined by climatic events
  - Instrumental variable approach: different biases for different sub-samples defined by climatic events
  - Clustered standard errors: different biases for different sub-samples defined by climatic event
  - Number of climatic controls: bias towards decrease in migration
  - Number of controls: bias towards an insignificant effect
  - Inclusion of income- and political stability-related controls: bias towards a decrease in climate migration
  - Main models: different biases for different sub-samples defined by climatic events

Chapter 4

Improving the Evidence Base on Climate Migration: Methodological Insights from Two Meta-Analyses[1]

Roman Hoffmann
Barbora Šedová
Kira Vinke

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Chapter Abstract

The question whether climatic factors influence human migration has gained both academic and public interest in the past years. Based on two recently completed meta-analyses, this paper examines the quantitative literature on climate-related migration from a methodological perspective. In total, information from 127 original macro- and micro-level studies is retrieved to assess how different concepts and analytical methods shape our understanding of climate migration. We provide an overview of common methodological approaches and present evidence on their potential implications for the estimation of climate-related impacts. We identify five challenges, which relate to the i) measurement of migration and of ii) climatic events, iii) integration and aggregation of data, iv) identification of causal relationships, and v) exploration of contextual factors and mechanisms. Advances in research and modelling are then discussed together with best cases to provide guidance to researchers studying the climate-migration nexus.

4.1 Introduction

Climate change is affecting people worldwide. Its impacts destroy livelihoods, threaten health and well-being, and increase vulnerabilities (IPCC, 2014). With continued global warming, adaptation to the changing conditions is increasingly difficult. Especially since under higher warming scenarios, some regions are expected to become uninhabitable in the future (Xu *et al.*, 2020). Under these circumstances, migration represents an important strategy to ensure survival and adapt to changing environmental conditions. Although the detrimental effects of climate change have only begun to unfold, the past decades have seen a steady increase in the number of quantitative studies analyzing the role of climatic and other environmental impacts on migration. These range from case studies in highly localized settings to macro studies considering global migration flows. While the majority of studies agrees that climatic conditions are important, the results of the individual studies vary, making it difficult to establish under which conditions climatic factors influence migration (Hunter *et al.*, 2015; Obokata *et al.*, 2014; Cattaneo *et al.*, 2019; Piguet, 2010).

For instance, on the one hand, it has been reported that internal migration increases with changes in precipitation, such as in rural Ethiopia (Gray and Mueller, 2012a), Tanzania (Afifi *et al.*, 2014) and Ecuador (Gray, 2009). Other studies meanwhile reported no consistent or an inhibiting effect of changes in rainfall patterns on migration, for example in Pakistan (Mueller *et al.*, 2014) and in the Philippines (Bohra-Mishra *et al.*, 2017). Given that most studies have been carried out in a specific context, it is often difficult to generalize the findings beyond the particular country or region. Overall, we still lack a comprehensive understanding of the relevant factors, which underline the observed heterogeneity in the results (Black *et al.*, 2011b). This paper sets in with an objective to investigate how different concepts and analytical methods shape our understanding of climate migration.

To explore this diversity, two recent meta-analyses, led by two of the authors (Hoffmann *et al.*, 2020; Šedová *et al.*, 2021), systematically synthesized and analyzed quantitative studies on climate migration. The first meta-analysis focused on macro studies at the country level (hereafter meta-analysis M1), the second one considered both micro and macro-level studies (hereafter meta-analysis M2). The analyses show that, partly, the mixed evidence in the literature stems from differences in the methodological approaches used. Studies apply a broad range of methods for collecting, managing and analyzing data to examine the climate-migration relationship and the choice of methods can be crucial for the estimation and interpretation of results.

In this paper, we review common methodological approaches used in the quantitative literature, highlight how these choices affect our understanding of the climate-migration nexus, and discuss how to overcome related challenges that might impede the correct interpretation of data. Our review is based on the extensive meta-data collected as part of the two meta-analyses, which covers 127 original micro- and macro-level studies on climate migration worldwide (see Appendix D.1 Table D.1). To be included in the analyses, the original studies had to report statistical model estimates on the relationship between a climatic factor and migration. In total, the studies estimated 4962 different relationship coefficients, which form the basis of our analyses. In addition to the estimates of the relationships, detailed information about the data sources, measurement, and analytical techniques were collected. Both meta-analyses take peer-reviewed articles and grey literature (reports and working papers) into account.

This paper complements previous methodological reviews (Auffhammer *et al.*, 2013; Fussell *et al.*, 2014b; Dell *et al.*, 2014; Piguet, 2010; Warner, 2011; McLeman, 2013; Berlemann and Steinhardt, 2017) by adding a distinctive meta-analytical perspective to understand how differences in the data and research design can influence the analysis of climate migration. The aggregate meta-analytic approach allows to effectively compare the statistical results of multiple studies and their characteristics across contexts and research settings. It can thus provide unique insights into challenges and gaps that exist when it comes to analyzing and modeling climate migration patterns. Beyond methodological questions, our paper also contributes to recent substantive literature reviews on climate migration by providing key insights to the field derived from the two meta-analyses, such as on the relative importance of different climatic impacts and the role of contextual factors in shaping climate migration patterns (Cattaneo *et al.*, 2019; Millock, 2015; Hunter *et al.*, 2015).

Conducting studies often comes with certain trade-offs. For instance, researchers may face the choice of collecting data on their own or of using available secondary data sources. The latter may require fewer resources, but might not cover all aspects of interest. We do not judge which approaches are best suited, as this very much depends on the concrete research questions and contexts. Instead, we highlight advantages, potential challenges and pitfalls, and implications of the use of certain methodologies. Our review shall thus help researchers to better recognize and understand inter-dependencies and complexities in the modeling of climate migration and provide them with an overview of state of the art methodical tools and data sources that can help them to address some of the pertinent challenges.

The paper starts with a descriptive overview of the conceptual frameworks, data, and research strategies used based on the collected meta-data (section 4.2). By highlighting key findings from the two meta-analyses, we also show how methodological choices can influence results. Implications of these are discussed in section 4.3, where we highlight challenges typical for analyses of the climate-migration relationship and how to overcome them. Finally, our paper presents an outlook to recent advancements in the field (section 4.4) and provides concluding remarks in the last section.

4.2 Approaches in the quantitative climate migration literature

4.2.1 Diverse schools of thought

The academic literature on migration and climate change has emerged from diverse schools of thought that conceptualize migration through different lenses. Scholars from both natural and social sciences have contributed to the development of the field. While scientists have investigated the entire cycle of migration, from intentions, the decision to migrate, the journey itself to the after-effects of climate migration, the field still lacks theoretical underpinning because of its complexity.

In this paper we focus on the first part of the migration cycle, on the relationship between climatic impacts, underlying conditions, and migration. This focus already has effects on the disciplinary representation of authors (Figure 4.1, Panel A-C), as political scientists, moral philosophers, sociologists, legal and development scholars may focus on different aspects of climate migration, such as the adaptive capacity of migrants, international protection frameworks, the role of climate-related displacement in conflicts, infringement of basic human and civil rights or normative considerations of climate justice. While these are important parts of the wider climate migration field, they have already been mapped by other scholars (Piguet *et al.*, 2018).

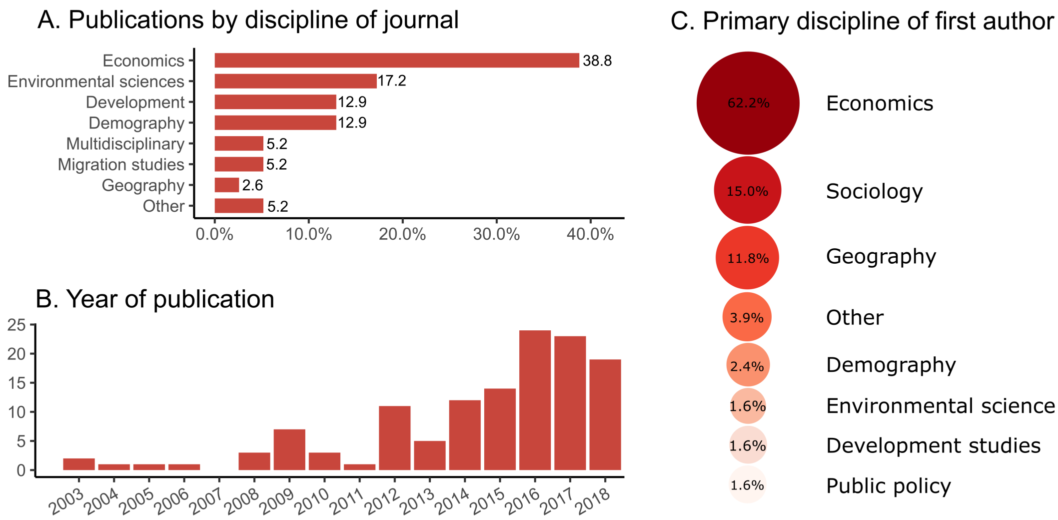

Figure 4.1: *Schools of thought and publication characteristics of 127 micro- and macro-level studies on climate migration between 2003 and 2018.*

Panel A shows the distribution of publications by journal discipline (grey literature excluded), Panel B shows the distribution of papers by year of publication (grey literature included), and Panel C shows the primary disciplines of the first authors.

From the 1970s, researchers have formally conceptualized climatic impacts in migration models. The seminal Harris and Todaro model, for example, explains rural-urban movements through expected wage differences between sending and destination areas (Harris and Todaro, 1970). Even though the model does not consider environmental factors explicitly, it provides a framework for understanding rural-urban migration in response to climatic events. These can lead to deteriorating conditions in the origin regions with long-term effects on wages and employment, affecting people's motivation to move to cities. Building on these contributions, recent studies use extensions of the Roy-Borjas model (Borjas, 1987; Roy, 1951) to analyze the effects of slow-onset climatic impacts on migration also accounting for migration costs (Benonnier *et al.*, 2019; Cattaneo and Peri, 2016; Šedová and Kalkuhl, 2020). In this setting, liquidity constraints imposed by adverse climatic events reduce the likelihood of emigration for poor segments of the populations and drive out-migration only for those who can afford it (see also the migration hump theory by Martin and Taylor (1996)). In line with this reasoning, both meta-analyses find a non-linear relationship between socio-economic status and migration with middle-income groups being most likely to migrate in response to climatic stress.

"The new economics of labor migration" (NELM) by Stark and Bloom (1985) goes a step beyond the individual's motivation for movement and considers entire households as decision-making entities. According to NELM, households engage in risk diversification by sending family members to areas unaffected by climatic impacts. Here, migration and remittance systems form an important part of livelihoods and risk mitigation *ex-ante* adverse shocks. In addition to conceptualizing migration as a preventive investment, Kleemans (2015) suggests that migration serves as an ex-post risk coping strategy after sudden events and income shocks, when alternative risk coping strategies fail (e.g., reducing savings, selling assets). This form of migration is sometimes referred to as distress or survival migration (Betts, 2010).

Beyond economic incentives, it is widely accepted that other factors also influence migration. Migrants do not only seek to increase economic opportunities and maximize profits, but rather weigh a variety of aspects in their decision making process. As is the case with all human behavior, the decision to migrate is generally multi-causal and may evolve over different time scales. The same is true for the interactions of climate change impacts, which occur in varying levels of magnitude and can materialize suddenly or over long periods of time, leading to migration or (forced) immobility.

Recent theoretical contributions have emphasized the importance of not only understanding whether but also how climate-related events affect migration (see Black *et al.* (2011b) for a conceptual overview). Climatic events can either directly influence migration decisions, e.g., by posing an immediate threat to health and well-being (Dimitrova and Bora, 2020; Muttarak and Dimitrova, 2019) or indirectly by affecting other migration drivers such as economic (Maurel and Tuccio, 2016; Marchiori *et al.*, 2012, 2017) and socio-political conditions (Abel *et al.*, 2019; Hsiang *et al.*, 2013). Indirect evidence from our meta-analyses also suggests an important role of income changes and conflict in explaining climatic impacts on migration.

Despite this important theoretical groundwork, explaining and projecting people's migration behavior under changing climatic conditions has not been fully accomplished. One reason could be that both more quantifiable factors, such as economic and demographic pressures, as well as subjective factors, like perception, well-being or place-attachment, are significant when trying to understand why some people stay and others go in the face of adverse climatic effects. The complexity to decipher these interactions between quantifiable and non-quantifiable factors is reflected in the multitude of data sources and methods used in the studies that were captured by the meta-analyses.

4.2.2 Data

Climate migration studies can be broadly categorized in micro studies, which focus mostly on individual and household migration, and macro studies, which analytically consider migration at the regional or national level. Depending on the level of analysis, different forms of research designs and data are used, ranging from highly localized case studies using surveys for data collection, to global comparisons based on country level data derived from administrative records. Whereas the former type of approaches allows researchers to gain a deeper understanding of processes and mechanisms on the ground, higher levels of aggregation enable to obtain a bigger picture via comparisons of different contexts. The choice of the level of analysis can affect the findings, as the meta-analysis M2 suggests, showing divergent migration patterns in response to increasing temperatures or droughts for micro and macro-level studies.

Both micro and macro studies are primarily focused on migration within or from low- and middle-income countries, with the US as a notable exception (e.g., Feng *et al.* (2012); Fussell *et al.* (2014a); Thiede and Brown (2013)). Figure 4.2 shows the representation of countries in samples used by original studies. Countries in darker red colors were found to be included in a larger number of samples. The representation of countries in the meta-data mirrors well the evidence on the distribution of climate migration studies, reported by Piguet *et al.* (2018). Based on the CliMig bibliographic database(Piguet *et al.*, 2019), which provides a comprehensive list of literature on migration, the environment and climate change, the authors identify a hemispheric asymmetry in research on climate migration with the majority of studies being conducted in developing countries and emerging economies by researchers from high-income countries. A particular research focus is placed on countries in West and East Africa, South Asia, and selected countries in Latin America and the Caribbean.

Studies typically consider short-term, temporal variations in weather rather than long-term climatic changes, which manifest themselves over decades. Considering

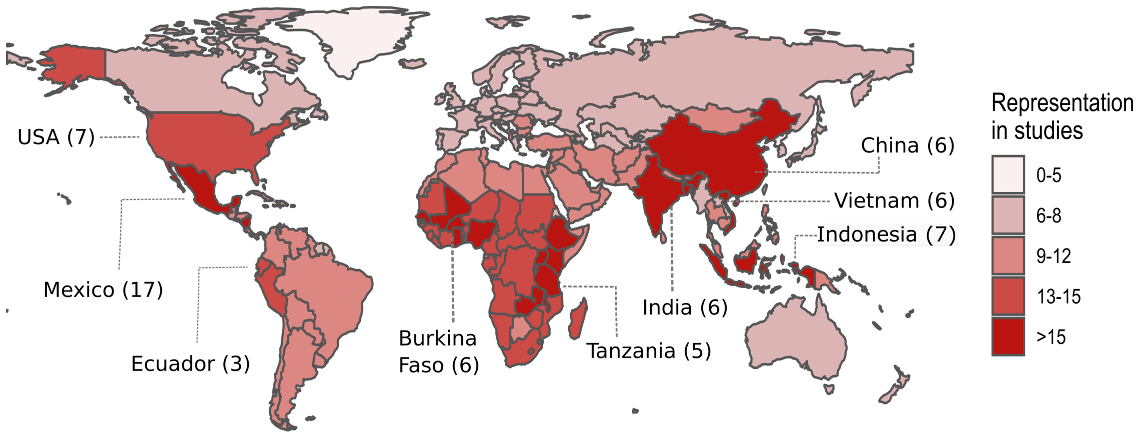

Figure 4.2: *Representation of countries in samples of 127 micro- and macro-level studies on climate migration.*

Darker shades of red indicate a higher frequency, meaning that the respective countries were included in a larger number of studies. Macro-level studies, which considered several countries at the same time, were counted by half in contrast to the micro-level studies with a focus on only one country. Countries represented in a large number of micro-level studies (in parentheses) are highlighted; e.g., there are 17 micro-level studies considering climate migration in Mexico and 3 in Ecuador.

short-term fluctuations has advantages for the analysis and the identification of impacts due to the better availability of and greater variation in the data. An increasing literature is showing how short-term events, such as storms, and medium-term events, such as droughts, are linked to anthropogenic climate change (Stott *et al.*, 2016; Otto, 2017; Lehmann *et al.*, 2018). In our meta-analyses, we considered broadly climatic impacts on migration, including extreme events and gradual changes that are in line with the observed and projected trends. Generally, the temporal dimension is critical for the measurement and modelling of climate impacts. As shown in meta-analysis M1, broader timeframes of measurement (five or ten years compared to one) are associated with an estimation of overall lower effects of climatic factors on migration. Moreover, as shown in M2, the introduction of time lags between the occurrence of an adverse climatic event and migration reduces the likelihood of finding evidence of climate migration.

4.2.3 Measurement

Typically, studies distinguish between sudden events that emerge quickly or unexpectedly, such as extreme storms or flash floods, and slow onset events, such as desertification or sea level rise, which emerge gradually and may appear less destructive at first (UNISDR, 2015). The boundaries between the two types are highly fluid with hazards typically ranging on a continuum from immediate to delayed threats, which has important implications for the conceptualization and measurement (Figure 4.3, Panel A). Distinguishing by types of hazards, most studies focus on changes in the level and variability of precipitation and temperature as two factors commonly linked to climate change (Figure 4.3, Panel B). The majority of studies consider slow-onset (76.5%) as compared to sudden events (23.5%).

Comparing a range of climatic drivers, findings of both meta-analyses provide evidence that higher temperatures are positively associated with migration. M1 further shows increased migration due to sudden events and precipitation variability and M2 provides evidence that drying conditions (i.e., lower precipitation levels and droughts) induce migration. No significant migration changes were observed for other sudden events in M2. There are two possible explanations. Either slow-onset events allow more time to gather resources to migrate, while sudden-onset events rapidly deplete resources, reducing the ability to move; or migratory patterns after sudden events are more difficult to capture. The differences in the findings suggest that conditions and factors beyond climatic impacts play a role in influencing migration in different contexts.

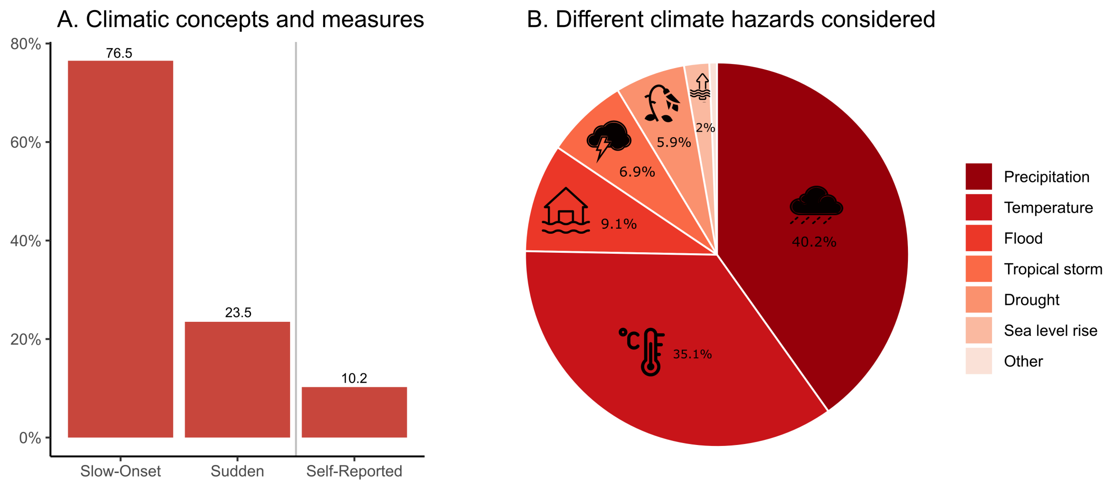

Figure 4.3: *Climatic concepts and measures used in 127 micro- and macro-level studies on climate migration.*

Panel A shows the percentage of studies focusing on slow and sudden climatic events and the percentage of studies using self-reported subjective climate measures. Slow-onset event refers to climatic events that manifest over a longer period, whereas sudden refers to abrupt events such as heavy storms, extreme rainfall, or flooding. Self-reported refers to climatic events that were reported by respondents in a survey. Panel B shows the distribution of studies by different types of climate hazards considered.

Studies use a myriad of different approaches to measure climatic hazards. Sudden events are typically captured either by binary treatment variables indicating whether a region or a country was exposed to an event or count or share variables measuring the number or proportion of affected populations. In addition to simply reflecting the occurrence of an event, measurements of the latter type also capture the event's intensity and the vulnerability of the affected populations. The way how these events are conceptualized and measured matters, as the results of both meta-analyses suggest. For example, M2 shows that studies measuring drought intensity, as compared to their mere occurrence, are more likely to find evidence of climate migration. Also, self-reported, subjective measurements tend to produce different results as compared to analyses based on objective climate data.

As regards slow-onset hazards, studies primarily consider the influence of changes in precipitation (40.4%) and temperature (34.1%) (Fig. 4.3B). Here, the broad set of measures can be divided into measures focusing on level changes, e.g., effects of increasing temperatures, and those focusing on variability changes and anomalies, such as irregular precipitation patterns or deviations from a location-specific long-term mean. Others take intermediary environmental outcomes and impacts of climatic processes into account, such as changes in soil quality or land degradation.

Migration can take very different forms, challenging the empirical conceptualization and measurement of the migration concept. For example, migration can be short-term or permanent, circular or linear, over a short or a long distance, within national borders or international, and forced or voluntary. Like with climatic hazards, studies consider migration as ranging along a continuum between these different poles. Demographers have developed a broad range of methods to collect and analyze migration data, which have been used in the climate migration literature. Unlike for other demographic events, such as birth or death, migration data is typically not recorded by administrations, but has to be collected either in censuses or surveys (Fussell *et al.*, 2014b). Within these, migration measures can be based on stated intentions, actually observed processes, indirect measures, retrospective information, or official migration statistics.

The results of studies are sensitive to the conceptualization and measurement of migration, as is also shown by Beine and Jeusette (2019) who have conducted another meta-analysis on the topic. Both of our meta-analyses find that climatic events are more likely to lead to internal or regional migration rather than international migration. M2 further refines the patterns of internal climate migration as well as characteristics of climate migrants. It shows that climate migration serves as an important livelihood and adaptation strategy, particularly in rural areas and that it is likely to drive urbanization. Further, men are more likely than women to respond to climatic events by adapting their migration strategy (Ayeb-Karlsson, 2020), while women are likely to become trapped in areas affected by adverse climatic conditions.

4.2.4 Statistical designs and models

To analyze the effects of a changing climate, researchers have applied different statistical designs to create a hypothetical counterfactual climate (Fig. 4.4A). The pioneering cross-sectional Ricardian approach was developed by Mendelsohn *et al.* (1994). In this framework, the identification of climatic impacts comes from the spatial variation in long-run average temperature and precipitation (and their squares). Further covariates typically cover variables that may be correlated with the climatic variables (e.g., elevation, distance to coast, or soil composition) and thus may affect the outcome of interest. The estimated marginal effect indicates the marginal value of a one unit change in a given climatic measure (see for example Bhattacharya and Innes (2008); Nawrotzki *et al.* (2016) or Šedová and Kalkuhl (2020)).

Another approach commonly used in the climate migration literature is the analysis of longitudinal panel or time series data (Auffhammer *et al.*, 2006; Deschênes and Greenstone, 2007). In this setting, response coefficients are derived from temporal (mostly annual or decadal) variation of the climatic and outcome variables. Typically, longitudinal studies control for unit of observation-specific intercepts and common time trends via fixed effects, comparing a given entity under different climatic conditions (Fig. 4.4A). The fixed effects absorb time-invariant factors and trends and thus allow the researcher to control for unobserved heterogeneity (Cai *et al.*, 2016; Chen and Mueller, 2019; Missirian and Schlenker, 2017). Outcomes from the two meta-analyses illustrate that accounting for the unobservable effects and time trends systematically changes the evidence on climate migration. For example, M1 shows that controlling for temporal trends strongly reduces the estimated effect sizes. Findings from M2 imply that applying causal inferences techniques reduces likelihood to find evidence of climate migration.

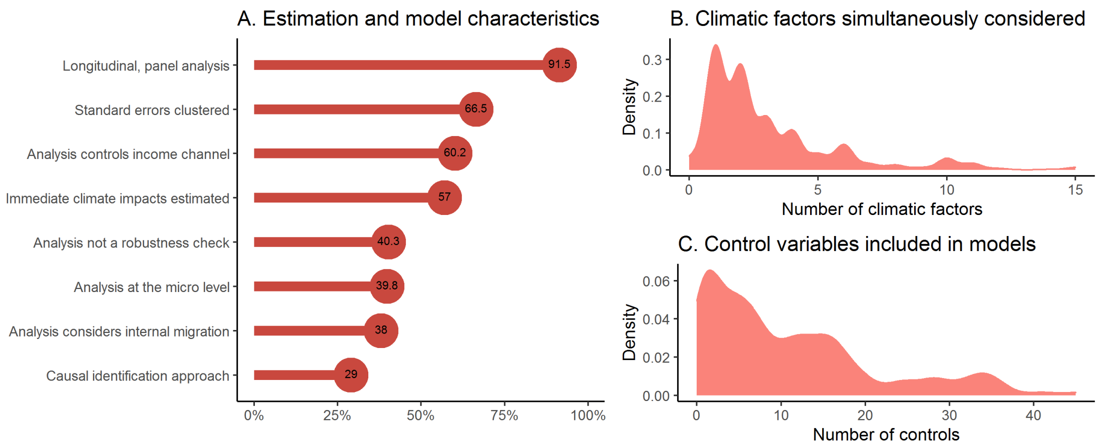

Figure 4.4: *Different modeling and estimation approaches used in the literature based on 127 micro- and macro-level studies on climate migration.*

Figure A captures the percentage of estimates derived from i) panel-data analyses, ii) models using clustered standard errors, iii) models controlling for income-related variables, iv) models estimating direct (as opposed to lagged) climatic effects, v) main models as opposed to robustness tests, vi) models estimated at the micro-level, vii) models using internal as opposed to international migration as main outcome and viii) models using causal inference techniques.

In terms of statistical approaches, studies use a broad variety of methods to estimate the climate migration relationship. When considering international migration, studies usually (but not exclusively) employ a variation of the gravity model. Gravity models explain migration by the population size of and the distance between the considered countries. If the dependent variable has few zero observations, Ordinary Least Square

(OLS) technique can be applied. If the dependent variable captures zero-inflated count data, studies typically employ Poisson regression approaches, or negative binomial models for over-dispersed count data (Angrist and Pischke, 2009; Wooldridge, 2010).

Micro studies are usually conducted at the individual or household level. Here, most of the times, the dependent variable is binary, capturing engagement in migration. For this type of outcomes, binary dependent variable models, such as logit, probit or linear probability models, are typically applied. In more detailed settings, when destinations are distinguished, multinomial models are used (Berlemann and Steinhardt, 2017) .

Studies typically include a number of climatic variables in their models, which are either considered iteratively in multiple or simultaneously in one model (Fig. 4.4B) (Auffhammer *et al.*, 2013). Both meta-analyses find that results are sensitive not only to the type and measurement of climatic factors considered but also to whether or not other influences are simultaneously accounted for in a model, suggesting correlations between the different factors. For example, if similar climatic signals are considered in the same model, effects are estimated to be smaller. Effects also change if different types of climatic influences are included: Effects of precipitation changes are typically found to be weaker if temperature changes are controlled for, whereas temperature effects are estimated larger if precipitation changes are controlled for, as shown by M1. Besides including different climatic factors, studies often control for a range of other factors that might be direct outcomes of climatic inputs considered (Fig. 4.4C). As we discuss in detail in the next section, the inclusion of further variables as controls can be problematic as these additional variables may be "bad controls", potentially biasing the estimation of climate impacts on migration (Angrist and Pischke, 2009).

4.3 Common challenges and how to address them

This section discusses challenges in the analysis of climatic impacts on migration as identified in our meta-analyses. We focus on outlining the major problems and corresponding best practices in addressing them. Figure 4.5 provides a summary of key messages about central methodological risks and challenges, which were identified in our review of the quantitative climate-migration literature.

4.3.1 Accurately measuring internal and international migration

An often politicized subject, migration is generally not well captured in large survey data. There is a risk that certain types of migration, especially those affected by climatic impacts, may be systematically omitted from the analysis. National surveys with information on migration, like censuses, are only completed once every several years or decade, potentially missing short-term and short-distance movements or displacement which often range below threshold temporal and geographical scales covered in surveys (for example within states or districts and below 6 months of absence). Lack of capacities and funding to document and process data contributes to the lack of consistency in both internal and international migration data, where gaps are widely prevalent. For example, migration from impoverished rural areas to informal urban settlements may be entirely undocumented, as many people who live in slums are not registered with local or national authorities. Also, climatic extreme events, like cyclones or large-scale flooding, can overwhelm local capacities and strain data collection efforts. Reasons for migration are often not captured or do not include environmental factors as possible answers. These gaps make attribution of migration to a specific climatic event or a gradual change difficult (Vinke and Hoffmann, 2020).

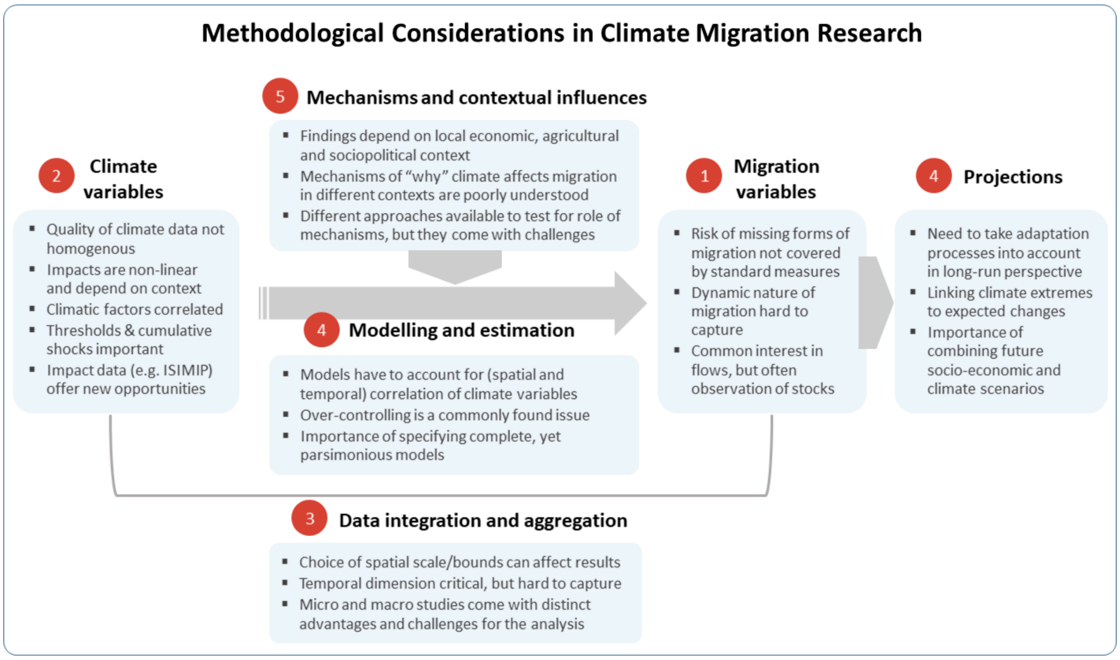

Figure 4.5: *Key messages from section 4.3: Methodological considerations in climate migration research.*

The numbers in the red circles refer to the sub-section numbering. The arrows indicate the line of reasoning: Migration variables (1) and climate variables (2) are combined in a joint dataset (3) and regressed on each other in quantitative models (4), which also form the basis of projections. Models also allow to test for the role of mechanisms and contextual influences (5) mediating and moderating the relationship between climatic variables and migration outcomes.

Migration is a dynamic phenomenon which is multi-faceted and complex. Temporal aspects and timing play an important role, but are particularly hard to comprehensively grasp in migration data collection efforts. For example, keeping track of migrants over time is often not feasible given the existing data and taking into account concerns of protection of personal data. Researchers instead rely on indirect information about migrants, e.g., whether a household member is a migrant or not, or retrospective data, which ex post captures migration histories. Both of these forms of data collection may be restricted in their scope and prone to measurement errors. The dearth of data makes it difficult to capture linked migration moves and trajectories, i.e., different migration stages and consecutive migration moves. Also, migration outcomes and the well-being of migrants in comparison to pre-migration conditions are rarely analyzed due to data limitations.

By abstracting from the micro level, macro level studies capture migration at a more aggregated level, typically considering migration rates or counts between regions or countries. Also this approach comes with certain limitations that are important for the interpretation of the results (Cattaneo *et al.*, 2019). Special difficulties arise when it comes to measuring international migration. Currently available data sources, such as the World Bank Global Bilateral Migration Database or the OECD Migration Database (see Appendix D.2 Table D.2), are based on migration stock data as opposed to flows, although this is the concept researchers are most commonly interested in. Most international migration measures also heavily rely on administrative sources, which can be prone to reporting and measurement biases, especially overlooking undocumented forms of migration. Macro studies often use information on net migration flows, which may not capture all (partly circular) migration moves. Studies considering the phenomenon from a distant perspective might also overlook certain forms of internal migration, such as rural-to-rural, and may thus have difficulties when it comes to correctly representing the migration situation in the area.

The lack of data, which varies especially between high and low-income countries, is often a determinant for the type of analytical method which can be used. In fact, the commissioning of studies to attain large amounts of data is cost-intensive. This circumstance again excludes research that is not in the focus of prominent funders, therefore a bias of European and US American perspectives in climate migration research is evident. When analyzing a set of studies that have used different migration datasets, it is important to understand that omissions of certain types of movements in datasets could affect the results. With a possibly very large part of climate-related movements undocumented, the aggregate knowledge of more than a hundred studies as represented in our meta-analyses still misses important interactions between climatic events and migration. Moreover, aggregate data veils motivations of migrants. Factors that lead people to move may differ from the factors that make them choose a particular destination. Financial, legal and social barriers will determine where a person can or cannot go. Family networks and diaspora can be important factors in choosing locations. Oftentimes, push and pull factors get mixed in the analysis of migration decisions. The different uncertainties also mean we still may not fully understand the magnitude and scope of current climate-related migration flows, also when it comes to the question of why some parts of the population may leave while others may decide to stay or lack options to leave.

4.3.2 Conceptualizing and representing climatic events and hazards

Different sources of climate-related data are used by researchers, ranging from weather station data, to grid cell, satellite and climate model data. Each of the data sources comes with advantages and disadvantages (for a detailed discussion see Auffhammer *et al.* (2013); Dell *et al.* (2014). For example, weather station data might be affected by the entry and exit of stations from the data, which may thus not be homogeneous over time. Also, lower-income and sparsely populated regions have far fewer weather stations and less continuous high quality data. Gridded data offers an alternative interpolating between stations and commonly adjusting for influences of missing data, elevation, and urban heat island effects. However, gridded data also suffers from the unequal distribution of weather stations across the globe. Moreover, measurements may differ depending on the interpolation approach used. The differences are particularly strong for precipitation data, which is more variable across space compared to, for example, temperature data. Because of the greater variability, measurements may not capture micro climates that influence outcomes in a specific location.

Data assimilation, producing reanalysis data, is another way climate scientists address missing observations, increasingly used by social scientists. This approach combines observational data from weather stations and remote sensing with a physics-based model, which translates information from regions with existing observations to regions with sparse observations. Reanalysis data allows tackling the endogeneity problem resulting from the weather station placement as well as issues with variations in data quality producing a consistent best estimate of atmospheric parameters over time and space (Auffhammer *et al.*, 2013; Donaldson and Storeygard, 2016). Researchers are advised to consult different sources of climatic data and to conduct robustness checks, which can help identifying and mitigating data problems.

In many cases, what constitutes a climatic hazard needs to take local conditions and potential inter-dependencies into account. When modeling climatic events, we often operate with broad categories and averages lacking information about how a particular change has affected local livelihoods. As our meta-analyses show, climatic influences are not independent, but may be correlated with each other. Models are commonly specified by either accounting only for one or few factors, or by including the broadest possible range of climatic factors in kitchen sink models, including different measures for temperature, precipitation, and sudden events. If correlated climatic variables are not simultaneously considered, this may lead to omitted variable biases (Auffhammer *et al.*, 2013; Berlemann and Steinhardt, 2017; Hsiang, 2016). On the other hand, including a broad range of variables capturing the same type of climatic hazard or event may come at the cost of losing interpretive value of the models. We recommend a refined approach, which focuses on the accurate representation of climatic events of relevance for the respective context and which takes inter-dependencies between different climatic influences into account, without over-specifying the model.

Climatic impacts are highly non-linear and context-dependent (Burke *et al.*, 2015b; Lenton *et al.*, 2008). Their marginal effect on livelihoods and ultimately migration depends to a large extent on the climatic conditions in a region, the respective season, as well as other contextual factors (see section 4.3.5). Climatic factors often become relevant only once their impact exceeds a certain threshold beyond which a system can no longer sustain or adapt. For instance, M2 finds that extreme rather than moderate changes in temperature and precipitation are linked to migration. However, it has not yet been well conceptualized under which conditions and impact levels households decide to migrate. Further research in this direction is needed. Also, current studies in the field are often focused on modeling the impact of a singular climatic factor over time, such as an idiosyncratic shock, but do not consider the impact of the accumulation of shocks over time (both environmental and non-environmental) and how these affect households and migration decisions.

Researchers have also emphasized the role of perceptions in understanding climate-related migration (Koubi *et al.*, 2016b,c). The use of objective and subjective measures may produce very different results and may strongly be influenced by cultural contexts and local perceptions (Bertrand and Mullainathan, 2001). For illustration, M2 shows that using self-reported climatic data produces systematically different evidence of climate-migration association compared to when more objective data is applied. Such potential differences between measured and perceived changes have further been documented, among others, by Shukla *et al.* (2019); Brüssow *et al.* (2019) and De Longueville *et al.* (2020) in different social and geographic settings. The link between measured changes in weather and climate, perceptions of these processes, and migration is an important area for further research. Psychological drivers – such as fear – can also be potent factors in determining whether people move, which has not been fully captured in previous empirical research on climate migration (Collmann *et al.*, 2016).

4.3.3 Data integration and aggregation

Given the increasing availability of climate-related and migration data from various sources, the question of how to best integrate and combine different types of data is of increasing importance. In a first step, researchers have to decide how narrow they want to define the spatial measurement frame. The available spatial scale of migration data, which is often defined by political or other arbitrary boundaries, such as census tracts, may not correspond to the scale of the climate variables (Fussell *et al.*, 2014b).

Researchers may thus have to choose how to best aggregate differently scaled data to find a common denominator for the analysis. This so called "modifiable areal unit problem" has important implications for the analysis and may be a source of statistical bias in the estimation of climatic impacts on migration. For example, the calculation of summary values, such as migration rates or the total number of households affected by a climatic event, can be influenced by both the shape and scale of the spatial aggregation unit (Fussell, 2001).

The spatial frame also plays a role for the question of how far reaching climatic impacts are across locations. For example, a climate-induced conflict may spill-over to neighboring regions influencing areas that have not been directly, but only indirectly affected by the climatic hazard. A broader scaling in the climate measure may thus result in differently estimated effects, comparable to a violation of the stable unit treatment value assumption (SUTVA) in experimental and intervention research. It is recommendable to explore different spatial scales and to document how these affect the analytical outcomes, as such differences may matter for the interpretation of the results. Spatial models, which take influences of neighboring regions into account, offer a possibility to directly test for indirect influences (Saldaña-Zorrilla and Sandberg, 2009a). However, these models are rarely used in the empirical literature.

The temporal dimension is critical for climate migration research. Besides choosing the right spatial aggregation approach, researchers have to make choices about how to measure and model the temporal dimension in their analysis. Understanding what role time plays for migration decisions requires high-frequency longitudinal data, which either might not be available or may only provide restricted information about migrants. Retrospective data offers an alternative, but is limited in the extent of information available and prone to measurement errors. Despite these challenges, considering the role of time is important as it might largely affect the way climatic hazards influence migration. For instance, M2 finds that migration is likely to take place in response to contemporaneous rather than lagged effects of climatic events. With few exceptions (Kleemans, 2015; Fussell, 2012) there is little conceptual and empirical work that explicitly considers temporal aspects of climate migration, including those that might affect household decision making processes, such as strategic waiting or inertia.

Climatic shocks may only have an impact on migration after a certain period, requiring researchers to use lags in their models. Distinguishing by seasons is another important factor as climate and weather variations may only play a role at certain points in time, for instance during the harvesting season. Broader time frames (e.g., 5 or 10 years compared to 1 year) allow to capture climate migration at a more coarse temporal scale accounting for adaptation, but may miss important (seasonal) dynamics and circular migration patterns. Like with the spatial dimension, the aggregation chosen to model influences over time should be inspired by the local context and the research questions at hand. Additional checks using different conceptualizations and specifications, e.g., by choosing a different measurement time frame or by including additional lags in the models, can help to identify interesting patterns that would have not been visible otherwise.

Commonly, the distinction is made between micro studies, using survey or small-scale administrative data, and macro studies conducted at a more aggregated level, analyzing migration between regions or countries. Depending on the particular research question at hand, both approaches have advantages and disadvantages. A higher level of aggregation may allow to capture general patterns of relationships and to effectively compare different contexts with each other. Yet, it may come at the loss of contextualization, for example in the measurement of climatic influences. Whereas macro level studies have to choose more generic approaches in their modeling, micro-level studies can more accurately represent influences of relevance for local contexts. In some cases, on the other hand, it is better to aggregate up, for example if data quality is low or not representative for lower levels of spatial aggregation. Generally, the importance of both types of studies is uncontested, especially since M2 finds that they produce different, but complementary insights on climate migration dynamics. Importantly, the questions discussed above of how to best aggregate over spatial and temporal scales affects micro and macro studies alike. In both cases, researchers should clearly define how and why they chose certain spatial and temporal scales and conduct robustness checks to test for the reliability of their findings.

Many new data sources, such as IPUMS Terra, offer researchers ready-made, integrated solutions, providing both climatic and migration data in one source. While this development has clearly made the study of the climate-migration relationship easier, it comes with the risk of not critically reflecting and questioning the provided climatic data. Interdependencies and the accumulation of uncertainties and measurement errors is also often not properly taken into account in the modeling and there is limited knowledge how these uncertainties may affect the estimation. The wide range of data sources and complexity of the measures makes inter- and cross-disciplinary collaborations more relevant. Despite their importance, disciplinary boundaries prevail in the climate-migration field and collaboration across disciplines is rather the exception than the rule, as also our meta-analyses show (see also Heberlein (1988); Lowe *et al.* (2013)).

4.3.4 Modeling and the identification of causal effects

There are different analytical approaches to estimate the causal impact of climatic events on migration (see section 4.2.4). Each of the estimation techniques have their costs and benefits. Reverse causality is often not a major issue, even in cross-sectional analyses, since climatic variables are exogenously determined. However, cross-sectional analysis may suffer from omitted variable biases. This bias arises when a variable that is simultaneously correlated with a climate signal and affects migration is omitted from the model, which then attributes the effect of the missing variables to the ones included. For example, characteristics of a region, such as its location or topography, may influence both its climate and observable migration patterns (Auffhammer, 2018; Dell *et al.*, 2014; Burke and Emerick, 2016). M2 shows that using causal inference techniques produces systematically different findings compared to the cross-sectional approach. To address omitted variable issues, it is recommendable to use longitudinal panel data analysis instead of purely cross-sectional approaches, which allow to control for unobserved heterogeneity through the use of fixed effects (Auffhammer *et al.*, 2006; Deschênes and Greenstone, 2007). These allow for a causal interpretation of the model response coefficients under certain assumption.

A variety of further issues related to the specification of models can result in biased estimates. First, because climatic events are correlated, when included in the models in isolation (i.e., without considering additional climatic variables) they might plausibly pick up the effect of other not-included, but correlated climatic events, which would result in an omitted variable bias (Auffhammer *et al.*, 2013). Both, M1 and M2 find evidence of systematic biases in climate migration findings from omitting climatic variables. At the same time, controlling for a broad range of factors measuring the same climatic concepts could reduce the interpretive value of the models as suggested in section 4.2.4. We recommend an accurate, context-specific modeling of climatic events, which accounts for interdependencies between different climatic influences, without over-specifying the model. A worthwhile starting point is to compare how their effects differ when climatic variables are included separately and simultaneously in the model, to understand the extent of their correlation and how they affect the model results.

A second essential specification issue, which can be commonly found in the literature, is the use of potentially mediating control variables, which are themselves influenced by the climatic event and have an impact on migration. For example, economic or sociopolitical variables such as income, conflict, or institutional quality are likely to be affected by climatic conditions. If a model controls for these factors, it would no longer estimate the relevant total impact of climatic events on migration, but only the partial impact net of the effect that runs through the controlled mediating channel (Berlemann and Steinhardt, 2017; Burke *et al.*, 2015a). This is referred to as so-called "over-controlling" (Dell *et al.*, 2014) or "bad control" problem (Angrist and Pischke, 2009). M2 reveals important biases in climate migration evidence caused by this issue. While having some models controlling for mediating factors can provide important information of mechanisms and channels at work (section 4.3.5), such models do not allow deriving conclusions about the total effect of climatic events on migration. Here, we encourage authors to choose controls depending on the specific research question in focus and to exclude problematic controls, such as income, from the analysis. It is recommendable to always present one well-specified parsimonious model, i.e., a model, which does not control for any mediating factors, as a baseline for model comparisons (Berlemann and Steinhardt, 2017). This also facilitates the synthesizing of coefficients across models in future meta-analyses.

Spatial autocorrelation is a third aspect of a high relevance for modelling. Not accounting for the spatial correlation of climatic variables might produce biased standard errors (Auffhammer *et al.*, 2013). Generally, there are four ways to address spatial correlation: i) application of spatial weights, which is an efficient approach if the weighting matrix is known; ii) application of clustered standard errors that allow for spatial correlation by clustering at a larger spatial resolution or that allow the correlation to decrease with distance (Conley, 1999); iii) usage of a grouped bootstrapping methods where years are re-sampled and replaced (Auffhammer *et al.*, 2013), and iv) spatial models, which explicitly model spatial interdependencies (Angrist and Pischke, 2009; Wooldridge, 2016).

A final question is to what extent model findings are generalizable and can be used for projections. Typically estimates are derived from observations of short-term weather variations rather than long-term changes and are thus not necessarily representative for population responses to a changing climate in the longer term, e.g., due to possible adaptation. Thus, derived conclusions only demonstrate temporal external validity, since the elasticity derived from short-term weather responses might not be representative for climate change in a long-term. Another issue are highly non-linear dynamics of climate change, which could significantly alter migration patterns. These non-analogue events, such as the complete melting of the Andes glaciers, are without precedent in human civilization and therefore existing studies cannot capture their effect on migration (Bergmann *et al.*, 2021). Recently, new approaches were developed to consider the impacts of longer term changes on migration, such as the "long-differences"[2], "Ricardo Meets Panels"[3] (Auffhammer, 2018) or the "partitioning variation"[4] methods (Kolstad and Moore, 2020; Bento *et al.*, 2021), addressing shortcomings of both cross-sectional and panel data analysis. These methods are fairly new and thus-far have only been used to a limited extent in the climate migration literature. They require a long time-series of climatic variables which increasingly get available with new weather data products. Yet, the "long-differences" and some applications of the "partitioning variation" approach also require a long time-series of migration data, which in specific contexts might be a bigger challenge in terms of data availability. Nevertheless, either of these approaches

[2]"Long-differences" approach utilizes changes in longer run averages of the left-hand side variable and temperature at two different points in time at a given location to estimate the effect of a changing climate. By using differences, the time-invariant factors drop out.

[3]"Ricardo Meets Panels" approach studies how the short-run response to weather events derived from a panel analysis changes as a function of a long-run climate change (Ricardian approach).

[4]New applications of the "partitioning variation" method use the fact that climate at one location varies over time. This enables an estimation of both the long- and short-run effects in a panel.

represent a promising way forward in approximating the climate change experiment, while also accounting for adaptation.

4.3.5 Exploring mechanisms and contextual interactions

The growing consensus among researchers is that climatic events indeed affect human migration, yet the prevailing questions are under which circumstances, how and why (Cattaneo *et al.*, 2019). Understanding what the contextual factors and mechanisms of influence are is especially critical for policy interventions aimed at protecting vulnerable populations.

There is an increasing acknowledgment that the character of climate migration is strongly determined by contextual factors, such as the socioeconomic (e.g., access to alternative *in-situ* adaptation options, ability to bear the costs of migration, previous migration experiences or migration networks at the destination) and political conditions in a region (Black *et al.*, 2011b). On the macro level, studies have for example empirically examined the role income and agricultural dependence play in shaping the relationships (Marchiori *et al.*, 2012; Cai *et al.*, 2016). On the micro level, the existing literature mostly provides evidence of heterogeneous climatic impacts based on gender, (agricultural) income or age (Cattaneo *et al.*, 2019; Šedová and Kalkuhl, 2020).

There are several empirical approaches that researchers can apply to analyze heterogeneities in the climatic effects on migration. Studies can draw on interaction terms or sub-sample analyses to understand how the effects of climatic events of interest differ in interaction with socioeconomic and political conditions. These approaches also allow to test for heterogeneous implications of climatic events for different sub-groups in a population. For example, Cattaneo and Peri (2016) employ interaction terms and sub-samples to analyze the effect of warming trends across countries on the probability of migrating, in dependence on wealth. Their study shows the presence of stricter liquidity constraint for poor economies as a result of higher temperatures inhibiting migration as an adaptation to the changing climate.

Moreover, there are different mechanisms at play determining whether or not climatic impacts result in migration, for instance of an economic (e.g., income differentials between origin and destination) or a sociopolitical character (e.g., conflicts). As noted in the previous section, extending a baseline model by adding further mediating factors provides an indirect way to study the role of different mechanisms in a mediation analysis (MacKinnon *et al.*, 2007). If an included factor actually represents a mechanism explaining the relationship between a climatic event and migration, then we would expect the estimated model coefficients of the climatic variable to change in a model that controls for the mediator compared to a baseline model that does not. The larger the difference between the coefficients, the stronger the role played by the mediating factor

(Hoffmann and Muttarak, 2017; Hoffmann and Lutz, 2019). Researchers can test for the strength of mediation using the Durbin-Wu-Hausman-Test (Hausman, 1978) or the KHB method for the comparison of non-linear coefficients (Breen *et al.*, 2013).

Instrumental variable methods are another commonly used approach to examine underlying mechanisms explaining climatic effects on migration (e.g., Feng *et al.* (2010)). Here, the focus is on obtaining unbiased estimates of the effects of a mediating channel, such as agricultural income, on migration. Climatic events are used as (plausibly) exogenous variables, so called instruments, to predict the mediators in a first stage to obtain an unbiased estimate of the effect of the mediating channel in a second stage. The method has strong assumptions. First, it is required that the instrument is strongly correlated with the mediator (relevance) and second, it should not influence the migration outcome through any other channel than the considered mediator (exclusion restriction). As pointed out by Burke *et al.* (2015a) and Koubi (2019), especially the exclusion restriction can be easily violated as there is typically more than one channel through which climatic events affect migration. Therefore, we generally recommend to only use this approach if researchers can plausibly argue that climatic variables only affect migration via their effect on the instrumented variable.

While the existing evidence emphasizes the important role of the (agricultural) income channel (Cattaneo *et al.*, 2019), there is still a lack of understanding of further underlying mechanisms that can explain climate migration. Urbanization and internal migration due to climatic stress can result in increased pressures on the labor market at the destination and trigger further out-migration, which can result in migration cascades (Maurel and Tuccio, 2016; Marchiori *et al.*, 2012, 2017). Conflicts play an important role, not only as a moderator, but also as a potential mediator of climatic effects (Abel *et al.*, 2019; Burke *et al.*, 2015a; Cattaneo and Bosetti, 2017; Ghimire *et al.*, 2015; Hsiang *et al.*, 2013). Environmental conditions also have immediate effects on health and productivity (Dimitrova and Bora, 2020; Muttarak and Dimitrova, 2019), which may further contribute to increasing human mobility (Deschênes and Greenstone, 2011; Deschênes, 2014; Burgess *et al.*, 2017; Graff Zivin and Neidell, 2013).

4.4 Advances in research and modeling

4.4.1 Data and measurement

Climate migration research is a quickly growing field with an increasing number of quantitative empirical studies. Researchers are confronted with a range of methodological choices. As we show in our analysis, these can have far-reaching implications for the findings and conclusions derived. Various issues related to the conceptualization and measurement of key indicators, the integration and aggregation of data, and the modeling of relationships can play a role. How migration is conceptualized and measured can determine whether certain types of migrants are overlooked or not. Climatic events, which affect outcomes in a highly non-linear manner and which can be conceptualized in different ways, can affect populations differently depending on the respective contexts. Climate- and migration-related data can be combined at different spatial and temporal scales using various approaches that differ in basic assumptions made. And issues in the choice of the right model specification can largely change the estimation of climatic effects on migration with consequences for our understanding of current and future climate migration.

A number of recent advances in the field provide new data and methods that allow researchers to address some of the outlined challenges. Comparable international migration data are now available for a wide range of countries, e.g., in a form of the World Bank Global Bilateral Migration Database. At the same time, there has been an increasing number of micro-level case studies that explore, how environmental drivers affect mobility patterns in selected local areas. Numerous countries carry out large-scale panel surveys with detailed information on migration, which can be combined with one of the various sources of publicly available climatic or disaster data (see Appendix D.2 Table D.2 for a comprehensive overview of data sources). Examples include the Indonesian Family Life Survey, the India Human Development Survey, the Tanzanian National Panel Study, or the Brazil National Household Sample Survey. Yet, census data is a primary source of information on migration. IPUMS International provides researchers with a unique collection of censuses and surveys, offering harmonized information across various countries, which can be used for migration modeling. For example, the IPUMS microdata was used to model internal migration flows (Garcia *et al.*, 2015) or to determine migration intensities in different parts of the world (Bell *et al.*, 2015, 2002). Further internal migration data at a very high resolution can be retrieved from the census-based Global Estimated Net Migration Grids By Decade Database (de Sherbinin *et al.*, 2015), which provides estimated net-migration flows for per $1km2$ grid cell for the 1970s, 1980s and 1990s.

As for climatic events data, new data products are available that offer climate data at very high temporal and spatial resolution, such as the reanalysis ERA5 data. Further, the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) developed by the Potsdam Institute for Climate Impact Research and the International Institute for Applied Systems Analysis explicitly models climatic impacts across affected sectors and spatial scales (Warszawski *et al.*, 2013). Beyond historical impacts, ISIMIP provides a consistent picture under different future climate-change scenarios. It has potential for climate migration research, yet thus-far it has only been applied to a limited extent, e.g., in the Groundswell Report (Rigaud *et al.*, 2018). In addition, catalogue-based search engines, such as the Google Earth Engine or the Google Data explorer, facilitate access to geospatial data and products. Despite these advancements, more efforts are necessary to streamline data collection globally and to improve data availability especially for low-income countries.

To adequately assess climate change-related movements, high time and spatial resolution are needed. Aside of large-scale geo-referenced survey data, such as the Demographic and Health Surveys (DHS) or the Multiple Indicator Cluster Surveys (MICS), new efforts have been undertaken to collect migration data using digital technologies, machine learning, and big data. In particular, digital trace data has become a fruitful source for migration researchers in the past years with a large untapped potential for climate migration research (Sîrbu *et al.*, 2020). They also offer a vast range of possibilities for integrating different data and modes of data collection (Stier *et al.*, 2019). The International Organization for Migration (IOM) Data Innovation Directory provides a comprehensive overview of recent innovative approaches and methods used to gather migration data.

Digital traces are records of activity, which can be collected from a multitude of technical systems and communication devices, such as websites, search engines, social media platforms, smartphone apps, or sensors (Cesare *et al.*, 2018; Stier *et al.*, 2019; Böhme *et al.*, 2020). Anonymized cellphone data, for example, has successfully been used in different contexts to identify migrants and to learn about their trajectories and destinations (Lu *et al.*, 2016b; Bengtsson *et al.*, 2011). At the same time, social media, such as Facebook or Twitter, provide innovative ways to learn about migration pathways and the profiles of migrants (see e.g., Blumenstock (2012); Chi *et al.* (2020); Spyratos *et al.* (2019); Zagheni *et al.* (2014). They also offer a range of useful complementary information that can be access via text mining and content analytical tools. Posts on Facebook or Tweets, for example, can provide information about the emotional well-being of migrants (Guntuku *et al.*, 2019; Park *et al.*, 2015) and thus serve as an indicator for migration outcomes.

Better data can certainly improve our understanding of migratory movements. Yet, it comes with various ethical challenges. The collection and analysis of digital trace data, for example, can have problematic implications for data protection and privacy (Bengtsson *et al.*, 2011; Lu *et al.*, 2016a). While researchers call for better data, it has to be considered that misuse such as the personalized monitoring, criminalized (im)migration or persecution of certain groups could ensue. Therefore, a carefully balanced approach between the protection of privacy and the advancements of data collection is required.

4.4.2 Analytical methods and modeling

Advances have not only occurred in terms of the availability of data, but also in the way how data is analyzed. An increasing number of studies use longitudinal models in their analyses controlling for unobserved heterogeneity and common time trends in form of fixed effects (Dell *et al.*, 2014). The availability of longer panels and time series allows for a better approximation of climate change impacts, which only manifests itself over decades. A stronger focus on space in modeling, for example in a form of spatial models, which explicitly account for spatial inter-dependencies, could be a fruitful direction for further empirical research. Machine learning is another approach, which could provide useful insights in data-heavy applications for which more traditional statistical approaches might not be suitable, such as medium- to long-term forecasts of climate migration trends.

Better modelling can help improve future migration projections. Typically, to derive end-of-century, out-of-sample projections, researchers combine estimated coefficients of climatic variables on migration with future climate predictions. Currently, the best practices to estimate climatic responses are those, which focus on long-run, causal climate change impacts and take adaptation processes into account. Nevertheless, also these methods do not overcome the issue that response coefficients are derived from historical climatic changes that are smaller in magnitudes compared to expected future changes and thus the responses might be understated. At the same time, if unprecedented adaptation takes place in the future, these predictions might overstate the effects.

An important element of recent projection exercises is the attribution of currently observed climatic extremes to long-term trends to derive predictions about how environmental conditions will change with global warming in the future (Stott *et al.*, 2016; Otto, 2017). Taken together, the goal is to combine knowledge about currently observed responses to climatic extremes with different scenarios for future climate change (Van Vuuren *et al.*, 2011) and socio-economic development (O'Neill *et al.*, 2014, 2017), as for example done by Carleton *et al.* (2020). Beyond these, there are additional data-related challenges. As a counterfactual of future climate, typically one would employ data from one of the spatially explicit physics-based models of the global climate referred to as General Circulation Models (GCMs). However, the choice of a GCM significantly affects the estimated future impacts, since for some of the indicators (e.g., precipitation), predictions vary heavily across models.[5] Thus, it is recommended either i) to average the impacts across models and indicate the variability in impacts, or ii) to report outcomes for a number of models. Another issue related to use of GCMs is the geographical and/or temporal aggregation bias, which affects the estimations of future impacts. There are several ways how to address and minimize these aggregation biases, which vary on case to case basis, for a detailed discussion, see also Auffhammer *et al.* (2013), or Fowler *et al.* (2007).

Gaining a better understanding about how individuals, households, and communities respond to climatic extremes is important to translate empirical findings to projections. Here, also further theoretical and conceptual contributions are needed to not only

[5]Predictions of temperature are commonly used for projections since climate models disagree on both the sign and magnitude of future precipitation change (Christensen *et al.*, 2013).

explore climate migration empirically, but also to extend our theoretical knowledge on the topic. Increasingly, migration models explicitly take climatic factors into account when modeling migration decisions (Marchiori *et al.*, 2012; Barrios *et al.*, 2006). Micro-founded simulations, such as agent-based models, offer possibilities to analyze complex decision- making processes and to study how migration may change in the future under different conditions. These approaches also increasingly include climatic factors as a migration driver (Entwisle *et al.*, 2016; Hassani-Mahmooei and Parris, 2012; Klabunde and Willekens, 2016). A stronger integration of the different perspectives and approaches across disciplines could prove very beneficial for the development of the climate migration research field in the future.

4.5 Conclusion

In this paper, we have presented several major methodological challenges for quantitative research on climate migration and possible solutions how to address them. Here we conclude with central recommendations for future research.

First, future studies of climate migration should strive to draw on climatic and migration data and fit models that reflect and are of relevance for the situation on the ground. This entails considerations of relevant climatic impacts and corresponding migration forms, their correct representation with respect to functional forms, or temporal and geographical scales. Available data-sources and their advantages and disadvantages should be thoroughly considered and the choice should be determined by their quality and the research questions at hand. Ideally, researchers would draw on different climatic and migration data to verify the derived conclusions. Innovative approaches, e.g., the use of big data or machine learning, are a promising way forward, for instance in contexts when conventional data is not available, e.g., for the monitoring of undocumented or short-distance migration.

Second, whenever possible, models of climate migration should employ longitudinal panel models controlling for spatial heterogeneity and time trends that allow for a causal interpretation of climatic impacts. Uncertainty estimates, such as standard errors, have to be adjusted to account for spatial and temporal clustering and auto-regression. With improved data availability and longer time series, the observation and analysis of long-term climatic changes becomes possible. The presented "long difference", "Ricardo Meets Panels" or "partitioning variation" approaches produce response coefficients, which allow for a causal interpretation of long-run climatic changes, also accounting for adaptation. The results of these models can also effectively be employed for projections using future climate and socio-economic scenarios.

Third, while considering all of the above, future studies on climate migration should employ parsimonious and comparable models capturing total climatic impacts on migration without controlling for mediating factors. This would also facilitate future meta-analyses on the topic aimed at quantifying climatic impacts on migration, such as the impact of increasing temperature levels. Such evidence is not only important to accurately assess the magnitude of climate migration in different parts of the world, it could also inform future projections and migration scenarios under climate change improving our abilities to respond to and mitigate related adverse consequences for affected populations.

Chapter 5

Global Food Prices, Local Weather and Migration in Sub-Saharan Africa[1]

Lars Ludolph
Barbora Šedová

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Chapter Abstract

In this paper, we study the effect of exogenous global crop price changes on migration from agricultural and non-agricultural households in Sub-Saharan Africa. We show that, similar to the effect of positive local weather shocks, the effect of a locally-relevant global crop price increase on household out-migration depends on the initial household wealth. Higher international producer prices relax the budget constraint of poor agricultural households and facilitate migration. The order of magnitude of a standardized price effect is approx. one third of the standardized effect of a local weather shock. Unlike positive weather shocks, which mostly facilitate internal rural-urban migration, positive income shocks through rising producer prices only increase migration to neighboring African countries, likely due to the simultaneous decrease in real income in nearby urban areas. Finally, we show that while higher producer prices induce conflict, conflict does not play a role for the household decision to send a member as a labor migrant.

5.1 Introduction

Variability in global food prices has increased significantly over the past two decades, with the annual standard deviation around the decade mean of the FAO food price index tripling in the 2000s compared to the 1990s and remaining high until today. This phenomenon became highly visible during the global food crisis of 2007/08, when international prices of most commodities, including staple grains, increased to an all time high (Minot, 2010; von Braun, 2008). The crisis was importantly driven by a decrease in agricultural production in Australia, the United States, Russia, and Ukraine, resulting from adverse climatic shocks (Headey and Fan, 2008).[2] Overall, variability in global climate has been responsible for approximately 32 to 39% of global crop yield variation between 1979 and 2008, with significant effects on international food prices (Ray *et al.*, 2015).

At the same time, climate-induced fluctuations in income have been shown to significantly impact the decision to move in the low- and middle-income countries, where a large share of households is dependent on agricultural production. In this context, the aggregate impact of short-term income shocks on the migration decision is determined through an interplay of two opposing forces: Households' ability to bear the up-front costs of migration on the one hand, and the opportunity costs of migration that increase with rising income levels on the other (Clemens, 2014; Cattaneo and Peri, 2016). To study and disentangle this phenomenon, empirical studies typically exploit exogenous income variation induced by local weather conditions (Cattaneo and Peri, 2016; McKenzie and Rapoport, 2007; Hirvonen, 2016a). This focus on implications of geographically localized shocks extends to the climate migration literature, which is primarily concerned with the effect of climatic events on areas where biophysical impacts occur (Hoffmann *et al.*, 2020; Šedová *et al.*, 2021). With the notable exception of Bazzi (2017), who analyzes migration implications of domestic rice price changes due to an import ban in Indonesia, the impact of global price fluctuations on migration in the low- and middle-income countries has thus far received almost no attention in the literature.

This paper therefore sets in with two main objectives. First, it provides a full picture of climatic effects on human migration in Sub-Saharan Africa during the decade of the global food price crisis, by i) studying the implications of exogenous global food price changes on the probability of households sending one of their members as a migrant, the pre-dominant type of migration in Sub-Saharan Africa, and ii) complementing the analysis by comparing the effects of global prices to those of local weather conditions. Second, it sheds light on heterogeneous effects of these climate-related factors on the

[2] The 2007/08 food price crisis was driven by a combination of various factors, including climate-related decrease in agricultural productivity, a lack of transparency in markets, rising costs of oil, biofuel demand, depreciation of the U.S. dollar and export restrictions on agricultural goods (Headey and Fan, 2008; von Braun, 2008).

migration decision along the household wealth distribution, arguing that both global crop prices and the quantity of agricultural produce importantly determine household incomes. Finally, the study also examines whether local conflict could have been a concurring mechanism at play, potentially explaining the price-migration association.[3]

Our focus is on Sub-Saharan Africa for two main reasons. First, the region is a net importer of food and agricultural commodities and a significant share of households are net consumers of staple crops (Minot, 2010; Berazneva and Lee, 2013). Second, countries in Sub-Saharan Africa are characterized by low average incomes and agricultural products represent a high average share of household production and consumption compared to other regions (McGuirk and Burke, 2020). Thus, changes in agricultural prices significantly affect real income of both crop producing and crop consuming households.[4]

For the analysis, we build a household panel dataset for Burkina Faso, Kenya, Nigeria, Uganda and Senegal by combining several data sources. We draw on the World Bank's African Migration and Remittances Surveys (AMRS) and use retrospectively reported data on internal and international migration at the household level to construct our dependent variable. We proxy local crop prices by constructing a producer price index (PPI) at the district-year level, our main variable of interest by following the methodology of McGuirk and Burke (2020). The PPI combines high-resolution, time-invariant spatial data on crop-specific agricultural land cover from 2000 with annual international commodity price data over the subsequent years. We then complement these with daily temperature data and monthly precipitation averages using ERA5 weather reanalysis data to calculate local degree days and average precipitation during the growing season at the district level, following Schlenker *et al.* (2007). Finally, to explore a possible mediating role of conflict, we draw on the Uppsala Conflict Data Program's geo-referenced conflict event dataset and the Armed Conflict Location and Event Data Project database.

We derive our main empirical specification from a simple theoretical framework where utility maximizing households are budget constrained. Our empirical analysis then incorporates household and year fixed effects such that our coefficients of interest capture the effect of global price and local weather deviations from their location specific long-term mean over time, thus allowing us to compare a given household under different global price and/or local weather regimes. Four reasons allow for a plausibly causal interpretation of the coefficients on global food prices in this particular setting: First, to isolate the effect of global crop prices from local weather conditions, we focus

[3]Both global food price changes (Bellemare, 2015; McGuirk and Burke, 2020; De Winne and Peersman, 2019) and local weather (Abel *et al.*, 2019; Hsiang *et al.*, 2013) may cause political instability and violent conflict, which may in turn constitute a mediating factor of climate-related migration (Cattaneo *et al.*, 2019).

[4]Strong evidence suggests that steadily rising global food prices over the past decades particularly affect the welfare of poor households that spend a large share of their income on food. (Valin *et al.*, 2014; Hallegatte and Rozenberg, 2017; Ivanic *et al.*, 2012).

on the observation period from 2000 to 2008. This time span covers the global food price crisis 2007/08, when global food prices rose sharply for reasons entirely exogenous to agricultural activity in Sub-Sahara African (Berazneva and Lee, 2013; Demeke *et al.*, 2009; Dorward, 2012). Second, between 1989-2013, the entire continent of Africa accounted for only 5.9% of global cereal production, minimizing its effect on global prices (McGuirk and Burke, 2020). Third, to ensure that out-migration and global food prices are not simultaneously determined by variation in third factors such as time-varying oil prices or global economic activity, we incorporate time fixed effects into our analyses. Finally, we show in all our analyses that the effect of global prices on our outcomes are not sensitive to conditioning estimates on the local quantity produced, proxied by local weather conditions.

Our findings complement the existing literature in a number of ways. First, by simultaneously analyzing implications of local and distant effects of climatic events, we depart from the existing climate migration research that has thus-far primarily focused on locally occurring climatic impacts as potential drivers of migration (Millock, 2015; Hoffmann *et al.*, 2020; Šedová *et al.*, 2021). We show that an increase in locally-relevant global crop prices by one standard deviation increases household out-migration at 37% of the net effect of a comparable local weather shock. Global prices thus constitute an important driver of household out-migration, implying that the link between short-term variation in climate and labour migration from agricultural households has thus-far been underestimated. Second, we contribute to the recent efforts to better understand the contextual effects, i.e., when and how climate migration emerges (Cattaneo *et al.*, 2019). We show that implications of both global and local shocks for migration similarly depend on the initial household wealth, i.e., positive income shocks from higher international food prices and local weather help to relax the budget constraint of poor agricultural households and facilitate migration. Finally, we contribute to the literature on the link between climate, migration and conflict. It has been shown that, while climate-related migration can lead to conflict, climate-related conflict can also trigger migration (Ash and Obradovich, 2020; Abel *et al.*, 2019; Missirian and Schlenker, 2017). In this study, we add to this literature by considering the implications of conflict induced by global crop price fluctuations on household out-migration. We find that, while crop prices are indeed associated with conflict, conflict does not play a role for the household decision to send a member as a labor migrant.

The remainder of this paper proceeds as follows. The next section presents the theoretical framework. In section 5.3, we provide an overview of the data and discuss our constructed variables in detail. In section 5.4, we lay out our empirical strategy. Our findings are presented in section 5.5. In section 5.6, we extend the analysis to considering conflict as a potential driver of climate migration. The last section provides a discussion and concluding remarks.

5.2 Theoretical framework and research hypotheses

As discussed in the above, the picture that emerges from the literature on the relation between variation in global food prices and household out-migration in the low- and middle-income countries is mixed and context specific. The framework that guides our thinking on the interdependence of global crop prices, local growing conditions and the household migration decision closely follows Dustmann and Okatenko (2014) and incorporates insights from Bazzi (2017) and Marchal and Naiditch (2020). We use this parsimonious framework to build the intuition that a) the effect of global food prices on household out-migration is a priori ambiguous on aggregate due to its differential effects along the household wealth distribution and b) can be expected to differ between agricultural and non-agricultural households.

5.2.1 General framework

In the simple framework we suggest in the following, households themselves are immobile and all decisions they make relate to sending one of their household members as a migrant. Similar to Dustmann and Okatenko (2014), we formalise this household decision as a comparison of utility flows in the current location compared to potential destinations. We use subscripts $l = h$ (home) and $l = d$ (destination) for all variables relating to location choices l of the potential migrant. The subscripts $y = a$ (agricultural household) and $y = n$ (non-agricultural households) describe the type of household y. The flow of utility in location l for household type y is then given by:

$$U_{hly} = INC_{hy}(p_{hy}, q_{hy}) + inc_{ly}(p_{ly}, q_{ly}) + \epsilon_{ly}, \tag{5.1}$$

where INC denotes the household real income generated by all non-migrant household members and inc denotes the real income generated by the potential migrant. ϵ_{ly} denotes a random variable capturing all non-income utility components. Both INC and inc are a function of the price of locally grown crops, p_l, and the local quantity produced, q_l. Both p_l and q_l are exogenously determined. For p_l, this is due to short-term fluctuations in world market prices. For q_l, it is due to unpredictable fluctuations in local growing conditions. In addition, we assume

$$corr(q_h, p_h) = 0. \tag{5.2}$$

Thus, we rule out feedback loops between the local quantity produced at home and the exogenously determined global prices, an assumption we will discuss further in section 4. The second term of $inc_{ly}(p_{ly}, q_{ly})$ is a simplification: The income generated by the potential migrant is a future (expected) income flow; however, since no information on the future is available, households maximise their utility based on contemporarily observed income flows in all destinations d, which they assume to be accurate measures of what the potential migrant would earn in the future.

Migration is costly and when households make the decision to send a migrant, households are budget constrained by their initial household wealth. Assuming that households face borrowing constraints we can write this budget constraint as:

$$W_x + INC_{hy}(p_{hy}, q_{hy}) + inc_{hy}(p_{hy}, q_{hy}) \geq C_d, \tag{5.3}$$

where C_d is the location specific migration cost and W_x is the initial, idiosyncratic wealth of household x. $INC_{hy}(p_{hy}, q_{hy})$ is the income generated by the core household and $inc_{hy}(p_{hy}, q_{hy})$ is the income earned by the migrant at home.[5] We therefore implicitly assume that the household decision to send a migrant is made after income is earned at home. Equation 5.3 thus describes the threshold above which we could potentially observe migration from a given household. Combing equation (5.1) and (5.3) allows us to write the probability of a household sending a migrant as:

$$Pr(migration) = Pr(U_{hdy} > U_{hhy}, W_x + INC_{hy}(p_{hy}, q_{hy}) + inc_{hy}(p_{hy}, q_{hy}) \geq C_d). \tag{5.4}$$

Thus, two potential reasons may lead us to observe changes in household out-migration rates when households experience exogenous shocks to their household income: First, for non-budget constrained households, i.e., when the following equation holds

$$W_x + INC_{hy}(p_{hy}, q_{hy}) + inc_{hy}(p_{hy}, q_{hy}) \geq C_d,$$

the opportunity costs of migration are altered in response to income shocks. A positive income shock increases U_h and renders staying home more attractive, while the reverse holds for a negative income shock. However, for households whose household budget lie marginally above C_d, a negative shock to $INC_{hy}(p_{hy}, q_{hy}) + inc_{hy}(p_{hy}, q_{hy})$ may push them below the budget constraint such that it becomes binding and out-migration rates decrease from these households.

Second, for households that are initially budget constrained such that

$$W_x + INC_{hy}(p_{hy}, q_{hy}) + inc_{hy}(p_{hy}, q_{hy}) < C_l,$$

a positive income shock may increase migration if the shock to $INC_{hy}(p_{hy}, q_{hy}) + inc_{hy}(p_{hy}, q_{hy})$ is sufficiently large and $U_d > U_h$ still holds. This is, household out-migration only increases if the increase to U_h is not too large to make staying the relatively most attractive option. For budget-constrained households, negative income shocks have no effect on the decision to send a migrant since they simply remain below C_l.

[5] The assumption that borrowing constraints are a negative function of household wealth would lead to a qualitatively similar conclusion.

5.2.2 Agricultural and non-agricultural households

In this subsection, we turn more closely to the household income, given by

$$INC_{hy}(p_{hy}, q_{hy}) + inc_{hy}(p_{hy}, q_{hy}),$$

and its dependence on globally determined prices and the growing conditions of locally produced crops by type of household. For the remainder of this section, we assume that both $INC_{h,y}$ and $inc_{h,y}$ are differentiable in p_h and q_h. The sign of the first derivative then depends on the type of household, y. We expect changes in global food prices of locally grown crops p_h to have a strictly non-negative effect on the household income of agricultural households, a, which we define as net producers. All other crop prices equal, only subsistence farming households that consume all their produce do not experience a positive income shock to their household wealth. Thus, we assume the following derivatives:

$$\frac{\partial inc_{ha}}{\partial p_{ha}} \geq 0; \frac{\partial INC_{ha}}{\partial p_{ha}} \geq 0. \tag{5.5}$$

Similarly, a positive (negative) shock to local growing conditions that increases (decreases) the quantity produced, increases the income of agricultural households:

$$\frac{\partial inc_{ha}}{\partial q_{ha}} \geq 0; \frac{\partial INC_{ha}}{\partial q_{ha}} \geq 0. \tag{5.6}$$

Note that in some cases, households farming at subsistence levels may consume all additional produce such that the derivative in equation is not strictly larger than zero.

For non-agricultural households, which we define as consumers of agricultural goods, this relation is unambiguously non-positive. If locally consumed and produced crop varieties partly coincide, i.e., if local crop consumption patterns are partly correlated with locally produced crops, real income - and thus household wealth - declines for non-agricultural households. If the correlation between local consumption patterns and local production equals zero, we would observe no effect of global prices relevant for local production on the household budget of non-agricultural households. Thus, for non-agricultural households, we have

$$\frac{\partial inc_{hn}}{\partial p_{ha}} \leq 0; \frac{\partial INC_{hn}}{\partial p_{ha}} \leq 0. \tag{5.7}$$

We further expect non-agricultural households to be significantly less affected by changes in local growing conditions. With their household income not directly related to the local quantity produced and local consumer prices following the world market, we expect real income of non-agricultural households to remain unaffected by the quantity of crop harvested locally. Thus, we assume that

$$\frac{\partial inc_{hn}}{\partial q_{ha}} = 0; \frac{\partial INC_{hn}}{\partial q_{ha}} = 0. \tag{5.8}$$

In summary, we derive the following research hypotheses from the above simple framework: The aggregate observed effect of exogenously determined fluctuations in household income on household out-migration is a priori ambiguous. It depends on two factors. First, it depends on the initial wealth distribution of households through the interplay of three forces: the opportunity costs of migration, the household budget constraint and the migration costs. Second, the aggregate effect depends on the type of household, which determines the direction of the wealth shock induced by global prices and the quantity produced locally: Agricultural households can be expected to experience an income (and thus, wealth) increase when locally relevant global crop prices rise or local growing conditions improve, whereas non-agricultural households experience an income shock that is unambiguously non-positive for global prices or strictly zero for local growing conditions.

In the following, we describe in detail how we test the derived hypotheses empirically.

5.3 Data

To create our dataset, we draw on several data sources. The household data are presented in section 5.3.1. Data used to generate the producer prices are discussed in section 5.3.2. Our variables related to weather data are presented in section 5.3.3. In section 5.3.4, we introduce the conflict data.

5.3.1 Household data

To generate our main dependent variable and the various derivatives of it, we draw on the World Bank's African Migration and Remittances Surveys (AMRS).

Within AMRS, households were surveyed in five countries in Sub-Saharan Africa. In Kenya, Burkina Faso, Nigeria and Senegal interviews were conducted in late 2009, in Uganda in early 2010.[6] AMRS contains retrospective information on non-resident household members' years of out-migration as well as their destination choices and their reasons for moving. In sum, this information is available for approximately 2000 households in each country. We draw on these household-specific migration histories to generate the dependent variable. To minimize the errors related to the retrospection, we limit our sample to the ten years prior to the year of the interview to generate a nine-year

[6] We treat all countries in our sample as being interviewed in 2009 for consistency reasons.

household time series from 2000 to 2008.[7] We restrict our sample to households whose head is 25 years or older in 2000 to account for the fact that households with heads younger than 25 years old were unlikely to exist in 2000 (Gray and Wise, 2016). We further include return migrants, defined as migrants who left the household in the past and returned at a later stage; however, these constitute less than 5 per cent of our migrant sample. Household members that left for the purpose of studying are not treated as migrants to account for the fact that migration for education reasons is guided by different dynamics than labor migration, which is the primary focus of our analysis. Our main dependent variable (M) is binary and takes on a value of one if the sum of households' (h) migrants (m) in a given year (t) increases compared to the preceding year and is equal to zero otherwise. More formally, we define

$$M_{ht} = \begin{cases} 1, & \text{if } m_{ht} > m_{ht-1} \\ 0, & \text{otherwise.} \end{cases}$$

To test our hypotheses as presented in section 5.2, we split our sample into households whose livelihoods do (throughout the text referred to as agricultural) and do not (throughout the text referred to as non-agricultural) depend on agricultural production. Households are considered to depend on agriculture if they own agricultural land or at least one of their members is full-time employed in agriculture. Non-agricultural households, on the contrary do not own land and none of their members works in agriculture. Districts are the finest geographical level that we are able to reliably identify our households at.

Table 5.1 presents the corresponding summary statistics where N indicates the number of household-years. The table shows that almost 8% of agricultural and almost 7% of non-agricultural households experience out-migration in every given year. Most of household out-migration takes place internally to urban areas for both types of households. International migrants from agricultural households are likely to move to other African countries, while international migrants from non-agricultural households are likely to move to OECD countries.

To proxy household wealth in the cross-section, we construct a household wealth index similar to Dustmann and Okatenko (2014). The index is based on the following seven survey questions:

- *Does the household own the house it lives in?* Yes/No.
- *Does the household have access to electricity?* Yes/No.
- *Does the household have access to piped water?* Yes/No.

[7] Using the AMRS data, Gray and Wise (2016) apply a similar approach to generate their migration variables for a six-year migration panel.

Table 5.1: *Summary statistics: Households' migration (by destination)*

Variable	Mean	Std. Dev.	Min.	Max.	N
Agricultural households					
Overall	0.076	0.265	0	1	52101
Internal	0.058	0.235	0	1	52101
Internal: Rural	0.013	0.113	0	1	52101
Internal: Urban	0.046	0.209	0	1	52101
Africa	0.02	0.141	0	1	52101
OECD	0.008	0.091	0	1	52101
Non-agricultural households					
Overall	0.066	0.248	0	1	17307
Internal	0.046	0.209	0	1	17307
Internal: Rural	0.007	0.082	0	1	17307
Internal: Urban	0.04	0.195	0	1	17307
Africa	0.009	0.093	0	1	17307
OECD	0.019	0.135	0	1	17307

All variables were constructed at the household-year level using World Bank's African Migration and Remittances Surveys data. They are binary and take on a value of one if a household increased its number of out-migrants to a given destination compared to the year before, and zero otherwise.

- *Does the household own a television?* Yes/No.
- *Does the household own a computer?* Yes/No.
- *Does the household own a bank account that was not set up in response to a migrant leaving the household?* Yes/No.
- *Has the head of household attended a school?* Yes/No.

We conduct a principal component analysis on these variables and use the factor loadings of the first principle component as weights to construct an aggregate wealth index. The corresponding Kaiser-Meyer-Olkin measure of sampling adequacy indicates a value of 0.74, supporting the suitability of the approach (Dziuban and Shirkey, 1974). The resulting wealth index is then normalized to lie between 0 and 1.

Since variables, which we use to construct the wealth index can only be observed in 2009, they can be endogenous to the previous migration decision. We therefore also approximate wealth by a wealth measure based only on variables with information for the year 2000, the first year in our household panel. The first variable we use to calculate the pre-migration wealth is the indicator on whether or not the household head received any kind of formal education, guided by the idea that the level of education of the household head is a good predictor of household wealth in African countries (Duflo, 2001, 2004; Maccini and Yang, 2009; Wantchekon *et al.*, 2015). We implicitly assume that the decision to receive formal education is finalised at the beginning of the observation period and does not change over time.[8] The second variable is based on the question whether the respective household - this is, anyone in the household - owns a bank account. The question is followed up by a second question on whether this bank account was opened in response to a previous member of household leaving the household, allowing us to correct the bank account indicator for reverse causality. We then combine these two survey questions to construct a parsimonious wealth measure exogenous to the household decision to send a migrant. This measure divides households into the following three categories: low wealth households (0) with no bank account and where the head has zero years of schooling, medium wealth households (1) with either a bank account or where the head has received some schooling and upper-wealth households (2) with both a bank account and where the head attended school. Table 5.2 presents the corresponding summary statistics.

Table 5.2: *Summary statistics: Households' wealth indexes*

Variable	Mean	Std. Dev.	Min.	Max.	N
Owns house	0.716	0.451	0	1	7712
Access to electricity	0.482	0.5	0	1	7712
Access to piped water or public well	0.718	0.45	0	1	7712
Attended school (head)	0.569	0.495	0	1	7712
Owns computer	0.116	0.32	0	1	7712
Owns television	0.471	0.499	0	1	7712
Bank account (pre-migration)	0.335	0.472	0	1	7712
Wealth index	0.406	0.297	0	1	7712
Wealth index pre-migration	0.903	0.813	0	2	7712

All wealth index variables were constructed at the household level using World Bank's African Migration and Remittances Surveys data. The variable *Wealth index* is a binary indicator constructed using household level information from 2009 as shown in the upper part of the table, with higher valuer indicating more wealth. *Wealth index pre-migration* uses information from 2000. It is a categorical variable dividing households into low (0), medium (1) and upper-wealth (2) categories.

5.3.2 Global prices

We follow McGuirk and Burke (2020) in the construction of a plausibly exogenous price index that allows us to analyse the causal effect of price changes on migration. Similar to the authors, we require price data that varies sufficiently over time, is not determined by local factors and that allows us to differentiate real income effects across households. We therefore generate district-specific price time series by combining exogenous *temporal* variation in global crop prices with local *spatial* variation in crop production at the beginning of our observation period.

(Producer) Price Index (PPI): To generate the spatial variation in the PPI, we utilise

[8]Since we limit our sample to households whose head is 25 years or older at the beginning of the observation period, the assumption of schooling being finalised is plausible.

the high-resolution crop-specific fraction of harvested area in year 2000 (i.e., the first year of our observation period) which contains information on harvested area and yield for 175 crops, initially compiled by Monfreda *et al.* (2008). The authors create this land use dataset by combining national-, state- and county-level census statistics with a global dataset of croplands with a 5×5 minute grid cell resolution. Using these data, in Figures E.5, E.6, E.7 and E.8 in Appendix E.2, we provide illustrative examples of how production of different commodities differs by country. To generate the temporal variation in the PPI, we draw on annual global commodity prices from the IMF International Finance Statistics series and the World Bank Global Economic Monitor. Prices are indexed at 100 in year 2010. We then compute the annual district-specific PPI by combining the temporal variation of commodity prices and the spatial variation of crop-specific fraction of harvested area in 2000 in the following way:

$$PPI_{dt} = \sum_{i=1}^{n}(P_{it} \times F_{idc}) \tag{5.9}$$

whereby crops ($i...n$) capture a set of 12 major traded crops for the five countries in our dataset that are simultaneously covered by the land use dataset and for which international prices exist, F_{idc} captures the district-specific crop share of land. For a full list of crops used to generate the international food prices, see Table E.1 in Appendix E.2. To better capture the nature of unexpected shocks, we express the PPI as a percentage change from its district-specific long-run mean constructed for the pre-sample period 1990-1999. To summarize, the district-level variation of PPI comes from annual global crop price changes and a district-specific mix of locally produced crops. In addition, following McGuirk and Burke (2020), we also generate two disaggregated versions of the PPI for robustness checks: i) PPI (food), which captures price index for crops that constitute more than 1% of calorie consumption in the overall sample as suggested by food consumption data from the UN Food and Agriculture Organization (FAO), and ii) PPI (cash) which is the price index covering the remaining crops.

Figure E.3 in Appendix E.2 further captures how the PPI developed over time, suggesting a sharp spike during years of the food price crisis in 2007/08 in all countries. The spatial distribution of average PPI for the years of 2007/08 food price crisis in Figure E.4 in Appendix E.2 suggests that, likely due to the spatial correlation of soil-suitability in combination with spatially correlated climatic conditions that result in geographically correlated crop-production, our price index shows patterns of spatial correlation. We will attend to this phenomenon in more detail in section 5.5.3.

One of the key identifying assumption in all subsequent analyses - and in fact, of all empirical studies utilising local weather as a source of exogenous variation in local agricultural income - is the exogeneity of global crop prices to local production in Sub-Saharan Africa. If the quantity of agricultural goods produced locally was a predictor of global commodity prices, these prices would, to some extent, co-move with local production and attenuate shocks on quantities produced locally. A number of reasons should convince the reader that agricultural households in Sub-Saharan Africa are indeed price takers: First, to isolate the effect of global crop prices from local weather conditions, we focus on the observation period from 2000 to 2008. This time span covers the global food price crisis 2007/08, when global food prices rose sharply for reasons entirely exogenous to agricultural activity in Sub-Sahara African (Berazneva and Lee, 2013; Demeke *et al.*, 2009; Dorward, 2012). Second, between 1989-2013, the entire continent of Africa accounted for only 5.9% of global cereal production, minimizing its effect on global prices (McGuirk and Burke, 2020). Finally, we show in all our analyses that the effect of global prices on our outcomes are not sensitive to conditioning estimates on the local quantity produced, proxied by local weather conditions.

5.3.3 Local weather

To generate a set of climate-related variables, we draw on ERA5 reanalysis data produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) (C3S, 2017). ERA5 is the fifth generation of ECMWF atmospheric reanalyses of the global climate. It is a high quality reanalysis dataset which relies on information from weather stations, satellites, and sondes. ERA5 provides data at a geographical resolution of 31km and has been regridded to a 0.25×0.25 degrees latitude-longitude grid. Currently, the weather data is available from January 1979 with a temporal resolution of up to one hour. We use the daily mean temperature as well as total monthly precipitation and aggregate these to the district level, using Google Earth Engine.

The existing literature shows that the effect of temperature on economic outcomes is highly non-linear (Burke *et al.*, 2015b; Carleton and Hsiang, 2016; Schlenker and Roberts, 2009; Kalkuhl and Wenz, 2020). Growing degree days (GDD) is one common way to capture this non-linear relationship. One degree day counts the total amount of degrees above a lower threshold as long as the mean local temperature is below an upper threshold on a given day. If mean temperature (t) exceeds the upper threshold, degree days are counted as the difference between the upper bound and a lower bound. More formally, growing degree days D above a lower threshold l_1 and below an upper threshold l_2 are defined as:

$$D = \begin{cases} l_2 - l_1 & \text{if } t > l_2 \\ t - l_1 & \text{if } l_1 < t \leq l_2 \\ 0 & \text{if } t \leq l_1. \end{cases}$$

GDD then capture the total number of degree days over the crop-growing season, defined as the time period stretching from June to August (JJA) (Dell *et al.*, 2014; Schlenker *et al.*, 2007; Schlenker and Roberts, 2009).

Following the literature, we generate two GDD-related variables at the district-level: i) degree days between 10 and 30°C, and ii) degree days above 30 °C. The intuition behind the choice of the bounds is that temperature between 10-30 °C generally enhances yield, while temperatures above 30 °C is considered yield-decreasing (Schlenker and Roberts, 2009; Schauberger *et al.*, 2017). We control for the average growing season precipitation, measured as the average of daily (total) precipitation during the growing season in meters height collected on each square meter. However, precipitation is not of the main interest in our analysis for several reasons. First, in the context of Sub-Saharan Africa, precipitation has been shown not to be an important predictor of migration (Missirian and Schlenker, 2017) and conflict (Burke *et al.*, 2009). Second, relative temperature changes under future climate change scenarios translate into much larger changes in yields than do precipitation changes in Sub-Saharan Africa (Schlenker and Lobell, 2010). Third, even though weather data sets agree on long-run averages, particularly in the case of precipitation they do not necessarily agree on anomalies (Auffhammer *et al.*, 2013). Since deviations from the mean are the main source of identification in our setting, this could potentially be problematic. We nevertheless control for precipitation in all regression analyses for completeness. Table 5.3 presents the summary statistics of main local climatic variables of interest at the district-level.

Table 5.3: *Summary statistics: Climate-related variables at the district-year level*

Variable	Mean	Std. Dev.	Min.	Max.	Units
Growing Degree Days (10-30 °C) (GDD1030)	13.993	2.844	4.889	17.722	Hundred
Growing Degree Days (>30 °C) (GDD30)	0.299	0.492	0	3.1	Hundred
Precip. (JJA)	0.121	0.073	0.008	0.45	m
N		1260			

All weather variables were constructed at the district-year level using ERA5 reanalysis data and capture conditions during the growing season covering months June-August.

5.3.4 Conflict data

We follow state-of-the-art approaches in conflict analyses (McGuirk and Burke, 2020; De Winne and Peersman, 2019) and distinguish between i) small-scale *output* conflicts associated with appropriation of surplus, and ii) large-scale *factor* conflicts over the control of territory. We only focus on conflicts in the second half of each year (i.e., the period from July to December) to link all conflict events to the district-specific crop yield of each growing season from June to August. Mid-growing season, households will have plausibly assessed their potential agricultural income.

Output conflicts: To capture output conflict, we draw on the Armed Conflict Location and Event Data Project (ACLED) database (Raleigh *et al.*, 2010). ACLED provides temporally and geographically disaggregated data on dates, actors, locations, fatalities, and types of all reported political violence and protest events, collected from a range of media and agency sources. Since output conflict is likely to be transitory and disorganized, we further draw on information on riots, protests and violence against civilians (McGuirk and Burke, 2020; De Winne and Peersman, 2019). We then construct a binary output conflict variable on the external margin of output conflict incident, covering our sampling period from 2000 to 2008.[9]

Factor conflicts: We further draw on geo-coded conflict-related fatality count data from the Uppsala Conflict Data Program (UCDP) (Sundberg and Melander, 2013; Pettersson and Öberg, 2020). UCDP provides temporally and geographically disaggregated information on conflict events, which entail the use of armed force by an organized actor against another organized actor, or against civilians, resulting in at least one direct death. It covers all dyads that have crossed a threshold of 25 battle deaths per year. The data is gathered from local and national media, agencies, NGOs and international organizations. Since UCDP data capture relatively larger scale conflicts, the data is suitable to approximate conflicts associated with the control of territory, i.e., factor conflicts (McGuirk and Burke, 2020). We aggregate the fatality counts to the district-year level for the period 2000-2008 to match the fatality counts with our other data sources. Similar to output conflict, our main variable of interest is binary and takes the value one if any conflict event took place in a given district-year between July to December, and zero otherwise.

The constructed conflict-related variables at the district level are summarized in Table 5.4 below.

Table 5.4: *Summary statistics: Conflict occurrence at the district-year level*

Variable	Mean	Std. Dev.	Min.	Max.
Output conflict (July - December)	0.2405	0.4275	0	1
Factor conflict (July - December)	0.0722	0.259	0	1
N		1260		

Output conflict was constructed using Armed Conflict Location and Event Data Project data and captures occurrence of smaller-scale conflicts at the district-year level. Factor conflict was constructed using Uppsala Conflict Data Program data and captures occurrence of large-scale conflicts at the district-year level.

[9]The decision to code our conflict variables as binary (and thus only consider the external margin) is guided by the conflict literature (Bazzi and Blattman, 2014; Berman *et al.*, 2017; Nunn and Qian, 2014; McGuirk and Burke, 2020) and reduces the potential measurement error stemming from the recording of the original conflict events (McGuirk and Burke, 2020)

5.4 Methodology

We first examine the effect of the exogenous variation in international food prices measured by the PPI on households' decision to send out a migrant, while controlling for local climatic variables. To do so, we estimate the following baseline equation:

$$Pr[M_{hdt} = 1|x_{dt}, \phi_t, \alpha_h] = \beta_0 + \beta_1 PPI_{dt} + \beta_2 GDD_{dt;10:30} + \beta_3 GDD_{dt;30:\infty} + \beta_4 GP_{dt} + \alpha_h + \phi_t + \epsilon_{hdt}. \quad (5.10)$$

Thus, our binary indicator capturing a household-specific (h) increase in migration in a given year (t) relative to the preceding year (M_{hdt}) is regressed on yearly district-specific (d) food price index (PPI), district-specific number of growing degree days (GDD) between 10-30 °C and above 30 °C, district-specific average precipitation during the growing season and its squared term (summarized by GP) and year (ϕ_t) and household (α_h) fixed effects. By applying a two-way fixed effects approach, the identification comes via deviation of global prices from their historical district-specific mean over time. Thus, a given households' out-migration rate is compared under different price regimes. The year fixed effects ensure that out-migration and global food prices are not simultaneously determined by variation in third factors, such that the estimated effect can be interpreted causally. Figure 5.1 presents the yearly, district-specific variation in PPI from the district-specific mean from 2000 to 2008, which serves as the main source of identification of the response coefficient. We cluster standard errors at the level of the treatment, i.e., at the district-level.

In our next specification, we then study how international prices interact with households' wealth and affect households' migration decision in the following way:

$$Pr[M_{hdt} = 1|x_{dt}, \phi_t, \alpha_h] = \beta_0 + \beta_1 PPI_{dt} + \sigma PPI_{dt} \times Wealth_h + \beta_2 GDD_{dt;10:30} + \beta_3 GDD_{dt;30:\infty} + \beta_4 GP_{dt} + \alpha_h + \phi_t + \epsilon_{hdt}. \quad (5.11)$$

Thus, the coefficients on β_1 and σ combined capture the differential effect of locally-relevant global prices along the household wealth distribution. $Wealth_h$ enters the equation as either a continuous (post-migration wealth) or categorical (pre-migration wealth) variable as explained in the previous section.

We estimate equations 5.10 and 5.11 using both a reduced-form linear probability model (LPM) and a logistic (Logit) model. The LPM assumes a linear relation between the household decision to send a migrant and the changing local income conditions. While no additional modelling choices are required, this assumption is potentially strong in a setting when the majority of household-years contain zero values. Maximum likeli-

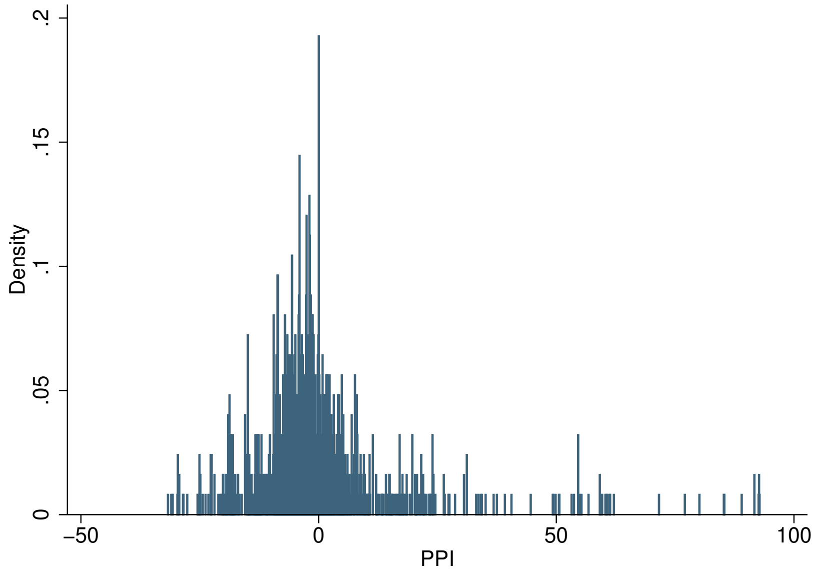

Figure 5.1: *Within-district variation in PPI*

hood based probability models such as the Logit allow for a more flexible, non-linear probability function more suitable for such a setting and recent advances in logistic models that incorporate large number of fixed effects also overcome the incidental parameter problem inherent to these models (see Lancaster (2000) for a detailed discussion).

However, maximum-likelihood based fixed effects Logit models also have their disadvantages in the setting at hand: First, since it is mathematically impossible for maximum-likelihood models to converge when there is no within-category variation, these models often fail to converge when high dimensional fixed effects are incorporated. For example, when including country-by-year fixed effects, the likelihood function fails to find a global maximum for all subsamples. Second, when reporting the marginal effects from the Logit models, additional assumptions on the values of the fixed effects -which are not estimated - are required.[10]

We therefore suggest an estimation strategy based on an LPM with a common time-trend and climatic controls to obtain our parameters of interest as our preferred specification. To ensure that the choice of the model does not drive our results, we also show obtained average marginal effects from the conditional fixed effects Logit specification following Kitazawa (2012) and Kemp *et al.* (2016). We then also estimate a more conservative specification of our models that include country by year fixed effects (LPM) or country-specific linear time trends (Logit). We do not choose these specification as our preferred ones for two main reasons. First, because of within-country spatial

[10]Some modellers in the migration literature choose to report the marginal effects by setting the fixed effects to zero (see for example (Bazzi, 2017). However, this is an arbitrary choice.

correlations in our main variable of interest - which we will explore further in subsection 5.5.3 - the country-year trends could potentially absorb a significant share of the variation of interest. Second, the additional loss in degrees of freedom is critical compared to the additional precision our estimates gain in a setting where the essential household fixed effects absorb a high number of degrees of freedom. Nevertheless, we will present these estimates for robustness.

As outlined in the introduction, we further aim to examine conflict as a potential mechanism that could in part explain the relationship between producer prices and household out-migration. The analysis of the channeling effect of conflict in similar econometric settings is a widely discussed empirical challenge (see for example Berlemann and Steinhardt (2017)). Including conflict as a control variable in 5.10 could bias the coefficient on our main independent variables if conflict itself is an outcome of changes in locally-relevant food prices and local climatic conditions, a problem commonly referred to as an *over controlling* (Dell *et al.*, 2014) or a *bad control* problem (Angrist and Pischke, 2009).

We therefore structure our thinking on the global prices-conflict-migration nexus as follows. We start out by estimating the association of household out-migration and the different types of conflict in the following parsimonious regression framework:

$$Pr[M_{hdt} = 1|x_{dt}, \phi_t, \alpha_h] = \theta_0 + \theta_1 Conflict_{dt} + \alpha_h + \phi_t + \epsilon_{hdt}, \tag{5.12}$$

where the dependent variable is defined as the household out-migration from household h, residing in district d in year t as before. We distinguish between output and factor conflict, both of which enter equation 5.12 separately as $Conflict_{dt}$. The estimated coefficient on conflict, θ_1, should not be interpreted causally due to the potential problems of reverse causality and omitted variable bias. Nevertheless, these correlations can provide us with first valuable information as they reveal how household out-migration and conflict relate to one another. To more directly explore the link between locally-relevant global prices and conflict, we study the district-level association between the PPI and the different types of conflict in Appendix E.6.

5.5 Results

In this section, we present all outcomes from our regression analyses. Specifically, in section 5.5.1, we present results of the aggregate association between global food prices and migration. In section 5.5.2, we study the heterogeneity of these effects along the initial household wealth distribution. Finally, in section 5.5.3, we turn to destination choices in response to changes in locally-relevant global food prices. We present outcomes from both the LPM and the Logit model in all of our main analyses and for the more specific results, only show our preferred specification as described in the previous section.[11]

5.5.1 Aggregate effect of global food prices

Tables 5.5 and 5.6 show the estimated effects of changes in global food prices (PPI) on the probability of migration for agricultural and non-agricultural households respectively. We will refer to model (5) as the result from our our preferred specification.

For the **sub-sample of agricultural households**, both the LPM and the Logit show similar outcomes throughout different specifications. Our preferred specification (5) suggests that a one percentage point increase in locally-relevant global food prices over its district specific long-run mean increases the likelihood that households send out a migrant by 0.06 percentage points. Even in the most demanding model specifications (3 and 6), the effect remains highly visible and does not change in its order of magnitude. Importantly, comparing models (1) to (2) and (3) to (4), it becomes evident that the magnitude of the effect of producer prices on household out-migration remains unchanged when conditioned on local weather. These controls even add precision to the obtained estimates, albeit only marginally. This first finding provides reassurance that international food prices and local weather are not linked causally.[12]

The estimated coefficients on the local weather variables indicate that an increase of the number of degree days during the growing season above 30 °C by 100 decreases the likelihood of households sending one of their members as a migrant in the same year by almost three percentage points (model 5). On the other hand, 100 additional growing degree days between 10 and 30 °C significantly increase the likelihood of households sending out a migrant by 2 percentage points. A note of caution is warranted when interpreting these findings. While the sign of the estimates on our generated weather variables is stable throughout all specifications, the coefficients are not always significant at conventional statistical levels. A potential reason for this is the inherent collinearity of the two variables at their intersection points around the bounds defined in the previous section; however, the particular modelling of the variables is necessary to capture the

[11] Note that output tables of the Logit regressions show the average semi-elasticity of $Pr[M_{hdt} = 1|x_{dt}, \phi_t, \alpha_h]$ with respect to our variables of interest. The magnitude of these coefficients is therefore not directly comparable to the OLS estimates, which capture level-level (percentage point) changes.

[12] To further test that PPI is exogenous and thus is not determined by local conditions we regressed it on local climatic variables. By using a fixed effects panel data regression, location and time effects absorb potential large-scale correlation of climatic events and related trends. The remaining variation identifies responses from deviations of local climatic conditions over time from the long-term, location-specific mean. The results suggest that local climate-related variations do not significantly predict variation in PPI. Since we use the same identification strategy in the main analysis, we can plausibly claim that the variation that identifies PPI responses is not defined by local conditions as potential sources of correlation are captured by fixed effects. The estimation results are available upon request.

non-linearity in increasing temperatures as discussed in 5.3.3.

For the **sub-sample of non-agricultural households**, we generally do not find any statistically significant effects of global food prices on household out-migration. However, the sign of the association is positive throughout specifications and turns significant at the five percent level in model (3); these outcomes could capture the pull effects of the agricultural sector, a potential explanation we will offer more detail on in section 5.5.3 and Appendix E.5. We do not find a significant impact of adverse local weather on non-agricultural households. This suggests that if local production conditions deteriorate, non-agricultural households are able to diversify their consumption via world markets, as implied by equation 5.8.

Taken together, for households whose livelihoods depend on agricultural production, we find that higher international food prices facilitate migration, an indication that positive producer price shocks have a similar migration-inducing effect as positive weather shocks. Our explanation as proposed by the theory in section 5.2 is that positive income shocks, either via increases in the PPI or yield enhancing temperatures, push households above the previously binding budget constraint. Lower PPI or yield decreasing temperatures, on the contrary, reduce migration by imposing a stricter budget constraint (Cattaneo and Peri, 2016; Deaton, 1989; Bellemare *et al.*, 2018; McGuirk and Burke, 2020). Households in the agricultural context of Sub-Saharan Africa are typically characterized by low income levels (McGuirk and Burke, 2020). Thus, the migration-inducing effect of the PPI appears to be larger than the rising opportunity costs of out-migration due to better income opportunities at home. We turn to these suggested interpretations of our aggregate findings in more detail in the next section.

To better understand the estimated associations, we further run the fully specified LPM model by distinguishing the PPI of cash and food crops (see Table E.2, Appendix E.3). Finally, we also run the fully specified LPM models with common and state-specific trends, presented in Appendix E.3, to check our results for robustness with respect to alternating definitions of the growing season. In Tables E.3 and E.4 we present the outcomes for agricultural and non-agricultural households respectively. Even though none of these robustness checks seem to change our main results, we find that these results are mainly driven by price changes of food crops rather than cash crops, further suggesting that domestic consumption plays an important role in the setting of Sub-Saharan Africa. Moreover, the sensitivity tests confirm that households respond most strongly and consistently to the growing season conditions as defined in the main analysis.

Finally, to put the effect of locally-relevant prices into perspective, it is useful to compare changes in the PPI to the effect of local weather directly. To do so, consider a hypothetical scenario where both the PPI and the DD30 increase by one standard deviation over their long-run mean. A back-of-the-envelope calculation that considers the

Table 5.5: *Aggregate effect of PPI on the probability of migration: Agricultural households*

	(1)	(2)	(3)	(4)	(5)	(6)
PPI	0.0051*	0.0052**	0.0106***	0.0006***	0.0006***	0.0004*
	(0.0026)	(0.0025)	(0.0025)	(0.0002)	(0.0002)	(0.0002)
DD1030		0.1800	0.0885		0.0219*	0.0203
		(0.1703)	(0.1493)		(0.0112)	(0.0135)
DD30		-0.3563	-0.2043		-0.0254*	-0.0448***
		(0.2322)	(0.2007)		(0.0148)	(0.0167)
N	23742	23742	23742	52101	52101	52101
R^2				0.012	0.013	0.017
Time trend	Year	Year	Country x Year	Year	Year	Country x Year
Model	Logit	Logit	Logit	LPM	LPM	LPM
Precip. controls	No	Yes	Yes	No	Yes	Yes

The dependent variable is binary and captures household-level out-migration incidence in a given year. The producer price index (*PPI*) is measured in percent and captures *PPI* change (%) compared to the long-run average (1990-1999). *DD1030* captures 100 degree days between 10 and 30 °C and *DD30* above 30 °C during the growing season (June-August). The migration variable is constructed using World Bank's African Migration and Remittances Surveys data. Weather variables are constructed using ERA5 data. PPI is constructed by combining crop-specific fraction of harvested area data by Monfreda *et al.* (2008) and annual global commodity prices from the IMF International Finance Statistics series and the World Bank Global Economic Monitor. The sample captures agricultural households only. Models 2-3 and 5-6 further control for growing season precipitation and their squared terms. Models 1-3 are estimated with fixed effects logit model and models 4-6 with LPM. Models 1-2 and 4-5 use a common and models 3 and 6 country-specific time trend. Model 5 corresponds to the preferred specification. Standard errors clustered at the district level are displayed in parentheses.* $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 5.6: *Aggregate effect of PPI on the probability of migration: Non- agricultural households*

	(1)	(2)	(3)	(4)	(5)	(6)
PPI	0.0039	0.0037	0.0077**	0.0004	0.0004	0.0003
	(0.0031)	(0.0031)	(0.0034)	(0.0003)	(0.0003)	(0.0004)
DD1030		0.2265	0.1836		0.0156*	0.0208*
		(0.1378)	(0.1380)		(0.0093)	(0.0113)
DD30		0.3363	0.5591		0.0205	0.0031
		(0.3793)	(0.3751)		(0.0214)	(0.0201)
N	7443	7443	7443	17307	17307	17307
R^2				0.016	0.016	0.023
Time trend	Year	Year	Country x Year	Year	Year	Country x Year
Model	Logit	Logit	Logit	LPM	LPM	LPM
Precip. controls	No	Yes	Yes	No	Yes	Yes

The dependent variable is binary and captures household-level out-migration incidence in a given year. The producer price index (*PPI*) is measured in percent and captures *PPI* change (%) compared to the long-run average (1990-1999). *DD1030* captures 100 degree days between 10 and 30 °C and *DD30* above 30 °C during the growing season (June-August). The migration variable is constructed using World Bank's African Migration and Remittances Surveys data. Weather variables are constructed using ERA5 data. PPI is constructed by combining crop-specific fraction of harvested area data by Monfreda *et al.* (2008) and annual global commodity prices from the IMF International Finance Statistics series and the World Bank Global Economic Monitor. The sample captures non-agricultural households only. Models 2-3 and 5-6 further control for growing season precipitation and their squared terms. Models 1-3 are estimated with fixed effects logit model and models 4-6 with LPM. Models 1-2 and 4-5 use a common and models 3 and 6 country-specific time trend. Model 5 corresponds to the preferred specification. Standard errors clustered at the district level are displayed in parentheses.* $p<0.10$, ** $p<0.05$, *** $p<0.01$.

non-linear effect of local temperatures on household out-migration (i.e., that accurately factors in the corresponding changes in DD1030), then shows that the overall climatic effect on migration of both, global prices and local temperature is positive. More precisely, the standardized effect of a global price increase on household out-migration is around 37% of the standardized (and so comparable) net effect of a rise in local temperature. Overall, these findings therefore suggest that in the context of Sub-Saharan Africa, the magnitude of short-term climatic effects on migration have thus-far been underestimated.[13]

5.5.2 The role of household wealth

In this section, we explore the role of households wealth, one of the contextual factors that could determine the direct associations between PPI and migration. To explore this particular heterogeneity, we turn to the results of regression model 5.11, detailed in 5.4. First, in Table 5.7 we interact the PPI with the continuous wealth index and present the results from a series of fully specified LPMs and Logit models with and without country-specific trends for agricultural (models 1-4) and non-agricultural (models 5-8) households. Second, because the continuous wealth index is based on values partially measured in 2009 and the wealth it captures could therefore be endogenous to the migration decision, in Appendix E.4 in Tables E.5 and E.6, we interact the PPI with the exogenous categorical wealth index based on values from 2000 for agricultural and non-agricultural households respectively. Using this more exogenous measure without time variation also solves the over-controlling problem (Dell *et al.*, 2014).

For the **sub-sample of agricultural households**, in Table 5.7 we find robust evidence across all specifications that wealthier households are less likely to send out migrants when the locally-relevant global prices increase. The marginal effects of PPI by wealth, i.e., the outcomes from the main specification (model 3), are depicted in Figure 5.2. The marginal effect is positive but decreases with increasing wealth. It remains statistically significant only for approximately the lower half of the wealth distribution. In Table E.5 (in Appendix E.4), we draw on the exogenous measure of wealth to test the validity of these results. In five out of six specifications, we find further evidence that richer households are less likely to send out migrants when the PPI increases. In our preferred model 5, the interactions show that if PPI increases by one p.p., medium-wealth and upper-wealth households become 0.03 p.p. and 0.09 p.p. less likely to send out migrants respectively, compared to households with low levels of wealth. Figure 5.3 further presents these outcomes visually only for the lower and upper wealth categories (i.e., the medium wealth households are not included). It shows that a higher PPI increases the marginal probability of low-wealth and decreases the probability of upper-wealth

[13]These calculations are available upon request.

households to send out migrants. When using this more exogenous wealth measure, the effect of the PPI is statistically significant from zero along the entire wealth distribution. The presented evidence underlines the interpretation of the direct effects of locally-relevant global prices on household out-migration, as suggested in the previous section. Implications of global price changes for migration differ depending on households' wealth. The findings strongly suggest that increases in household income induced by exogenous changes in relevant agricultural commodity prices push poor households above the previously binding budget constraint and facilitate their out-migration, exceeding contrary opportunity costs effect. The opportunity costs only start to play a more significant role for wealthier households, reducing their likelihood to send out migrant as income increases.

We do not find similar evidence for **sub-sample of non-agricultural households**. Both the baseline effect of the PPI and its interaction with household wealth show no statistically significant association with household out-migration, visible in both Table 5.7 and E.6 (in Appendix E.4). We interpret this as evidence that PPI does not capture prices of locally consumed crops, but rather captures the conditions in the agricultural sector. Thus, the weak evidence of positive aggregate effects of the PPI on out-migration from non-agricultural, net-consuming households shown in 5.5.1 seem to rather capture pull effects. We will discuss these in more detail in the next section.

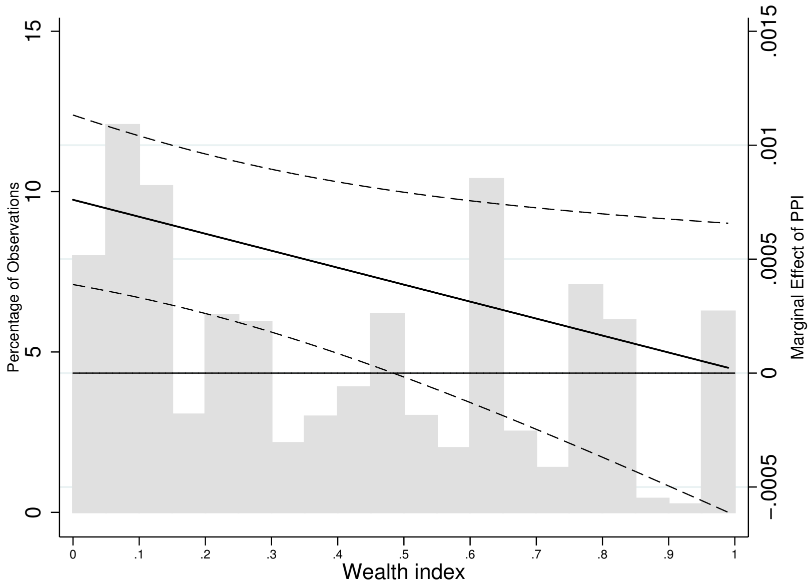

Figure 5.2: *Partial effect of PPI by wealth according to model 3, Table 5.7 with 90% CIs*

Table 5.7: *Heterogeneous effects of PPI by household wealth: Agricultural (models 1-4) and non-agricultural (models 5-8) households*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PPI	0.0069**	0.0128***	0.0008***	0.0006**	0.0033	0.0087	0.0005	0.0002
	(0.0027)	(0.0024)	(0.0002)	(0.0002)	(0.0081)	(0.0083)	(0.0007)	(0.0007)
PPI × Wealth	-0.0078*	-0.0106***	-0.0007*	-0.0005*	0.0007	-0.0018	-0.0002	0.0002
	(0.0043)	(0.0036)	(0.0004)	(0.0003)	(0.0115)	(0.0116)	(0.0010)	(0.0010)
DD30	-0.3819*	-0.2289	-0.0264*	-0.0435**	0.3334	0.5687	0.0209	0.0024
	(0.2270)	(0.1950)	(0.0146)	(0.0168)	(0.3802)	(0.3812)	(0.0214)	(0.0203)
DD1030	0.1958	0.1044	0.0228**	0.0203	0.2262	0.1845	0.0157*	0.0208*
	(0.1679)	(0.1461)	(0.0111)	(0.0135)	(0.1390)	(0.1391)	(0.0094)	(0.0113)
N	23742	23742	52101	52101	7443	7443	17307	17307
R^2			0.013	0.017			0.016	0.023
Time trend	Year	Country x Year	Year	Country x Year	Year	Country x Year	Year	Country x Year
Model	Logit	Logit	LPM	LPM	Logit	Logit	LPM	LPM
Precip. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Agri.	Agri.	Agri.	Agri.	Non-agri.	Non-agri.	Non-agri.	Non-agri.

The dependent variable is binary and captures household-level out-migration incidence in a given year. The producer price index (*PPI*) is measured in percent and captures *PPI* change (%) compared to the long-run average (1990-1999). *DD1030* captures 100 degree days between 10 and 30 °C and *DD30* above 30 °C during the growing season (June-August). The wealth index lies between 0 and 1, where higher values represent higher wealth. The migration and wealth variables are constructed using World Bank's African Migration and Remittances Surveys data. Weather variables are constructed using ERA5 data. PPI is constructed by combining crop-specific fraction of harvested area data by Monfreda *et al.* (2008) and annual global commodity prices from the IMF International Finance Statistics series and the World Bank Global Economic Monitor. Models 1-4 capture agricultural and models 5-8 non-agricultural households. All models further control for growing season precipitation and their squared terms. Models 1-2 and 5-6 are estimated using a Logit model and models 3-4 and 7-8 using LPM. Models 1, 3, 5 and 7 use a common and models 2, 4, 6 and 8 country-specific time trend. Standard errors clustered at the district level are displayed in parentheses.* $p<0.10$, ** $p<0.05$, *** $p<0.01$.

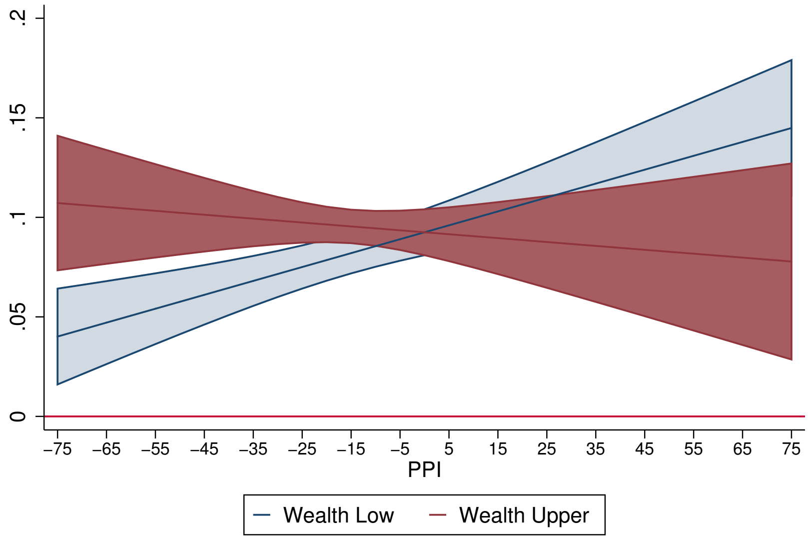

Figure 5.3: *Partial effect of PPI on agricultural households by wealth according to model 5, Table E.5 (Appendix E.4) with 90% CIs*

5.5.3 Destination choices

Throughout this paper, we have made the case for both global prices and local weather being a) exogenously determined and b) the two factors being uncorrelated. A third, albeit less crucial source of potential bias in our estimates is the spatial correlation in production pattern and local weather conditions. Due to the necessary arbitrariness in drawing district borders, neighbouring districts tend to grow similar crops and may therefore experience income shocks that are spatially correlated. Similarly, neighbouring regions may experience climatic and weather conditions that are not entirely dissimilar across districts. We illustrate the presence of spatial correlations in our setting in figures E.4, E.1 and E.2 of Appendices E.2 and E.1.

The consequence of these spatial correlations follows immediately from our characterization of the household out-migration probability in equation 5.4: For example, spatial correlations in local production patterns mean that a positive income shock through a rise in locally-relevant global crop prices that increases the utility of the potential migrant staying home, U_{hhy}, simultaneously changes the households' expected utility flows in destination districts, U_{hdy}. Thus, the attractiveness of some nearby destinations may co-move when locally relevant global prices change. It follows that, due to spatial correlations, locally-relevant global prices can be expected to have less of an impact on internal rural migration, a type of migration that makes only for a very small share of total migration (see Table 5.1).

However, destination choices may not only be influenced by spatial correlations.

Unless local production and local consumption of agricultural products are uncorrelated, the real income in urban areas will be negatively affected by increases in locally relevant global crop prices (see equation 5.7). For potential migrants in agricultural rural households, this means that with rising income at home, urban destinations in the same district (or nearby districts if spatial correlations are considered) may become less attractive whenever income at home rises through increases in producer prices. We note that the same reasoning does not hold for local weather shocks: Local weather conditions, which act on the locally produced quantity have no effect on the attractiveness of urban areas (see equation 5.8), where real income remains unaffected. In sum, these points lead us to conclude that the aggregate positive effect of locally-relevant global prices on out-migration in agricultural households is unlikely to be driven by an increase in rural-urban migration.

We test these consideration within our baseline specification (5.10) for each of the destination choices we observe in the data.[14] Table 5.8 shows the results of these analyses derived from our preferred specification. For completeness, we present the results for non-agricultural households in Appendix E.5, Table E.7. We also present robustness tests of specifications that include country-by-year fixed effects in the Appendix E.5 in Tables E.8 and E.9 gor agriculutral and non-agricultural households, respectively. Including these more demanding fixed effects does not alter our results.

The results confirm that the aggregate effect of changes in locally-relevant prices on household out-migration among agricultural households is driven by migration to destinations in other African countries. On the other hand, changes in local weather mostly affects internal migration into urban areas within agricultural households. While our data does not allow us to precisely pin down the effect of spatial correlations, our results are highly suggestive of a simultaneous decline in real income in urban areas when locally-relevant prices rise. Thus, while the aggregate income effect of locally-relevant global prices and local weather is positive in our sample, the type of migration induced through the income channel differs: A rise in global prices increases migration into neighbouring African countries, while an improvement in local weather conditions increases internal rural-urban migration.

It should further be noted that the income fluctuations agricultural households experience from exogenous changes in global prices and local weather conditions are unlikely to be sufficient to cover the necessary investment cost of migration into OECD countries. These have been shown to be significantly higher than the costs of internal migration and migration into nearby African destinations (Marchal and Naiditch,

[14]We consider each destination separately at a time and set all other destinations to zero in these analyses. An alternative econometric approach would be to condition estimates on locally-relevant global producer prices and weather conditions in nearby district, potentially weighing these by distance. However, due to the high spatial correlation of adjacent districts in our setting, the collinearity introduced by such an approach does not allow for reliable inference.

Table 5.8: *Effect of PPI by destination choice: Agricultural households*

	(1) Total	(2) Internal	(3) Internal: rural	(4) Internal: urban	(5) Other African	(6) OECD
PPI	0.0006***	-0.0001	-0.0000	-0.0001	0.0006***	-0.0000
	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0000)
DD1030	0.0219*	0.0233***	0.0006	0.0234***	0.0033	0.0031
	(0.0112)	(0.0081)	(0.0033)	(0.0079)	(0.0041)	(0.0048)
DD30	-0.0254*	-0.0257**	0.0002	-0.0261**	-0.0068	-0.0043*
	(0.0148)	(0.0118)	(0.0040)	(0.0100)	(0.0061)	(0.0026)
N	52101	52101	52101	52101	52101	52101
R^2	0.013	0.014	0.004	0.011	0.008	0.000
Time trend	Year	Year	Year	Year	Year	Year
Model	LPM	LPM	LPM	LPM	LPM	LPM

The dependent variables are binary and capture household-level out-migration incidence by destination in a given year. The producer price index (*PPI*) is measured in percent and captures *PPI* change (%) compared to the long-run average (1990-1999). *DD1030* captures 100 degree days between 10 and 30 °C and *DD30* above 30 °C during the growing season (June-August). The migration variable is constructed using World Bank's African Migration and Remittances Surveys data. Weather variables are constructed using ERA5 data. PPI is constructed by combining crop-specific fraction of harvested area data by Monfreda *et al.* (2008) and annual global commodity prices from the IMF International Finance Statistics series and the World Bank Global Economic Monitor. All models capture agricultural households, control for growing season precipitation and their squared terms and are estimated with LPM. Standard errors clustered at the district level are displayed in parentheses.* p<0.10, ** p<0.05, *** p<0.01.

2020). Our results indeed suggest that migration to these destinations are unaffected by fluctuations in both prices and weather.

5.6 The role of conflict

Here, we explore whether in addition to wealth, conflict is a concurring mechanism behind the PPI - migration association, revealed in section 5.5. Socio-political conditions importantly affect the relationship between climate-related events and human migration (Black *et al.*, 2011b; Cattaneo *et al.*, 2019). Ample evidence suggests a general link between local climatic pressure and conflict (Abel *et al.*, 2019; Hsiang *et al.*, 2013), which can spill over into migration and displacement (Missirian and Schlenker, 2017; Abel *et al.*, 2019). Fluctuations in global food prices specifically have been shown to affect political instability and violent conflicts (Bazzi and Blattman, 2014; Bellemare, 2015; McGuirk and Burke, 2020; De Winne and Peersman, 2019). Therefore, while not making general claims about wider displacement, we study if these changes in international food prices can indirectly influence the specific type of labour migration at hand, household out-migration.

As detailed in section 5.4, analyzing the channeling effect of conflict in such settings is connected to numerous empirical challenges. We therefore first estimate equation 5.12 to study the general correlation between household out-migration and conflict in the setting of Sub-Saharan Africa. The results are shown in Table 5.9. Models 1-2 and 5-6 show the effects of output conflict on migration from agricultural and non-agricultural households, respectively. Models 3-4 and 7-8 then show the effects of factor conflict for agricultural and non-agricultural households, respectively. For agricultural households, we do not find any statistically significant association between output conflict and migration or between factor conflicts and migration. For non-agricultural households, we find a weak evidence that household out-migration may be negatively correlated with factor conflicts. One explanation of this negative correlation could be that out-migration serves as an *escape valve* for local tensions (Bosetti *et al.*, 2020); however, we abstain from a strong interpretation of the result.

To complete our analyses, we also examine the general link between global commodity price changes and their effect on output and factor conflicts in Table E.10 of Appendix E.6. Our results reveal that a rise in producer commodity prices decreases the likelihood of output conflicts (for a more in-depth discussion, see Appendix E.6). Thus, we find no evidence for a link between rising producer prices and conflict onset as a mechanism for migration in our particular setting. Taken together, the association between prices and conflict previous studies have documented does not seem to play a role for the household decision to send a member as a labor migrant, the predominant type of migration in Sub-Saharan Africa. If anything, household out-migration shows a negative correlation with conflict, possibly since migration decreases the local tensions and competition over resources, as documented by previous literature (Bosetti *et al.*, 2020).

5.7 Concluding remarks

In this paper, we conduct household-level analyses on the relation between global prices, local weather and the household decision to send a migrant. We derive a series of new conclusions on climate-related migration. First, we study how international crop price changes, to a large extent induced by distant climatic shocks in agricultural production, affect migration in Sub-Saharan Africa. By acknowledging the importance of transmission of climatic shocks in an interconnected world, our study provides a new perspective on climate migration. Second, we provide new evidence on households' budget constraints that can affect households' ability using migration to optimally adapt to these global change dynamics. We find that higher food prices can help agricultural households to overcome their budget constraint and higher producer prices thus facilitate migration similar to positive income shocks from local weather. The aggregate positive effect of global prices on household out-migration is driven by the low average household wealth level in agricultural Sub-Saharan Africa. With household wealth rising over time, the opportunity cost channel is likely to take over, at least

Table 5.9: *Effect of conflict on migration*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Output conflict	0.0074	0.0076			-0.0002	-0.0009		
	(0.0054)	(0.0051)			(0.0052)	(0.0056)		
Factor conflict			-0.0167	-0.0118			-0.0169	-0.0160*
			(0.0127)	(0.0086)			(0.0118)	(0.0081)
N	52101	52101	52101	52101	17307	17307	17307	17307
R^2	0.012	0.016	0.012	0.016	0.016	0.023	0.016	0.023
Time trend	Year	Country x Year	Year	Country x Year	Year	Country x Year	Year	Country x Year
Model	LPM	LPM	LPM	LPM	LPM	LPM	LPM	LPM
Precip. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Agri.	Agri.	Agri.	Agri.	Non.-agri.	Non.-agri.	Non.-agri.	Non.-agri.

The dependent variable is binary and captures household-level out-migration incidence in a given year. The *Output conflict* variable is binary and measures smaller scale conflict incidence. The *Factor conflict* variable is binary and measures smaller larger conflict incidence. The migration and wealth variables are constructed using World Bank's African Migration and Remittances Surveys data. *Output conflict* is constructed using ACLED data. *Factor conflict* is constructed using UCDP data. All models are estimated using LPM. Models 1-4 capture agricultural and models 5-8 non-agricultural households. Models 1, 3, 5 and 7 use a common and models 2, 4, 6 and 8 country-specific time trend. Standard errors clustered at the district level are displayed in parentheses.* $p<0.10$, ** $p<0.05$, *** $p<0.01$.

in partial equilibrium. Third, unlike positive weather shocks, which mostly facilitate internal rural-urban migration, positive income shocks through rising producer prices only increase migration to neighboring African countries, likely due to the simultaneous decrease in real income in nearby urban areas. This finding has important implications for projected migration dynamics in the poor regions of Sub-Saharan Africa: While we confirm that climate change scenarios rightly assume that local climatic conditions mostly drive internal migration, interconnected global shocks with repercussions for wider geographical areas may trigger migration into regions outside the home country. We further estimate that the magnitude of the standardized global price effect on household out-migration is around one third of the standardized effect of local weather, implying that in the context of Sub-Saharan Africa the magnitude of climate-related impacts on migration has thus-far been underestimated. Finally, despite the significant effect global prices have on output conflict, we show that conflict does not play a role for the household decision to send a member as a labor migrant.

The implications of our results will become increasingly important in the future and have direct policy implications. For instance, the cereal demand in Sub-Saharan Africa is expected to triple by 2050 and the subcontinent is likely to depend on imports to a larger extent than it does today (De Winne and Peersman, 2019). At the same time, episodes of rising food prices are expected more frequently as a result of the adverse climate change impacts on agricultural productivity (Lobell *et al.*, 2011; Burke and Emerick, 2016). On the one hand, higher food prices could help particularly poorer agricultural households cover migration-related costs. Migration is often used as an important livelihood strategy for these households and a rise in income could ease existing budget constraints. On the other hand, higher international prices are likely to impose adverse income effects on net-consumers. These opposing implications should be comprehensively considered by policy makers when designing policies to minimize welfare losses in a changing climate.

A few limitations apply and need to be discussed in this context. Based on our empirical results, we can derive only weak conclusions on the implications of rising producer prices for non-agricultural households, which mostly reside in urban areas. Data limitations do not allow the approximation of consumer prices relevant for local consumption at geographical levels similar to the district level analyses we conduct for producer prices. For instance, by combining annual variation on global crop prices with country variation of consumption fractions, McGuirk and Burke (2020) calculate international consumer prices at the country-year level. In our sample of five countries and nine years of observation, this approach would leave us with 45 data points, insufficient to capture meaningful effects. Future scientific efforts should therefore aim to improve the evidence base on migration implications of international price changes for non-agricultural households.

Considering migration of whole households rather than labor migration would be an additional promising avenue for future research on the global prices - conflict - migration nexus. By incorporating household wealth data that varies over time, one could then test the absolute importance of household wealth compared to the conflict mechanism. Such analysis would enable us to evaluate the overall welfare effects of international price variations in a changing climate.

Discussion and Conclusion

Climate change impacts already significantly disrupt natural and human systems and these effects will substantially increase in the future (IPCC, 2014, 2018). Despite the expansion of empirical evidence on the climate-human system relationship over the past decades (Carleton and Hsiang, 2016; Dell *et al.*, 2014), many open questions prevail. Yet, it is indisputable that an improved understanding on these matters would enable better management of climate change-related risks. With my dissertation, I contribute to closing research gaps about climate-migration association in low- and middle-income countries. The central contribution is the identification of contextual conditions under which climate-related events induce/inhibit migration as an adaptation. These new insights can serve as entry points for climate and development policies, with an overarching goal to maximize human welfare in a changing climate. In what follows, I discuss concrete implications of the findings from this dissertation for policy and future research.

Implications for climate change mitigation policy

Design of optimal policies to mitigate climate change requires a solid understanding of the related costs and benefits. Integrated assessment models (IAMs) are the central tool applied to calculate optimal mitigation policies by maximizing future global welfare (Nordhaus, 1993; Stern, 2006; Waldhoff *et al.*, 2011). They are centered around damage functions, which link global mean temperature changes to economic costs from the impacts (e.g., changes in sea level, cyclone frequency, and agricultural productivity). Then, the IAMs translate estimated future damages into a present monetary value, the social cost of carbon (SCC) (Carleton and Hsiang, 2016; Kalkuhl and Wenz, 2020; Revesz *et al.*, 2014).[15] A growing body of research suggests that currently, economic damages from climate change are systematically underestimated. This is partially due to an incomprehensive coverage of sectoral and spatial climate change impacts, especially of

[15]SCC captures the marginal costs of emitting an additional tonne of carbon dioxide into the atmosphere at any point in time. The calculation of SCC enables taking corrective measures on climate change-related negative externalities. For instance, charging emitters a price equal to the monetary value of the damage caused by the emissions (i.e. SCC) via carbon price could encourage them to reduce GHGs to economically optimal levels (Pigou, 1920).

non-market goods other than mortality (Carleton and Hsiang, 2016; Auffhammer, 2018).

My thesis contributes to closing these research gaps with four studies. In chapters 1, 2 and 5, I deliver novel causal evidence of climate change impacts on inequality and human migration from low- and middle-income countries (i.e., India and Sub-Saharan Africa). In chapters 2 and 5, I show that while adverse climate change impacts may be associated with migration increase, this positive relationship is not necessarily universal. The aggregate effect is, among other things, determined by the household wealth, which determines households' ability to afford the up-front costs of moving. Therefore, while chapter 2 shows on aggregate a positive association between adverse climatic shocks and migration in rural India, chapter 5 reveals a negative association in the agricultural context of Sub-Saharan Africa, where the average wealth levels are much lower. Chapter 1 further confirms that climate change impacts on household wealth constitute an important mechanism at play particularly in rural contexts, where the effects are felt strongly due to the importance of the primary sector. Using a meta-regression analysis, in chapter 3, I then validate these findings in a larger framework by comprehensively synthesizing empirical climate migration evidence representative of the literature landscape at the time. The findings provide further support of an inverted U-shaped relationship between countries' income levels and climate migration. Namely, a climate-related income decline may depress migration of the very poor, but provide incentives to move to the less poor populations (Cattaneo and Peri, 2016).

While the importance of understanding the localized climate change impacts is uncontested, in a highly interconnected world, climatic shocks can also reverberate through international markets and affect societies, for instance through food trade (Bren d'Amour *et al.*, 2016). However, there is a dearth of evidence on migration implications of distant climatic effects. We address this gap in chapter 5. In addition to local climatic impacts, we study the implications of exogenous global crop price changes on migration in Sub-Saharan Africa during the decade of the global food crisis of 2007/08. Among other things, the crisis was prominently driven by a decrease in agricultural production in major producing regions resulting from adverse climatic shocks (Headey and Fan, 2008). We show that local and global climatic impacts on migration of agricultural households similarly depend on household wealth, as discussed in the previous paragraph.

It is *a priori* not clear whether climate migration increases or reduces damages from climate change. Earlier academic and policy debates typically associated climate migration with welfare losses. Notably, climate migration has often been framed as a security threat (Baldwin *et al.*, 2014, p. 125). Since the 2000s, the discourse has moved towards reframing migration as a possible means for adaptation to the changing climate. This shift in the discourse can be attributed to the evidence that, particularly in the rural areas of low- and middle-income countries, migration has been a part of a risk management portfolio for a long time, where households consciously weigh various available options and decide for the optimal one, given their situation (Bilsborrow, 1992; McLeman and Smit, 2006; McLeman, 2016; Vinke *et al.*, 2020). The overall costs and benefits of climate migration outcomes essentially depend on characteristics of the migrants and of the receiving areas. Both features ultimately determine how smoothly climate migrants can be absorbed into the structures at the destination.

This dissertation contributes with evidence on the socio-economic profiles (see chapters 2 and 3) and destination choices (see chapters 2, 3 and 5) of climate migrants. The outcomes suggest that climate migrants are likely to be male, drawn from the lower end of the skill distribution and from households dependent on agricultural production. As for geographical patterns of migration in response to adverse local climate-related impacts, we find robust evidence that it is likely to originate in rural areas and to take place especially in middle-income countries, internally and to urban destinations. However, chapter 5 further indicates that unlike local weather shocks, income shocks from producer prices affect migration of agricultural households to neighboring countries. An important step for future research is to improve our understanding of the socio-economic and political implications of climate migration at the origin and destination, to better assess the related damages.

Policy makers should simultaneously keep in mind that climate change can also reduce households' ability to move by imposing a stricter budget constraint, as suggested above. In this way, it can impede adaptation in contexts in which it is not optimal to remain. This dissertation shows that the likelihood to become immobile is particularly high for socio-economically vulnerable groups, i.e., the poorest segments of population (e.g. chapters 3 and 5) and women (chapter 3). Therefore, not only an increase in climate migration but also a climate-related increase in immobility has substantial implications for economic damages from the changing climate.

Implications for climate change adaptation and development

While mitigation policies should strive to reduce climate change in the future, its impacts already render societies vulnerable, requiring them to adapt. The literature identifies the following three cornerstones of adaptation: i) reduce the sensitivity, ii) alter the exposure, and iii) increase the resilience (Adger *et al.*, 2005). Evidence from this dissertation provides important entry points for such adaptation policies for sending and receiving communities with an intention to minimize damages in a changing climate.

In the rural areas in low- and middle-income countries, migration is an important livelihood strategy. Typically, households send out migrants to cities to receive remittances, which can increase farmers' resilience against bad climatic shocks (Townsend, 1995). Even if such spatial risk diversification is not a conventional part of households' risk management portfolios, as a consequence of climate change, it might gain in importance if the *in situ* adaptation becomes too costly (Xu *et al.*, 2020). However, as shown in chapters 1, 3 and 5, particularly the socio-economically vulnerable populations may be unable to migrate due to reduced financial means in the aftermath of bad weather shocks. It is crucial that decision makers recognize the development and adaptation potential of migration and implement measures relaxing costs of moving, which would enable also the vulnerable groups to migrate if needed. For illustration, evidence from randomized control trials in Bangladesh reveals that reducing costs of moving is an efficient tool that helps poor households to cope with famine (Bryan *et al.*, 2014).

In this regard, chapter 1 proposes to improve access to financial institutions and adaptation technologies especially in the rural areas in low- and middle-income countries. Neither current informal risk sharing arrangements nor public policies seem to efficiently protect these populations from aggregate income shocks (Burgess *et al.*, 2014), leaving particularly the poor disproportionately sensitive to climate change. Better access to bank accounts or credits would enable saving up and borrowing money. Improved accessibility of adaptive technologies such as irrigation and air-conditioning could reduce first-order impacts of global warming, such as precipitation decrease and heat stress. These measures would render households less sensitive to weather, facilitating engagement in migration and consumption smoothing for the ones that remain in place.

While some populations might become immobile, climate change is on aggregate associated with an increase in migration to urban areas. In anticipation of an inflow of primarily male (chapter 3) migrants with lower levels of education (chapter 2) in the wake of climate change, it is crucial that cities take *ex-ante* steps to integrate climate migrants with these characteristics into their labor markets. Prior work has shown that the capacity of non-agricultural sectors to absorb workers is an important strategy for agricultural laborers to manage weather-driven decrease in productivity in the primary sector (Colmer, 2018). Hence, labor market integration and diversification can play a crucial role in attenuating adverse economic or political consequences of climate change.

However, implications of these findings go beyond labor market policies. In the economically developing countries, a significant share of the urban population lives in the largest cities (Kahn, 2017). Since climate migration will prominently take place in these regions, climate change might contribute to the growth of megacities. This phenomenon is linked to numerous challenges (Hardoy and Satterthwaite, 1991), such as increased population density in cities' poorest areas, where infectious disease rates are particularly high due to poor access to water or sanitation (Costa and Kahn, 2015). This has been very problematic during the current COVID-19 pandemic, which has disproportionately impacted persons living in displacement contexts and other socio-economically vulnerable groups (Harper and Vinke, 2021). Thus, in order to reduce aggregate damages from climate change, it is crucial to improve living conditions in migration and displacement settings.

Overall, rapid population growth puts pressure on governments at the destination to provide employment and basic services (e.g., housing, health care and water). If migration is planned and cities are well prepared, increased urbanization can offer economic opportunities. However, if poorly managed, climate migration can have devastating consequences for the well-being of migrants and host populations. These can translate into violence and instability (Koubi, 2019) and even trigger international migration cascades threatening international peace and security (Abel *et al.*, 2019; Ash and Obradovich, 2020; Missirian and Schlenker, 2017).

Implications for future research and concluding remarks

This dissertation further identifies existing gaps in the empirical climate migration research, which are of pressing scientific and societal relevance. First, there is a dearth of empirical evidence on migration implications of particular climatic hazards such as sea level rise, sudden-onset events or distant climatic shocks transmitted via, e.g., international markets. Second, many obvious geographical research gaps prevail. Thus far, the primary focus has been on rural out-migration, yet we still lack evidence from cities. Moreover, most of the climate migration research has focused on Africa, United States of America and Asia. Yet, it remains unclear how climate migration plays out, e.g., in Europe or small island states located in the Pacific Ocean. Third, while evidence on contextual effects of climate migration has recently increased, further causes of heterogeneous migration responses should be explored, including health, human capital and conflict. Fourth, it is essential that the literature explicitly distinguishes between different migration outcomes. In particular, more evidence is needed on irregular migration forms, likely triggered by rapid-onset events, which are much harder to capture. Fifth, another important avenue for future research is to improve the understanding of implications of climate migration both at the origin and at the destination. Lastly, future empirical studies of climate migration should follow the methodological guidance provided in chapter 4 to avoid typical pitfalls and maintain the highest scientific rigor.

To conclude, this dissertation contributes to the recent efforts to understand the inconsistent evidence of climate migration. I have shown that the climatic impacts on migration are nuanced; for example, they depend on wealth, gender, education, or access to alternative adaptation strategies. Overall, this dissertation underlines the importance of accounting for the many contextual factors that influence climate migration.

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Appendix A

Appendix to Chapter 1

A.1 Cross-correlations

Table A.1: *Cross-correlation table: Controls (IHDS-I data)*

Variables	Poor	Land	Bank account	Air cooler	Irrigation
Poor	1.000				
Land	-0.046	1.000			
Bank account	-0.153	0.108	1.000		
Air cooler	-0.132	0.031	0.159	1.000	
Irrigation	-0.079	0.487	0.111	0.096	1.000

Table A.2: *Cross-correlation table: Changes in weather and historical climate (ERA5 data)*

Variables		ΔTemperature				ΔPrecipitation				Temp. hist.				Precip. hist			
		Winter	Spring	Kharif	Rabi	Winter	Spring	Kharif	Rabi	Winter	Spring	Kharif	Rabi	Winter	Spring	Kharif	Rabi
ΔTemp.	Winter	1.000															
	Spring	0.507	1.000														
	Kharif	0.241	0.557	1.000													
	Rabi	-0.115	-0.246	-0.202	1.000												
ΔPrecip.	Winter	-0.122	-0.200	-0.093	-0.093	1.000											
	Spring	-0.187	-0.594	-0.208	0.171	0.080	1.000										
	Kharif	-0.150	-0.109	-0.132	-0.065	0.104	-0.112	1.000									
	Rabi	0.026	0.157	0.008	0.093	-0.014	-0.298	0.164	1.000								
Temp. hist.	Winter	0.474	0.545	0.159	-0.200	0.140	-0.424	-0.100	0.321	1.000							
	Spring	0.317	0.203	-0.289	0.035	0.120	-0.146	-0.150	0.164	0.796	1.000						
	Kharif	-0.079	-0.267	-0.583	0.261	0.046	0.096	-0.123	-0.131	0.225	0.694	1.000					
	Rabi	0.376	0.395	-0.013	-0.094	0.151	-0.345	-0.106	0.242	0.948	0.899	0.493	1.000				
Precip. hist.	Winter	-0.302	-0.297	0.157	0.017	-0.196	0.286	0.081	-0.317	-0.822	-0.864	-0.447	-0.887	1.000			
	Spring	-0.086	0.146	0.488	-0.202	-0.104	-0.208	0.199	-0.311	-0.255	-0.610	-0.495	-0.356	0.528	1.000		
	Kharif	0.089	0.201	0.348	-0.144	0.039	-0.213	0.507	-0.213	0.043	-0.149	-0.264	0.001	0.050	0.495	1.000	
	Rabi	0.157	0.459	0.558	-0.271	-0.073	-0.414	0.111	0.208	0.351	-0.162	-0.430	0.172	0.088	0.616	0.233	1.000

All variables are constructed using ERA5 data and capture change in seasonal weather or seasonal historical climate. Four seasons are distinguished: winter (January-February), spring (March-May), kharif (June-September) and rabi (October-December).

A.2 Consumption types

Table A.3: *Effects of seasonal weather on households' food consumption by wealth group*

	ΔFood consumption								
	All (1)			*Farming* (2)			*Non-farming* (3)		
	Non-poor	*Poor*	*Diff.*	*Non-poor*	*Poor*	*Diff.*	*Non-poor*	*Poor*	*Diff.*
Temperature									
ΔTemp. winter	-0.006	0.069**	0.075***	-0.007	0.074**	0.081***	0.001	0.070**	0.069**
	(0.017)	(0.027)	(0.026)	(0.021)	(0.031)	(0.030)	(0.018)	(0.030)	(0.029)
ΔTemp. spring	0.058**	-0.135***	-0.193***	0.038	-0.166***	-0.204***	0.049*	-0.107***	-0.156***
	(0.025)	(0.036)	(0.034)	(0.029)	(0.044)	(0.040)	(0.028)	(0.040)	(0.038)
ΔTemp. kharif	0.086***	0.141***	0.055	0.105***	0.084	-0.021	0.078**	0.182***	0.104
	(0.029)	(0.051)	(0.056)	(0.032)	(0.061)	(0.066)	(0.033)	(0.061)	(0.065)
ΔTemp. rabi	0.024	0.056**	0.032***	0.043	0.066**	0.023**	0.012	0.059*	0.047***
	(0.027)	(0.026)	(0.009)	(0.030)	(0.029)	(0.010)	(0.028)	(0.030)	(0.011)
Precipitation									
ΔPrecip. winter	0.126**	0.045	-0.081	0.056	-0.059	-0.114	0.290***	0.231*	-0.058
	(0.056)	(0.111)	(0.104)	(0.062)	(0.138)	(0.128)	(0.071)	(0.120)	(0.124)
ΔPrecip. spring	0.043	-0.291***	-0.334***	0.003	-0.438***	-0.441***	0.116**	-0.126*	-0.242***
	(0.054)	(0.070)	(0.079)	(0.068)	(0.111)	(0.131)	(0.055)	(0.069)	(0.075)
ΔPrecip. kharif	-0.050**	0.034	0.084***	-0.039	0.028	0.067**	-0.055**	0.050	0.105***
	(0.023)	(0.027)	(0.028)	(0.024)	(0.034)	(0.033)	(0.027)	(0.031)	(0.034)
ΔPrecip. rabi	0.147***	0.135**	-0.012	0.207***	0.105	-0.102	0.100**	0.165***	0.065
	(0.047)	(0.063)	(0.066)	(0.058)	(0.103)	(0.109)	(0.051)	(0.061)	(0.062)
N		25482			15060			10422	
R^2		0.052			0.053			0.059	
Time trend		Yes			Yes			Yes	
Month dummies		Yes			Yes			Yes	
Year dummies		Yes			Yes			Yes	
ΔAnnual temp.	0.162	0.132	-0.031	0.179	0.058	-0.121	0.140	0.204	0.064
	(0.041)	(0.056)	(0.054)	(0.045)	(0.060)	(0.06)	(0 .043)	(0.069)	(0.065)
ΔAnnual precip.	0.266	-0.077	-0.344	0.228	-0.363	-0.591	0.451	0.321	-0.130
	(0.099)	(0.152)	(0.141)	(0.119)	(0.197)	(0.187)	(0.104)	(0.149)	(0.157)

All models are estimated using first-difference approach that eliminates the time invariant, direct effects. The sample in model 1 consists of all, in model 2 of farming and in model 3 of non-farming households in rural India. The dependent variable is constructed using data from IHDS-I and II. It captures the change in logarithms of food consumption per adult equivalent household member between the two IHDS rounds. The binary variable Poor is derived from IHDS-I and takes on a value of one if a household lives below the poverty line and zero otherwise (Non-poor). All weather variables are constructed using ERA5 data and capture the change in households' exposure to seasonal temperature (in °) and precipitation (in 100mm) between the two IHDS rounds. Four seasons are distinguished: winter (January-February), spring (March-May), kharif (June-September) and rabi (October-December). We also include a time trend and control for months and years of the interviews (see Appendix A.3, Table A.6). The first two columns of every model display the marginal effects of weather variables separately for poor and non-poor and the third column presents the same results differently, by showing the difference in their responses. The bottom part of the table presents the aggregate (annual) effect of temperature and precipitation. Standard errors clustered at the district-level are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table A.4: *Effects of seasonal weather on households' non-food consumption by wealth group*

	ΔNon-food consumption								
	All (1)			*Farming* (2)			*Non-farming* (3)		
	Non-poor	*Poor*	*Diff.*	*Non-poor*	*Poor*	*Diff.*	*Non-poor*	*Poor*	*Diff.*
Temperature									
ΔTemp. winter	-0.045	-0.044	0.001	-0.051*	-0.030	0.021	-0.028	-0.071	-0.044
	(0.027)	(0.060)	(0.064)	(0.030)	(0.066)	(0.212)	(0.034)	(0.064)	(0.070)
ΔTemp. spring	0.065*	-0.255***	-0.320***	0.051	-0.317***	-0.368***	0.057	-0.229***	-0.286***
	(0.034)	(0.069)	(0.068)	(0.039)	(0.084)	(0.071)	(0.043)	(0.074)	(0.071)
ΔTemp. kharif	-0.116**	-0.044	0.072	-0.128**	-0.069	0.059	-0.098	0.020	0.118
	(0.050)	(0.090)	(0.095)	(0.054)	(0.112)	(0.082)	(0.063)	(0.103)	(0.106)
ΔTemp. rabi	0.025	0.093*	0.068***	0.010	0.086*	0.076***	0.041	0.089	0.048*
	(0.045)	(0.048)	(0.022)	(0.046)	(0.049)	(0.119)	(0.055)	(0.059)	(0.026)
Precipitation									
ΔPrecip. winter	-0.121	-0.865***	-0.744***	-0.187*	-0.717***	-0.529*	-0.044	-1.172***	-1.128***
	(0.105)	(0.236)	(0.247)	(0.111)	(0.269)	(0.023)	(0.121)	(0.219)	(0.239)
ΔPrecip. spring	-0.042	-0.876***	-0.834***	0.065	-1.232***	-1.297***	-0.191*	-0.668***	-0.477**
	(0.090)	(0.204)	(0.221)	(0.099)	(0.294)	(0.274)	(0.102)	(0.194)	(0.201)
ΔPrecip. kharif	-0.106***	0.380***	0.486***	-0.104***	0.362***	0.466***	-0.120***	0.401***	0.521***
	(0.037)	(0.059)	(0.058)	(0.038)	(0.069)	(0.312)	(0.045)	(0.057)	(0.062)
ΔPrecip. rabi	0.165**	-0.208	-0.373	0.197***	-0.327	-0.524**	0.159*	-0.091	-0.250
	(0.071)	(0.202)	(0.228)	(0.071)	(0.210)	(0.064)	(0.096)	(0.213)	(0.249)
N		24969			14811			10158	
R^2		0.118			0.122			0.124	
Time trend		Yes			Yes			Yes	
Month dummies		Yes			Yes			Yes	
Year dummies		Yes			Yes			Yes	
ΔAnnual temp.	-0.071	-0.250	-0.179	-0.118	-0.329	-0.211	-0.028	-0.191	-0.163
	(0.066)	(0.108)	(0.095)	(0.069)	(0.119)	(0.106)	(0.082)	(0.122)	(0.114)
ΔAnnual precip.	-0.104	-1.568	-1.464	-0.029	-1.913	-1.884	-0.196	-1.531	-1.335
	(0.167)	(0.368)	(0.409)	(0.170)	(0.405)	(0.425)	(0.199)	(0.388)	(0.433)

All models are estimated using first-difference approach that eliminates the time invariant, direct effects. The sample in model 1 consists of all, in model 2 of farming and in model 3 of non-farming households in rural India. The dependent variable is constructed using data from IHDS-I and II. It captures the change in logarithms of non-food consumption per adult equivalent household member between the two IHDS rounds. The binary variable Poor is derived from IHDS-I and takes on a value of one if a household lives below the poverty line and zero otherwise (Non-poor). All weather variables are constructed using ERA5 data and capture the change in households' exposure to seasonal temperature (in °) and precipitation (in 100mm) between the two IHDS rounds. Four seasons are distinguished: winter (January-February), spring (March-May), kharif (June-September) and rabi (October-December). We also include a time trend and control for months and years of the interviews (see Appendix A.3, Table A.7). The first two columns of every model display the marginal effects of weather variables separately for poor and non-poor and the third column presents the same results differently, by showing the difference in their responses. The bottom part of the table presents the aggregate (annual) effect of temperature and precipitation. Standard errors clustered at the district-level are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

A.3 Seasonal effects

Table A.5: *Effects of seasonal weather on households' consumption by wealth group: Coefficients of the remaining controls from the main analysis (Table 1.4)*

	ΔConsumption		
	All (1)	*Farming* (2)	*Non-farming* (3)
	ME *Diff.*	*ME* *Diff.*	*ME* *Diff.*
Interview years			
Round 1 (2004)	-0.035	0.108**	-0.220***
	(0.056)	(0.053)	(0.074)
Round 2 (2011)	-0.237	-0.173	-0.343*
	(0.152)	(0.155)	(0.194)
Interview months			
January	0.019	0.035	0.003
	(0.033)	(0.037)	(0.041)
February	0.011	0.015	0.019
	(0.028)	(0.033)	(0.032)
March	0.012	0.021	0.003
	(0.028)	(0.032)	(0.033)
April	0.066**	0.062*	0.076**
	(0.031)	(0.037)	(0.036)
May	0.007	0.021	-0.003
	(0.031)	(0.036)	(0.039)
June	0.075**	0.072*	0.099**
	(0.032)	(0.037)	(0.040)
July	0.032	0.042	0.035
	(0.035)	(0.039)	(0.042)
August	0.088*	0.115**	0.072
	(0.046)	(0.051)	(0.051)
September	0.166***	0.158***	0.218***
	(0.046)	(0.047)	(0.061)
October	-0.006	-0.117*	0.089
	(0.069)	(0.065)	(0.087)
November	0.045	-0.058	0.171**
	(0.056)	(0.054)	(0.071)
December	0.051	-0.070	0.202***
	(0.061)	(0.060)	(0.076)
N	25482	15060	10422
R^2	0.114	0.112	0.125
Time trend	Yes	Yes	Yes

This Table presents the outcomes on the remaining month and year controls from the main analysis, presented in Table 1.4. The sample in model 1 consists of all, in model 2 of farming and in model 3 of non-farming households in rural India. The dependent variable is constructed using data from IHDS-I and II. It captures the change in logarithms of consumption per adult equivalent household member between the two IHDS rounds. Variable Round 1 is binary and takes on a value of one if a household was interviewed in the year 2004 in IHDS-I and zero otherwise. Round 2 is binary and takes on a value of one if a household was interviewed in the year 2011 in IHDS-II and zero otherwise. The remaining variables are month dummies that take on a value of one if a household was interviewed in a specific month at least in one of the two IHDS rounds. Standard errors clustered at the district-level are in parentheses.
* p<0.10, ** p<0.05, *** p<0.01.

Table A.6: *Effects of seasonal weather on households' food consumption by wealth group: Coefficients of the remaining controls from the main analysis (Table A.3)*

	Δ*Food consumption*		
	All (1)	*Farming* (2)	*Non-farming* (3)
	ME *Diff.*	*ME* *Diff.*	*ME* *Diff.*
Interview years			
Round 1 (2004)	-0.025	0.053	-0.123
	(0.063)	(0.063)	(0.079)
Round 2 (2011)	-0.302**	-0.334**	-0.276*
	(0.139)	(0.164)	(0.153)
Interview months			
January	-0.027	-0.007	-0.050
	(0.032)	(0.038)	(0.036)
February	-0.025	-0.011	-0.032
	(0.030)	(0.035)	(0.033)
March	0.041	0.051	0.023
	(0.030)	(0.036)	(0.031)
April	0.059*	0.058	0.054*
	(0.033)	(0.042)	(0.032)
May	-0.007	-0.015	0.026
	(0.032)	(0.039)	(0.035)
June	0.042	0.041	0.064*
	(0.035)	(0.042)	(0.036)
July	0.004	0.004	0.017
	(0.034)	(0.040)	(0.038)
August	0.028	0.053	0.013
	(0.040)	(0.050)	(0.040)
September	-0.017	-0.029	0.060
	(0.050)	(0.063)	(0.051)
October	0.098	0.005	0.177**
	(0.070)	(0.075)	(0.073)
November	0.048	-0.046	0.144**
	(0.066)	(0.069)	(0.073)
December	0.054	0.011	0.081
	(0.065)	(0.069)	(0.075)
N	25482	15060	10422
R^2	0.052	0.053	0.059
Time trend	Yes	Yes	Yes

This Table presents the outcomes on the remaining month and year controls from the main analysis, presented in Table A.3. The sample in model 1 consists of all, in model 2 of farming and in model 3 of non-farming households in rural India. The dependent variable is constructed using data from IHDS-I and II. It captures the change in logarithms of food consumption per adult equivalent household member between the two IHDS rounds. Variable Round 1 is binary and takes on a value of one if a household was interviewed in the year 2004 in IHDS-I and zero otherwise. Round 2 is binary and takes on a value of one if a household was interviewed in the year 2011 in IHDS-II and zero otherwise. The remaining variables are month dummies that take on a value of one if a household was interviewed in a specific month at least in one of the two IHDS rounds. Standard errors clustered at the district-level are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table A.7: *Effects of seasonal weather on households' non-food consumption by wealth group: Coefficients of the remaining controls from the main analysis (Table A.4)*

	Δ*Non-food consumption*		
	All (1)	*Farming* (2)	*Non-farming* (3)
	ME *Diff.*	*ME* *Diff.*	*ME* *Diff.*
Interview years			
Round 1 (2004)	-0.098	0.155*	-0.434***
	(0.087)	(0.094)	(0.151)
Round 2 (2011)	-0.246	-0.011	-0.547
	(0.262)	(0.270)	(0.350)
Interview months			
January	0.055	0.070	0.040
	(0.048)	(0.052)	(0.061)
February	0.033	0.028	0.060
	(0.041)	(0.048)	(0.050)
March	-0.018	-0.014	-0.018
	(0.043)	(0.049)	(0.053)
April	0.046	0.030	0.079
	(0.051)	(0.062)	(0.059)
May	0.000	0.033	-0.044
	(0.049)	(0.059)	(0.058)
June	0.093*	0.085	0.120**
	(0.048)	(0.057)	(0.058)
July	0.038	0.054	0.033
	(0.050)	(0.061)	(0.059)
August	0.175*	0.212**	0.145
	(0.091)	(0.100)	(0.092)
September	0.367***	0.373***	0.387***
	(0.079)	(0.086)	(0.098)
October	-0.012	-0.213*	0.174
	(0.095)	(0.118)	(0.150)
November	0.124	-0.022	0.323**
	(0.085)	(0.103)	(0.132)
December	0.122	-0.127	0.458***
	(0.092)	(0.105)	(0.151)
N	24969	14811	10158
R^2	0.118	0.122	0.124
Time trend	Yes	Yes	Yes

This Table presents the outcomes on the remaining month and year controls from the main analysis, presented in Table A.4. The sample in model 1 consists of all, in model 2 of farming and in model 3 of non-farming households in rural India. The dependent variable is constructed using data from IHDS-I and II. It captures the change in logarithms of non-food consumption per adult equivalent household member between the two IHDS rounds. Variable Round 1 is binary and takes on a value of one if a household was interviewed in the year 2004 in IHDS-I and zero otherwise. Round 2 is binary and takes on a value of one if a household was interviewed in the year 2011 in IHDS-II and zero otherwise. The remaining variables are month dummies that take on a value of one if a household was interviewed in a specific month at least in one of the two IHDS rounds. Standard errors clustered at the district-level are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

A.4 Sensitivity analyses

Table A.8: *Effects of seasonal weather on households' assets by wealth group*

	Δ*Assets*		
	All (1)	*Farming* (2)	*Non-farming* (3)
Temperature			
ΔTemp. winter x Non-poor	0.031**	0.027*	0.036*
	(0.014)	(0.014)	(0.019)
ΔTemp. winter x Poor	0.041	0.058**	0.021
	(0.026)	(0.027)	(0.039)
ΔTemp. spring x Non-poor	0.039**	0.033**	0.045*
	(0.017)	(0.017)	(0.025)
ΔTemp. spring x Poor	-0.038	-0.032	-0.041
	(0.030)	(0.031)	(0.045)
ΔTemp. kharif x Non-poor	0.023	0.028*	0.012
	(0.018)	(0.017)	(0.031)
ΔTemp. kharif x Poor	0.059	0.050	0.074
	(0.042)	(0.044)	(0.053)
ΔTemp. rabi x Non-poor	-0.025	-0.021	-0.027
	(0.019)	(0.018)	(0.027)
ΔTemp. rabi x Poor	-0.025	-0.023	-0.024
	(0.020)	(0.020)	(0.028)
Precipitation			
ΔPrecip. winter x Non-poor	0.089**	0.065	0.143**
	(0.040)	(0.044)	(0.062)
ΔPrecip. winter x Poor	-0.153	-0.161*	-0.111
	(0.095)	(0.085)	(0.140)
ΔPrecip. spring x Non-poor	0.021	0.013	0.057
	(0.039)	(0.039)	(0.047)
ΔPrecip. spring x Poor	-0.156**	-0.235**	-0.056
	(0.076)	(0.101)	(0.078)
ΔPrecip. kharif x Non-poor	-0.045***	-0.053***	-0.034*
	(0.016)	(0.017)	(0.020)
ΔPrecip. kharif x Poor	-0.039	-0.034	-0.037
	(0.028)	(0.025)	(0.040)
ΔPrecip. rabi x Non-poor	0.053	0.038	0.071*
	(0.036)	(0.037)	(0.039)
ΔPrecip. rabi x Poor	-0.062	-0.075	-0.034
	(0.066)	(0.084)	(0.069)
N	25482	15060	10422
R^2	0.031	0.033	0.030
Time trend	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes

All models are estimated using first-difference approach that eliminates the time invariant, direct effects. The sample in model 1 consists of all, in model 2 of farming and in model 3 of non-farming households in rural India. The dependent variable is constructed using data from IHDS-I and II. It captures the change in logarithms of assets per adult equivalent household member between the two IHDS rounds. The binary variable Poor is derived from IHDS-I and takes on a value of one if a household lives below the poverty line and zero otherwise (Non-poor). All weather variables are constructed using ERA5 data and capture the change in households' exposure to seasonal temperature (in °) and precipitation (in 100mm) between the two IHDS rounds. Four seasons are distinguished: winter (January-February), spring (March-May), kharif (June-September) and rabi (October-December). We also include a time trend and control for months and years of the interviews. Standard errors clustered at the district-level are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table A.9: *Effects of seasonal temperature on households' consumption by wealth group*

	Δ*Consumption*		
	All (1)	*Farming* (2)	*Non-farming* (3)
Temperature			
ΔTemp. winter x Non-poor	-0.005	-0.005	-0.002
	(0.021)	(0.023)	(0.025)
ΔTemp. winter x Poor	-0.079**	-0.045	-0.114***
	(0.038)	(0.044)	(0.041)
ΔTemp. spring x Non-poor	0.098***	0.085***	0.100***
	(0.022)	(0.025)	(0.028)
ΔTemp. spring x Poor	-0.159***	-0.177***	-0.153***
	(0.037)	(0.040)	(0.046)
ΔTemp. kharif x Non-poor	-0.043	-0.049	-0.032
	(0.031)	(0.032)	(0.042)
ΔTemp. kharif x Poor	-0.002	-0.109	0.093
	(0.062)	(0.076)	(0.067)
ΔTemp. rabi x Non-poor	0.011	0.020	0.004
	(0.026)	(0.027)	(0.033)
ΔTemp. rabi x Poor	0.087***	0.095***	0.080**
	(0.028)	(0.030)	(0.034)
N	25482	15060	10422
R^2	0.082	0.083	0.087
Time trend	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes

All models are estimated using first-difference approach that eliminates the time invariant, direct effects. The sample in model 1 consists of all, in model 2 of farming and in model 3 of non-farming households in rural India. The dependent variable is constructed using data from IHDS-I and II. It captures the change in logarithms of consumption per adult equivalent household member between the two IHDS rounds. The binary variable Poor is derived from IHDS-I and takes on a value of one if a household lives below the poverty line and zero otherwise (Non-poor). All weather variables are constructed using ERA5 data and capture the change in households' exposure to seasonal temperature (in $^{\circ}$) between the two IHDS rounds. Four seasons are distinguished: winter (January-February), spring (March-May), kharif (June-September) and rabi (October-December). We also include a time trend and control for months and years of the interviews. Standard errors clustered at the district-level are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table A.10: *Effects of seasonal weather on households' consumption by wealth group*

	ΔConsumption		
	All (1)	*Farming* (2)	*Non-farming* (3)
Temperature			
ΔTemp. winter x Non-poor	-0.025	-0.027	-0.020
	(0.018)	(0.021)	(0.022)
ΔTemp. winter x Poor	0.018	0.021	0.008
	(0.031)	(0.032)	(0.038)
ΔTemp. spring x Non-poor	0.064***	0.042	0.064**
	(0.024)	(0.026)	(0.031)
ΔTemp. spring x Poor	-0.214***	-0.260***	-0.189***
	(0.038)	(0.044)	(0.046)
ΔTemp. kharif x Non-poor	0.008	0.040	-0.008
	(0.051)	(0.058)	(0.065)
ΔTemp. kharif x Poor	0.088	0.071	0.123
	(0.072)	(0.095)	(0.078)
ΔTemp. rabi x Non-poor	0.026	0.033	0.021
	(0.027)	(0.029)	(0.032)
ΔTemp. rabi x Poor	0.076***	0.087***	0.062*
	(0.029)	(0.030)	(0.033)
Precipitation			
ΔPrecip. winter x Non-poor	0.028	-0.049	0.142
	(0.078)	(0.084)	(0.090)
ΔPrecip. winter x Poor	-0.301***	-0.273**	-0.386***
	(0.114)	(0.126)	(0.137)
ΔPrecip. spring x Non-poor	0.017	0.045	-0.017
	(0.057)	(0.066)	(0.062)
ΔPrecip. spring x Poor	-0.638***	-0.884***	-0.441***
	(0.107)	(0.154)	(0.098)
ΔPrecip. kharif x Non-poor	-0.079***	-0.071***	-0.092***
	(0.025)	(0.024)	(0.031)
ΔPrecip. kharif x Poor	0.149***	0.119***	0.185***
	(0.030)	(0.033)	(0.036)
ΔPrecip. rabi x Non-poor	0.195***	0.229***	0.190***
	(0.052)	(0.049)	(0.061)
ΔPrecip. rabi x Poor	0.053	-0.051	0.151
	(0.107)	(0.130)	(0.098)
Interactions			
ΔTemp. winter x ΔPrecip. winter	0.059	0.054	0.042
	(0.073)	(0.076)	(0.089)
ΔTemp. spring x ΔPrecip. spring	0.004	0.039	-0.028
	(0.067)	(0.073)	(0.074)
ΔTemp. kharif x ΔPrecip. kharif	-0.051	-0.085	-0.024
	(0.060)	(0.059)	(0.077)
ΔTemp. rabi x ΔPrecip. rabi	-0.038*	-0.032	-0.057**
	(0.023)	(0.026)	(0.029)
N	25482	15060	10422
R^2	0.114	0.113	0.126
Time trend	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes

All models are estimated using first-difference approach that eliminates the time invariant, direct effects. The sample in model 1 consists of all, in model 2 of farming and in model 3 of non-farming households in rural India. The dependent variable is constructed using data from IHDS-I and II. It captures the change in logarithms of consumption per adult equivalent household member between the two IHDS rounds. The binary variable Poor is derived from IHDS-I and takes on a value of one if a household lives below the poverty line and zero otherwise (Non-poor). All weather variables are constructed using ERA5 data and capture the change in households' exposure to seasonal temperature (in °) and precipitation (in 100mm, not displayed) between the two IHDS rounds. Four seasons are distinguished: winter (January-February), spring (March-May), kharif (June-September) and rabi (October-December). We also include a time trend and control for months and years of the interviews. Standard errors clustered at the district-level are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

A.5 Vulnerabilities

Table A.11: *T-test of differences in historical climate by wealth group (ERA5 data and IHDS-I data)*

	Mean(Poor=1)	Mean(Poor=0)	Diff.	Std. Error	Obs.
Temp. winter hist.	19.380	18.574	-0.806***	0.081	25482
Temp. spring hist.	28.848	27.527	-1.321***	0.063	25482
Temp. kharif hist.	27.768	27.443	-0.325***	0.045	25482
Temp. rabi hist.	21.812	21.211	-0.602***	0.059	25482
Precip winter hist.	0.181	0.249	0.068***	0.004	25482
Precip. spring hist.	0.323	0.422	0.099***	0.007	25482
Precip kharif hist.	2.389	2.167	-0.223***	0.017	25482
Precip rabi hist.	0.335	0.407	0.071***	0.006	25482

All climate variables are constructed using ERA5 data and capture seasonal historical climate. Four seasons are distinguished: winter (January-February), spring (March-May), kharif (June-September) and rabi (October-December). The binary variable Poor is derived from IHDS-I and takes on a value of one if a household lives below the poverty line and zero otherwise (Non-poor). The t-test analyzes whether poor and non-poor households inhabit significantly different climates.

Table A.12: *Effects of seasonal weather on households' consumption by wealth group (results from equation 1.3)*

	Δ*Consumption*		
	All (1)	*Farming* (2)	*Non-farming* (3)
Temperature			
ΔTemp. winter x Non-poor	0.197***	0.109	0.170
	(0.076)	(0.078)	(0.150)
ΔTemp. winter x Poor	0.249***	0.174**	0.187
	(0.080)	(0.083)	(0.154)
ΔTemp. spring x Non-poor	-0.056	0.047	-0.337
	(0.102)	(0.096)	(0.225)
ΔTemp. spring x Poor	-0.332***	-0.260**	-0.583**
	(0.109)	(0.107)	(0.230)
ΔTemp. kharif x Non-poor	0.697**	0.372	1.151**
	(0.349)	(0.368)	(0.568)
ΔTemp. kharif x Poor	0.756**	0.385	1.275**
	(0.363)	(0.391)	(0.575)
ΔTemp. rabi x Non-poor	-0.017	0.031	-0.284*
	(0.086)	(0.081)	(0.148)
ΔTemp. rabi x Poor	0.032	0.083	-0.242*
	(0.085)	(0.082)	(0.146)
Precipitation			
ΔPrecip. winter x Non-poor	0.123	0.242	-0.396
	(0.165)	(0.178)	(0.515)
ΔPrecip. winter x Poor	-0.243	-0.018	-0.953*
	(0.167)	(0.180)	(0.532)
ΔPrecip. spring x Non-poor	0.125	0.199	1.105
	(0.218)	(0.285)	(0.739)
ΔPrecip. spring x Poor	-0.523**	-0.750**	0.696
	(0.242)	(0.337)	(0.740)
ΔPrecip. kharif x Non-poor	-0.110	-0.088	-0.374*
	(0.078)	(0.093)	(0.198)
ΔPrecip. kharif x Poor	0.113	0.099	-0.108
	(0.075)	(0.093)	(0.199)
ΔPrecip. rabi x Non-poor	-0.044	-0.218	-0.342
	(0.158)	(0.191)	(0.422)
ΔPrecip. rabi x Poor	-0.155	-0.452*	-0.359
	(0.192)	(0.233)	(0.436)
N	25482	15060	10422
R^2	0.124	0.122	0.140
Time trend	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes

This table presents results from equation 1.3). Coefficients of further controls are displayed in figures 1.2 and 1.3 as well as in Table 1.5. All models are estimated using first-difference approach that eliminates the time invariant, direct effects. The sample in model 1 consists of all, in model 2 of farming and in model 3 of non-farming households in rural India. The dependent variable is constructed using data from IHDS-I and II. It captures the change in logarithms of consumption per adult equivalent household member between the two IHDS rounds. The binary variable Poor is derived from IHDS-I and takes on a value of one if a household lives below the poverty line and zero otherwise (Non-poor). All weather variables are constructed using ERA5 data and capture the change in households' exposure to seasonal temperature (in °) and precipitation (in 100mm) between the two IHDS rounds. Four seasons are distinguished: winter (January-February), spring (March-May), kharif (June-September) and rabi (October-December). We also include a time trend and control for months and years of the interviews. Standard errors clustered at the district-level are in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Appendix B

Appendix to Chapter 2

B.1 Inequality and poverty in rural and urban India

Table B.1: *Inequality and poverty in rural and urban India (IHDS data)*

	Rural	**Urban**
Poor Round 1	.2469	.2218
Poor Round 2	.2107	.1065
Std. dev. Income Round 1	.9263	.8648
Std. dev. Income Round 2	.9701	.9094
N	24820	11242

The variables were constructed using IHDS data. Poor is a binary variable capturing households living under the poverty line (one), in each IHDS round. To calculate the standard deviation of income, we apply the survey weights and use the logarithm of income per adult equivalent household member. We apply the OECD equivalence scale, which assigns a value of one to the household head, of 0.5 to each additional adult household member and of 0.3 to each child.

B.2 Construction of weather extremes variables

We calculate total monthly positive $A(+)$ and negative $A(-)$ temperature and precipitation anomalies as follows:

$$A(+)_{ri} = \sum_{t=1}^{x_i} \max\left\{0, \frac{w_{d,T_{r,i}-t} - \bar{w}_d}{\sigma_d}\right\} \tag{B.1}$$

$$A(-)_{ri} = \sum_{t=1}^{x_i} \max\left\{0, -\frac{w_{d,T_{r,i}-t} - \bar{w}_d}{\sigma_d}\right\} \tag{B.2}$$

where:

A(+)/ (-) refer to total positive and absolute total negative weather (temperature or precipitation) anomalies respectively

$r = 1, 2$ the respective IHDS round

$T_{r,i}$ the time household i was interviewed in IHDS round r

x_i is the number of months between the two IHDS rounds in which household i was interviewed, $x_i = T_{2,i} - T_{1,i}$.

$w_{d,t}$ is realized weather (temperature or precipitation) at time (month) t in district d

$\bar{w}_d$ is historical (1979–1998) average temperature or precipitation in district d

σ_d is historical (1979–1998) standard deviation in district d

B.3 Comparative analysis of weather datasets

Table B.2: *Descriptive statistics: State-specific standard deviations of change in weather anomalies by dataset (ERA5 vs. CRU)*

Variable	Mean	Std. Dev.	Min.	Max.	N
Std. dev. Δ Temp. anom. (+) (ERA5)	9.0114	4.1168	0.08	22.8902	24845
Std. dev. Δ Temp. anom. (+) std. dev. (CRU)	3.9925	1.577	0.3849	7.1198	24659
Std. dev. Δ Temp. anom. (-) std. dev. (ERA5)	3.937	1.4286	0	8.7733	24845
Std. dev. Δ Temp. anom. (-) std. dev. (CRU)	2.6795	0.6636	0	3.676	24659
Std. dev. Δ Precip. anom. (+) std. dev. (ERA5)	8.2479	3.722	0	16.4079	24845
Std. dev. Δ Precip. anom. (+) std. dev. (CRU)	6.5349	4.0852	0	16.6898	24659
Std. dev. Δ Precip. anom. (-) std. dev. (ERA5)	2.781	0.9412	0.1049	4.2716	24845
Std. dev. Δ Precip. anom. (-) std. dev. (CRU)	3.2402	1.7083	0.3105	6.5159	24659

Table B.3: *Correlation coefficients among weather variables generated by two different datasets (ERA5 and CRU)*

Weather variables	Corr. coefficients: ERA5 and CRU
Temperature hist. mean	0.9802
Precipitation hist. mean	0.8921
Δ Temp. anom. (+)	0.3867
Δ Temp. anom. (-)	0.4175
Δ Precip. anom. (+)	0.6756
Δ Precip. anom. (-)	0.6343

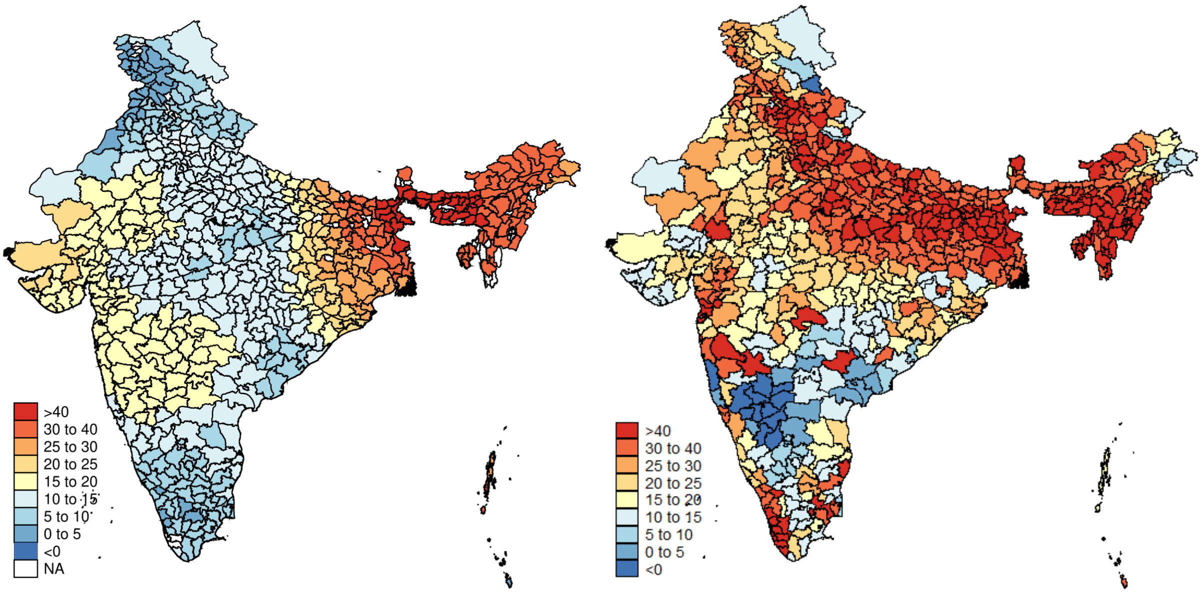


Figure B.1: *Change in total positive temperature anomalies (totals for time spans 1999-2003 and 2006-2010) between IHDS rounds (CRU-data left, ERA5 data right).*

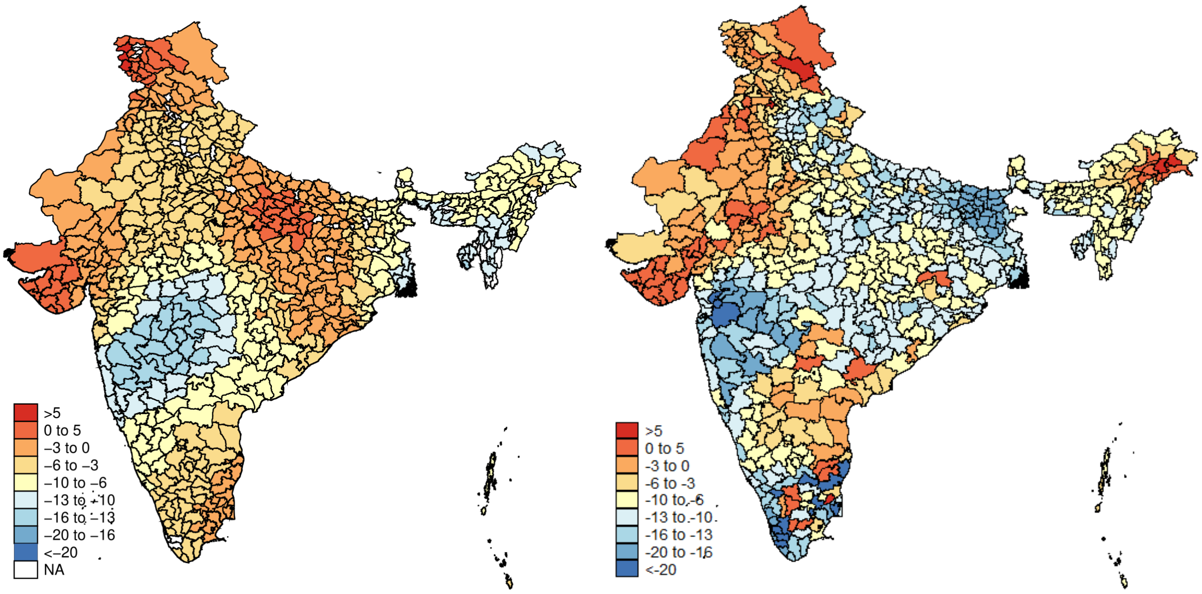


Figure B.2: *Change in total absolute negative temperature anomalies (totals for time spans 1999–2003 and 2006–2010) between IHDS rounds (CRU-data left, ERA5 data right)*

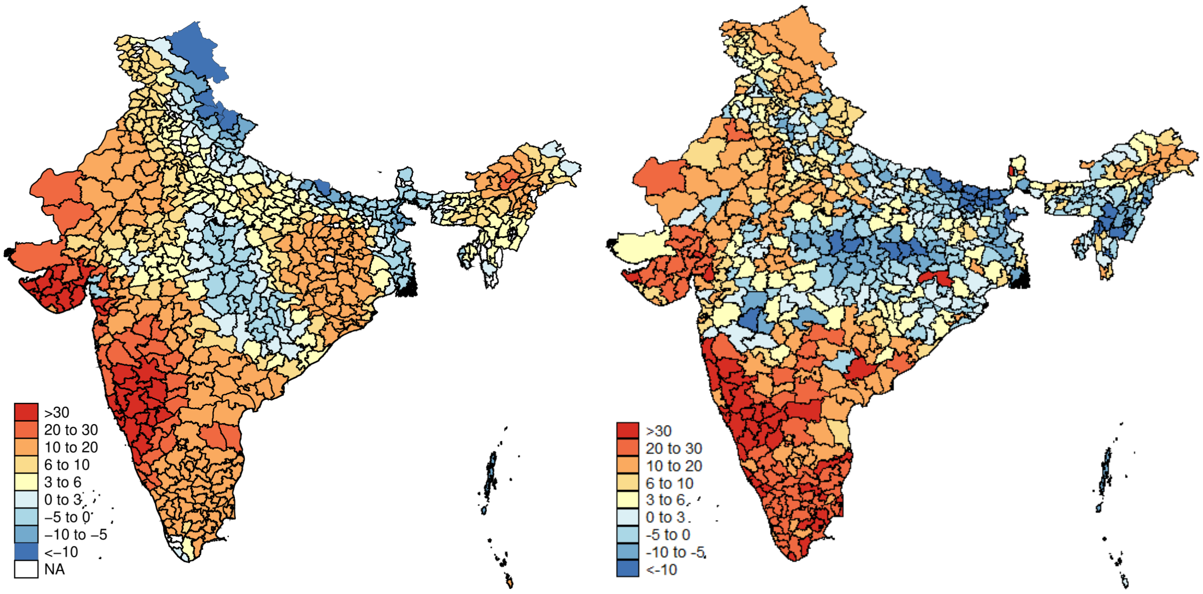


Figure B.3: *Change in total positive precipitation anomalies (totals for time spans 1999–2003 and 2006–2010) between IHDS rounds (CRU-data left, ERA5 data right)*

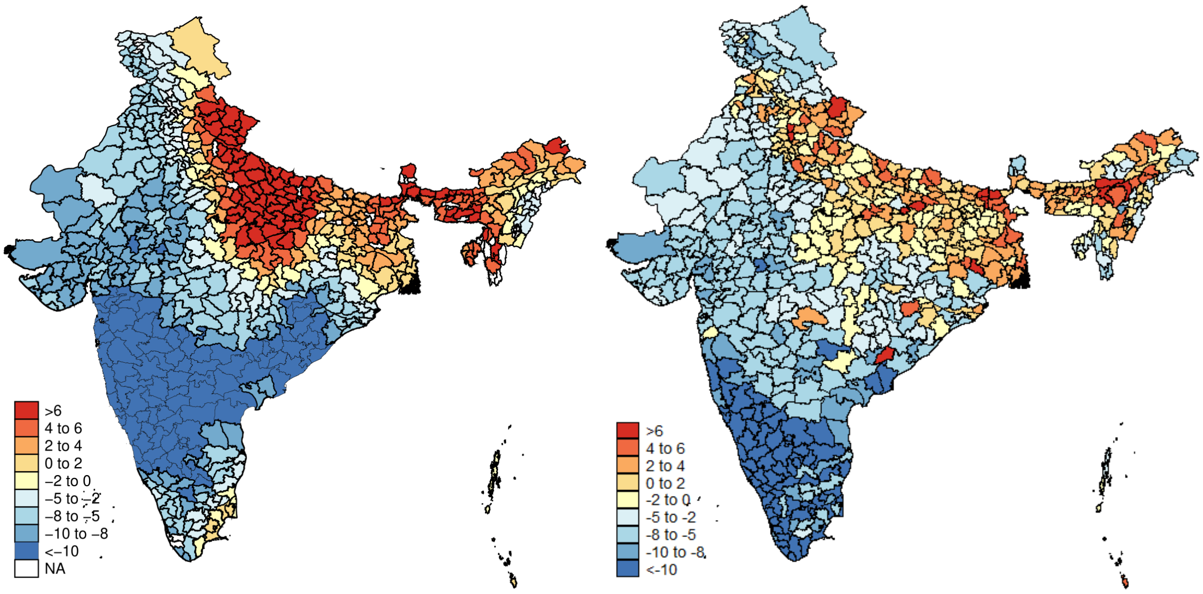


Figure B.4: *Change in total absolute negative precipitation anomalies (totals for time spans 1999–2003 and 2006–2010) between IHDS rounds (CRU-data left, ERA5 data right)*

B.4 Attrition analysis

Table B.4: *Analysis of attrition of rural households in IHDS dataset*

	(1) Out
Household head	
Age	-0.00000291
	(0.0000271)
Female	-0.00101
	(0.00140)
Literate	-0.00142
	(0.00105)
Dependency ratio	0.00216
	(0.00274)
Household characteristics	
Sex ratio	-0.000515
	(0.000986)
Married females	0.00111
	(0.00385)
Married males	0.0000691
	(0.00323)
Members	-0.000229*
	(0.000135)
Assets	0.000157
	(0.000203)
Land	-0.000983
	(0.00102)
Bank account	-0.00250
	(0.00247)
Agricultural	0.00224
	(0.00205)
Irrigation	-0.000843
	(0.00109)
N	27581
R^2	0.308
Fixed effects	Yes
Clustering	District

The model corresponds to a liner probability model. The outcome variable *Out* is binary and takes on a value of one if the household is not present in IHDS-II and zero otherwise. The household characteristics correspond to controls used in the main analysis and take on values from IHDS-I. Reported fixed effects are at the state-level. Clustered standard errors are displayed in parentheses. $p<0.10$, ** $p<0.05$, *** $p<0.01$.

B.5 Cross-sectional analysis

In the cross-sectional analysis, we estimate the following equation:

$$\bar{M}_{id} = \beta_0 + \beta_1 \bar{T}_{id} + \beta_2 \bar{P}_{id} + \beta_3 X_{id1} + \beta_4 G_d + \alpha_s + \epsilon_{id1} \tag{B.3}$$

where:

$\bar{M}$ is a binary variables that takes on a value of one if a household i has engaged into migration at least in one of the two IHDS rounds and zero otherwise. Hence, $\bar{M}$ captures households' average migration over time.

$\bar{T}$ captures the average temperature between January 1979 and the month/year of the interview conducted during IHDS-II.

$\bar{P}$ captures the average precipitation between January 1979 and the month/year of the interview conducted during IHDS-II.

X_{id1} captures characteristics of household i from IHDS-I, as suggested in section 1.3.1.

G_d captures district-specific geographic characteristics. Specifically, we control for variables traditionally utilized in the cross-sectional analyses of climate impacts, i.e. distance to city (derived from IHDS data), coast (Wessel and Smith, 1996) and river (Lehner and Grill, 2013), as well as latitude, elevation and soil characteristics (% of clay and ph) Fischer *et al.* (2008). The coefficients of these variables are, however, not reported.

α_s captures the state-specific fixed effects.

B.6 Five destination models

Table B.5: *Direct effects of weather extremes on the probability of out-migration: Five destination model*

	Δ *Migration*				
	Same State		Different State		International
	Rural	Urban	Rural	Urban	
Weather & climate					
ΔTemp. anomaly (+)	-0.000661***	0.000208	-0.0000279	0.000620	-0.000265**
	(0.000169)	(0.000217)	(0.0000678)	(0.000543)	(0.000115)
Δ. anomaly (-)	-0.000621	-0.000349	-0.0000342	-0.000291	-0.00159***
	(0.000425)	(0.000516)	(0.000204)	(0.00115)	(0.000415)
ΔPrecip. anomaly (+)	0.0000619	0.000995***	-0.0000632	0.000144	0.000438**
	(0.000167)	(0.000235)	(0.0000866)	(0.000541)	(0.000180)
ΔPrecip. anomaly (-)	-0.0000919	0.000513	-0.000288	0.00299**	0.000336
	(0.000461)	(0.000795)	(0.000255)	(0.00151)	(0.000454)
Household head					
Age	0.000295***	0.000683***	-0.0000154	0.000582***	0.0000106
	(0.0000973)	(0.000111)	(0.0000437)	(0.000128)	(0.0000601)
Female	-0.00485	-0.00243	0.00292	0.00648	0.00272
	(0.00436)	(0.00508)	(0.00259)	(0.00675)	(0.00377)
Literate	0.00113	0.0106***	0.000141	-0.00224	0.000932
	(0.00274)	(0.00306)	(0.00103)	(0.00413)	(0.00190)
Household characteristics					
Dependency ratio	-0.00826***	-0.0134***	0.00128	-0.00219	-0.00251
	(0.00259)	(0.00359)	(0.00112)	(0.00326)	(0.00169)
Sex ratio	0.00437**	0.00450*	-0.00128	0.000670	-0.00203
	(0.00189)	(0.00242)	(0.00102)	(0.00305)	(0.00166)
Married females	-0.0231***	-0.0119	0.00639**	0.0148	0.0106***
	(0.00601)	(0.00738)	(0.00302)	(0.00930)	(0.00394)
Married males	-0.00179	-0.0270***	-0.00340	-0.0649***	-0.0162***
	(0.00622)	(0.00751)	(0.00365)	(0.0105)	(0.00489)
Members	-0.000725*	-0.00147***	0.000119	-0.000839	0.000482*
	(0.000391)	(0.000518)	(0.000143)	(0.000623)	(0.000274)
Assets	0.0000379	0.00119***	0.000176	0.000587	0.000972***
	(0.000323)	(0.000380)	(0.000123)	(0.000513)	(0.000193)
Land	0.00181	0.0118***	-0.000172	0.0137***	-0.000750
	(0.00298)	(0.00349)	(0.00130)	(0.00486)	(0.00226)
Bank account	-0.00476*	0.00560*	0.000599	-0.000676	0.00148
	(0.00260)	(0.00334)	(0.00122)	(0.00395)	(0.00145)
Agricultural	-0.00344	-0.00404	-0.00117	-0.0114**	0.00150
	(0.00281)	(0.00331)	(0.00118)	(0.00516)	(0.00190)
Irrigation	-0.00215	-0.0124***	-0.00133	-0.00557	-0.00169
	(0.00273)	(0.00313)	(0.00133)	(0.00539)	(0.00192)
N			24845		
Fixed effects			Yes		
Clustering			District		

The outcomes correspond to a multinomial logit model, where the dependent variable indicates an increase in households' migration by destination (same state rural, same state urban, different state rural, different state urban and international) between the two IHDS rounds. All weather variables are constructed using ERA5 data. Dependent variable uses information from both IHDS rounds. Household-level controls use information from IHDS-I. The sample is composed of rural households in India. Reported fixed effects are at the state-level. Clustered standard errors are displayed in parentheses.* p<0.10, ** p<0.05, *** p<0.01.

B.7 Robustness analysis: Direct effects

Table B.6: *Heterogeneous effects of weather extremes on the probability of out-migration conditional on agriculture: Five destination model*

	Δ *Migration*				
	Same State		Different State		International
	Rural	Urban	Rural	Urban	
ΔTemp. anomaly (+) ×Non-agricultural	-0.000620**	0.000445	-0.0000801	0.000399	-0.000212*
	(0.000246)	(0.000296)	(0.000105)	(0.000652)	(0.000112)
ΔTemp. anomaly (+) × Agricultural	-0.000675***	0.000144	0.0000122	0.000731	-0.000319**
	(0.000183)	(0.000225)	(0.0000795)	(0.000501)	(0.000137)
p diff.	0.8298	0.2868	0.4462	0.3825	0.3258
ΔTemp. anomaly (-) ×Non-agricultural	-0.000352	0.000580	-0.000274	-0.00101	-0.00134***
	(0.000587)	(0.000654)	(0.000268)	(0.00125)	(0.000394)
ΔTemp. anomaly (-) × Agricultural	-0.000691	-0.000763	0.000111	0.000126	-0.00179***
	(0.000443)	(0.000533)	(0.000196)	(0.00115)	(0.000503)
p diff.	0.5375	0.0189	0.0787	0.1346	0.2651
ΔPrecip. anomaly (+) ×Non-agricultural	0.000265	0.000725***	0.0000434	0.000140	0.000439**
	(0.000219)	(0.000273)	(0.000118)	(0.000627)	(0.000201)
ΔPrecip. anomaly (+) × Agricultural	-0.0000505	0.00111***	-0.000159**	0.000214	0.000484**
	(0.000185)	(0.000256)	(0.0000806)	(0.000524)	(0.000203)
p diff.	0.1490	0.1086	0.0653	0.8463	0.7869
ΔPrecip. anomaly (-) ×Non-agricultural	0.000587	-0.000202	-0.000232	0.00240	0.0000371
	(0.000634)	(0.00100)	(0.000380)	(0.00163)	(0.000445)
ΔPrecip. anomaly (-) × Agricultural	-0.000447	0.000889	-0.000366	0.00343**	0.000702
	(0.000537)	(0.000836)	(0.000248)	(0.00156)	(0.000552)
p diff.	0.1452	0.2320	0.7127	0.3431	0.1119
N			24845		
Time trend			Yes		
Clustering			District		

The outcomes correspond to a multinomial logit model, where the dependent variable indicates an increase in households' migration by destination (same state rural, same state urban, different state rural, different state urban and international) between the two IHDS rounds. The coefficients can be interpreted as the rate of change in probability of sending out a migrant separately for agricultural and non-agricultural households. The p-values indicate significant difference in the effects. Other household-specific characteristics are controlled for, but are not reported. The weather variables are constructed using ERA5 data. Dependent variable uses information from both IHDS rounds. Household-level controls use information from IHDS-I. The sample is composed of rural households in India. Reported fixed effects are at the state-level. Clustered standard errors are displayed in parentheses.* p<0.10, ** p<0.05, *** p<0.01.

Table B.7: *Heterogeneous effects of weather extremes on the probability of out-migration conditional on education: Five destination model*

	Δ *Migration*				
	Same State		Different State		International
	Rural	Urban	Rural	Urban	
ΔTemp. anomaly (+) $\times$ Illiterate	-0.000792***	-0.0000278	-0.0000698	0.000570	-0.000322**
	(0.000202)	(0.000262)	(0.0000895)	(0.000628)	(0.000130)
ΔTemp. anomaly (+) $\times$ Literate	-0.000558***	0.000350	0.00000172	0.000654	-0.000239*
	(0.000197)	(0.000259)	(0.0000794)	(0.000518)	(0.000122)
p diff.	0.2826	0.189839	0.468067	0.78746	0.418039
ΔTemp. anomaly (-) $\times$ Illiterate	-0.000470	0.0000615	-0.000155	-0.000240	-0.00181***
	(0.000507)	(0.000564)	(0.000219)	(0.00121)	(0.000471)
ΔTemp. anomaly (-) $\times$ Literate	-0.000790	-0.000683	0.0000744	-0.000268	-0.00147***
	(0.000495)	(0.000612)	(0.000226)	(0.00119)	(0.000444)
p diff.	0.5562	0.2066	0.2146	0.9697	0.3082
ΔPrecip. anomaly (+) $\times$ Illiterate	0.000154	0.000889***	-0.000107	0.000374	0.000423**
	(0.000212)	(0.000284)	(0.0000914)	(0.000587)	(0.000213)
ΔPrecip. anomaly (+) $\times$ Literate	-0.0000306	0.00106***	-0.0000289	-0.0000709	0.000453**
	(0.000188)	(0.000257)	(0.000107)	(0.000548)	(0.000207)
p diff.	0.4017	0.4745	0.4576	0.1958	0.8887
ΔPrecip. anomaly (-) $\times$ Illiterate	0.0000871	0.000907	-0.000321	0.00445***	0.000330
	(0.000617)	(0.000810)	(0.000290)	(0.00162)	(0.000519)
ΔPrecip. anomaly (-) $\times$ Literate	-0.000268	0.000278	-0.000257	0.00190	0.000311
	(0.000545)	(0.000922)	(0.000300)	(0.00155)	(0.000500)
p diff.	0.6162	0.3985	0.8332	0.0138	0.9676
N			24845		
Fixed effects			Yes		
Clustering			District		

The outcomes correspond to a multinomial logit model, where the dependent variable indicates an increase in households' migration by destination (same state rural, same state urban, different state rural, different state urban and international) between the two IHDS rounds. The coefficients can be interpreted as the rate of change in probability of sending out a migrant separately for literate and illiterate households. The p-values indicate significant difference in the effects. Other household-specific characteristics are controlled for, but are not reported. The weather variables are constructed using ERA5 data. Dependent variable uses information from both IHDS rounds. Household-level controls use information from IHDS-I. The sample is composed of rural households in India. Reported fixed effects are at the state-level. Clustered standard errors are displayed in parentheses.* p<0.10, ** p<0.05, *** p<0.01.

Table B.8: *Direct effects of extremes on the probability of out-migration: Logit*

	Δ *Migration*
Weather & climate	
ΔTemp. anomaly (+)	-0.000337
	(0.000585)
ΔTemp. anomaly (-)	-0.00304**
	(0.00132)
ΔPrecip. anomaly (+)	0.00193***
	(0.000603)
ΔPrecip. anomaly (-)	0.00303*
	(0.00164)
Household head	
Age	0.00134***
	(0.000187)
Female	-0.00311
	(0.00975)
Head literate	0.00912
	(0.00579)
Household characteristics	
Dependency ratio	-0.0232***
	(0.00589)
Sex ratio	0.0116**
	(0.00458)
Married females	-0.0190
	(0.0139)
Married males	-0.0966***
	(0.0144)
Members	-0.00224**
	(0.000967)
Assets	0.00300***
	(0.000717)
Land	0.0252***
	(0.00688)
Bank account	0.00151
	(0.00603)
Agricultural	-0.0153**
	(0.00662)
Irrigation	-0.0220***
	(0.00712)
N	24793
Fixed effects	Yes
Clustering	District

The model corresponds to a logit model. The dependent variable is a binary variable that indicates an increase in households' migration between the two IHDS rounds. The weather variables capture the change in households' exposure to total positive and negative temperature and precipitation anomalies between the two IHDS rounds. All weather variables are constructed using ERA5 data. Dependent variable uses information from both IHDS rounds. Household-level controls use information from IHDS-I. The sample is composed of rural households in India. Reported fixed effects are at the state-level. Clustered standard errors are displayed in parentheses.* p<0.10, ** p<0.05, *** p<0.01.

Table B.9: *Direct effects of weather extremes on the probability of out-migration: Errors clustered at the state-level*

	(1)	(2)	(3)		
	Migration	Δ *Migration*	Δ *Migration*		
			Rural	Urban	International
Weather & climate					
Temperature	0.0225*				
	(0.0129)				
Precipitation	1.0285				
	(0.7392)				
ΔTemp. anomaly (+)		0.0000934	-0.000707***	0.000650	-0.000263***
		(0.000587)	(0.000161)	(0.000638)	(0.0000761)
ΔTemp. anomaly (-)		-0.00241**	-0.000617	-0.00154	-0.00158***
		(0.000938)	(0.000514)	(0.00134)	(0.000266)
ΔPrecip. anomaly (+)		0.00184***	-0.00000574	0.00163**	0.000436***
		(0.000585)	(0.000213)	(0.000664)	(0.000157)
ΔPrecip. anomaly (-)		0.00277**	-0.000316	0.00290***	0.000342
		(0.00129)	(0.000425)	(0.00106)	(0.000659)
Household head					
Age	0.00275***	0.00167***	0.000284***	0.00128***	0.0000108
	(0.000356)	(0.000251)	(0.000102)	(0.000189)	(0.0000597)
Female	0.112***	0.00821	-0.000854	0.00598	0.00269
	(0.0269)	(0.0101)	(0.00415)	(0.00836)	(0.00261)
Head literate	0.00916	0.0120*	0.00126	0.00792	0.000937
	(0.00646)	(0.00640)	(0.00337)	(0.00520)	(0.00185)
Household characteristics					
Dependency ratio	-0.00377	-0.0163**	-0.00631*	-0.0118*	-0.00256
	(0.00808)	(0.00704)	(0.00350)	(0.00618)	(0.00169)
Sex ratio	-0.0447***	0.0207**	0.00295	0.00457	-0.00203
	(0.0147)	(0.00900)	(0.00230)	(0.00601)	(0.00133)
Married females	0.139***	-0.0327	-0.0163***	0.00608	0.0105**
	(0.0457)	(0.0242)	(0.00524)	(0.0189)	(0.00427)
Married males	-0.224***	-0.0646**	-0.00637	-0.0922***	-0.0162***
	(0.0464)	(0.0262)	(0.00808)	(0.0222)	(0.00358)
Members	-0.00526**	-0.00209	-0.000657	-0.00246**	0.000483
	(0.00219)	(0.00124)	(0.000419)	(0.00114)	(0.000323)
Assets	0.00548***	0.00360***	0.000245	0.00182**	0.000973***
	(0.000882)	(0.000944)	(0.000316)	(0.000782)	(0.000237)
Land	0.0483***	0.0268***	0.00180	0.0262***	-0.000752
	(0.00786)	(0.00687)	(0.00305)	(0.00457)	(0.00152)
Bank account	0.00577	0.00107	-0.00381	0.00408	0.00149
	(0.00728)	(0.00503)	(0.00290)	(0.00603)	(0.00107)
Agricultural	-0.0300***	-0.0135	-0.00459*	-0.0164*	0.00151
	(0.0109)	(0.00943)	(0.00247)	(0.00929)	(0.00273)
Irrigation	-0.0267***	-0.0243**	-0.00380	-0.0170**	-0.00170
	(0.00869)	(0.00931)	(0.00244)	(0.00797)	(0.00209)
N	24845	24845	24845	24845	24845
R^2	0.103	0.189			
Fixed effects	Yes	Yes		Yes	
Clustering	State	State		State	

Model 1 corresponds to a linear probability model. It is a cross-sectional regression of households' average engagement into migration over time on district-level historical temperature, precipitations and geographic variables and household-level controls. The dependent variable is binary and takes on a value of one if a household has sent at least one migrant in any of the two IHDS rounds. The geographic variables capture distance to city, coast and river, latitude, elevation and soil characteristics. The coefficients of these variables are not reported. Model 2 corresponds to a linear probability model. The dependent variable is a binary variable that indicates an increase in households' migration between the two IHDS rounds. The weather variables capture the change in households' exposure to total positive and negative temperature and precipitation anomalies between the two IHDS rounds. Model 3 corresponds to a multinomial logit model, where the dependent variable indicates an increase in households' migration by destination (rural, urban, international) between the two IHDS rounds. All weather variables are constructed using ERA5 data. Dependent variables use information from both IHDS rounds. Household-level controls use information from IHDS-I. The sample is composed of rural households in India. Reported fixed effects are at the state-level. Clustered standard errors are displayed in parentheses.* p<0.10, ** p<0.05, *** p<0.01.

Table B.10: *Direct effects of weather extremes on the probability of out-migration: No state trends*

	(1)	(2)	(3)		
	Migration	Δ *Migration*	Δ *Migration*		
			Rural	Urban	International
Weather & climate					
Temperature	0.00736				
	(0.00875)				
Precipitation	-0.2389				
	(0.759)				
ΔTemp. anomaly (+)		0.000949**	-0.000459**	0.000810*	0.000345***
		(0.000472)	(0.000215)	(0.000420)	(0.0000825)
ΔTemp. anomaly (-)		0.00105	0.000109	0.00116	0.000180
		(0.00116)	(0.000377)	(0.00112)	(0.000266)
ΔPrecip. anomaly (+)		0.000429	-0.000506***	0.000757	0.0000430
		(0.000582)	(0.000187)	(0.000538)	(0.0000926)
ΔPrecip. anomaly (-)		0.00158	-0.000622	0.00318**	-0.000450
		(0.00170)	(0.000510)	(0.00154)	(0.000343)
Household head					
Age	0.00299***	0.00149***	0.000308***	0.00142***	0.00000982
	(0.000280)	(0.000209)	(0.000113)	(0.000182)	(0.0000677)
Female	0.122***	0.00697	0.000349	0.0102	0.00377
	(0.0174)	(0.0116)	(0.00534)	(0.00959)	(0.00390)
Head literate	0.0180**	0.0124**	0.00364	0.0103*	-0.000510
	(0.00737)	(0.00596)	(0.00280)	(0.00527)	(0.00207)
Household characteristics					
Dependency ratio	0.00160	-0.0179***	-0.00615**	-0.00674	-0.00211
	(0.00702)	(0.00600)	(0.00280)	(0.00519)	(0.00166)
Sex ratio	-0.0556***	0.00715	0.00211	-0.00169	-0.00279
	(0.00977)	(0.00583)	(0.00215)	(0.00445)	(0.00201)
Married females	0.170***	-0.00489	-0.0142**	0.0275*	0.0131***
	(0.0298)	(0.0171)	(0.00690)	(0.0145)	(0.00483)
Married males	-0.246***	-0.105***	-0.00849	-0.114***	-0.0185***
	(0.0251)	(0.0152)	(0.00686)	(0.0149)	(0.00613)
Members	-0.00317**	-0.000381	-0.000187	-0.000600	0.000412
	(0.00151)	(0.00112)	(0.000443)	(0.000911)	(0.000347)
Assets	-0.00114	-0.00116	-0.000606**	-0.00222***	0.00147***
	(0.00125)	(0.000927)	(0.000308)	(0.000823)	(0.000310)
Land	0.0653***	0.0424***	0.00747**	0.0420***	-0.00404
	(0.00967)	(0.00903)	(0.00310)	(0.00768)	(0.00320)
Bank account	0.0215**	0.00740	-0.00520*	0.0131**	0.000284
	(0.0101)	(0.00765)	(0.00316)	(0.00643)	(0.00148)
Agricultural	-0.0494***	-0.0342***	-0.00655**	-0.0348***	0.00129
	(0.00887)	(0.00741)	(0.00304)	(0.00659)	(0.00257)
Irrigation	0.00364	0.00159	-0.000748	0.00283	-0.000334
	(0.0111)	(0.0103)	(0.00337)	(0.00840)	(0.00220)
N	24845	24845	24845	24845	24845
R^2	0.056	0.018			
Fixed effects	No	No		No	
Clustering	District	District		District	

Model 1 corresponds to a linear probability model. It is a cross-sectional regression of households' average engagement into migration over time on district-level historical temperature, precipitations and geographic variables and household-level controls. The dependent variable is binary and takes on a value of one if a household has sent at least one migrant in any of the two IHDS rounds. The geographic variables capture distance to city, coast and river, latitude, elevation and soil characteristics. The coefficients of these variables are not reported. Model 2 corresponds to a linear probability model. The dependent variable is a binary variable that indicates an increase in households' migration between the two IHDS rounds. The weather variables capture the change in households' exposure to total positive and negative temperature and precipitation anomalies between the two IHDS rounds. Model 3 corresponds to a multinomial logit model, where the dependent variable indicates an increase in households' migration by destination (rural, urban, international) between the two IHDS rounds. All weather variables are constructed using ERA5 data. Dependent variables use information from both IHDS rounds. Household-level controls use information from IHDS-I. The sample is composed of rural households in India. Clustered standard errors are displayed in parentheses.* p<0.10, ** p<0.05, *** p<0.01.

B.8 Robustness analysis: Heterogeneous effects, agriculture

Table B.11: *Heterogeneous effects of weather extremes on the probability of out-migration conditional on agriculture: Errors clustered at the state-level*

	Δ *Migration*		
	Rural	Urban	International
ΔTemp. anomaly (+) $\times$ Non-agricultural	-0.000683***	0.000727	-0.000212**
	(0.000218)	(0.000844)	(0.0000845)
ΔTemp. anomaly (+) $\times$ Agricultural	-0.000719***	0.000641	-0.000314**
	(0.000171)	(0.000556)	(0.000128)
p diff.	0.8783	0.8379	0.4864
ΔTemp. anomaly (-) $\times$ Non-agricultural	-0.000567	-0.00120	-0.00134***
	(0.000692)	(0.00183)	(0.000370)
ΔTemp. anomaly (-) $\times$ Agricultural	-0.000590	-0.00173	-0.00177***
	(0.000480)	(0.00116)	(0.000370)
p diff.	0.9680	0.6770	0.4107
ΔPrecip. anomaly (+) $\times$ Non-agricultural	0.000269	0.00110	0.000440***
	(0.000284)	(0.000756)	(0.000164)
ΔPrecip. anomaly (+) $\times$ Agricultural	-0.000170	0.00194***	0.000479**
	(0.000197)	(0.000644)	(0.000193)
p diff.	0.0467	0.1271	0.7993
ΔPrecip. anomaly (-) $\times$ Non-agricultural	0.000404	0.00151	0.0000450
	(0.000739)	(0.00176)	(0.000605)
ΔPrecip. anomaly (-) $\times$ Agricultural	-0.000746**	0.00375***	0.000707
	(0.000379)	(0.000826)	(0.000740)
p diff.	0.0844	0.1181	0.0501
N		24845	
Fixed effects		Yes	
Clustering		State	

The outcomes correspond to a multinomial logit model, where the dependent variable indicates an increase in households' migration by destination (rural, urban, international) between the two IHDS rounds. The coefficients can be interpreted as the rate of change in probability of sending out a migrant separately for agricultural and non-agricultural households. The p-values indicate significant difference in the effects. Other household-specific characteristics are controlled for, but are not reported. The weather variables are constructed using ERA5 data. Dependent variable uses information from both IHDS rounds. Household-level controls use information from IHDS-I. The sample is composed of rural households in India. Reported fixed effects are at the state-level. Clustered standard errors are displayed in parentheses.* p<0.10, ** p<0.05, *** p<0.01.

Table B.12: *Heterogeneous effects of weather extremes on the probability of out-migration conditional on agriculture: No state trends*

	Δ *Migration*		
	Rural	Urban	International
ΔTemp. anomaly (+) $\times$ Non-agricultural	-0.000263	0.000607	0.000330***
	(0.000285)	(0.000574)	(0.0000982)
ΔTemp. anomaly (+) $\times$ Agricultural	-0.000562**	0.00101**	0.000349***
	(0.000242)	(0.000406)	(0.000101)
p diff.	0.3310	0.3861	0.8659
ΔTemp. anomaly (-) $\times$ Non-agricultural	0.000384	0.00178	0.000278
	(0.000538)	(0.00147)	(0.000338)
ΔTemp. anomaly (-) $\times$ Agricultural	0.0000267	0.000654	0.000125
	(0.000380)	(0.00104)	(0.000308)
p diff.	0.4706	0.2686	0.6572
ΔPrecip. anomaly (+) $\times$ Non-agricultural	-0.000281	0.0000587	-0.0000150
	(0.000232)	(0.000794)	(0.000101)
ΔPrecip. anomaly (+) $\times$ Agricultural	-0.000651***	0.00119**	0.000107
	(0.000218)	(0.000470)	(0.000130)
p diff.	0.1474	0.0550	0.3685
ΔPrecip. anomaly (-) $\times$ Non-agricultural	-0.000124	0.00260	-0.000863**
	(0.000633)	(0.00201)	(0.000397)
ΔPrecip. anomaly (-) $\times$ Agricultural	-0.000943	0.00340**	0.0000605
	(0.000615)	(0.00153)	(0.000448)
p diff.	0.2714	0.6167	0.0308
N		24845	
Fixed effects		No	
Clustering		District	

The outcomes correspond to a multinomial logit model, where the dependent variable indicates an increase in households' migration by destination (rural, urban, international) between the two IHDS rounds. The coefficients can be interpreted as the rate of change in probability of sending out a migrant separately for agricultural and non-agricultural households. The p-values indicate significant difference in the effects. Other household-specific characteristics are controlled for, but are not reported. The weather variables are constructed using ERA5 data. Dependent variable uses information from both IHDS rounds. Household-level controls use information from IHDS-I. The sample is composed of rural households in India. Clustered standard errors are displayed in parentheses.* p<0.10, ** p<0.05, *** p<0.01.

B.9 Robustness analysis: Heterogeneous effects, education

Table B.13: *Heterogeneous effects of weather extremes on the probability of out-migration conditional on head's schooling (alternative measure)*

	Δ *Migration*		
	Rural	Urban	International
ΔTemp. anomaly (+) × No schooling	-0.000932***	0.000445	-0.000266**
	(0.000237)	(0.000657)	(0.000135)
ΔTemp. anomaly (+) × Schooling	-0.000532**	0.000724	-0.000250**
	(0.000216)	(0.000579)	(0.000125)
p diff	0.0965	0.5106	0.8893
ΔTemp. anomaly (-) × No schooling	-0.000788	-0.000895	-0.00172***
	(0.000604)	(0.00136)	(0.000451)
ΔTemp. anomaly (-) × Schooling	-0.000503	-0.00197	-0.00149***
	(0.000572)	(0.00138)	(0.000453)
p diff	0.5737	0.1969	0.4856
ΔPrecip. anomaly (+) × No schooling	0.0000742	0.00174***	0.000433*
	(0.000223)	(0.000630)	(0.000222)
ΔPrecip. anomaly (+) × Schooling	-0.0000965	0.00151***	0.000450**
	(0.000210)	(0.000558)	(0.000205)
p diff	0.4407	0.5347	0.9420
ΔPrecip. anomaly (-) × No schooling	-0.000151	0.00475***	0.000428
	(0.000708)	(0.00164)	(0.000531)
ΔPrecip. anomaly (-) × Schooling	-0.000497	0.00165	0.000283
	(0.000610)	(0.00169)	(0.000503)
p diff	0.6173	0.0097	0.7709
N		24845	
Time trend		Yes	
Clustering		District	

The outcomes correspond to a multinomial logit model, where the dependent variable indicates an increase in households' migration by destination (rural, urban, international) between the two IHDS rounds. The coefficients can be interpreted as the rate of change in probability of sending out a migrant separately for households with schooling and without schooling. The p-values indicate significant difference in the effects. Other household-specific characteristics are controlled for, but are not reported. The weather variables are constructed using ERA5 data. Dependent variable uses information from both IHDS rounds. Household-level controls use information from IHDS-I. The sample is composed of rural households in India. Reported fixed effects are at the state-level. Clustered standard errors are displayed in parentheses.* p<0.10, ** p<0.05, *** p<0.01.

Table B.14: *Heterogeneous effects of weather extremes on the probability of out-migration conditional on education: Errors clustered at the state-level*

	Δ *Migration*		
	Rural	Urban	International
ΔTemp. anomaly (+) × Head illiterate	-0.000892***	0.000341	-0.000319***
	(0.000200)	(0.000699)	(0.0000932)
ΔTemp. anomaly (+) × Head literate	-0.000566***	0.000798	-0.000237***
	(0.000149)	(0.000618)	(0.0000811)
p diff.	0.0167	0.2127	0.2994
ΔTemp. anomaly (-) × Head illiterate	-0.000624	-0.000967	-0.00180***
	(0.000515)	(0.00151)	(0.000295)
ΔTemp. anomaly (-) × Head literate	-0.000650	-0.00187	-0.00147***
	(0.000602)	(0.00129)	(0.000304)
p diff.	0.9579	0.2159	0.2852
ΔPrecip. anomaly (+) × Head illiterate	0.0000751	0.00177**	0.000422***
	(0.000277)	(0.000824)	(0.000158)
ΔPrecip. anomaly (+) × Head literate	-0.0000897	0.00148**	0.000451**
	(0.000187)	(0.000599)	(0.000212)
p diff.	0.3855	0.4949	0.8989
ΔPrecip. anomaly (-) × Head illiterate	-0.000140	0.00516***	0.000330
	(0.000445)	(0.00158)	(0.000644)
ΔPrecip. anomaly (-) × Head literate	-0.000489	0.00141	0.000320
	(0.000621)	(0.00104)	(0.000759)
p diff.	0.6432	0.0065	0.9861
N		24845	
Fixed effects		Yes	
Clustering		State	

The outcomes correspond to a multinomial logit model, where the dependent variable indicates an increase in households' migration by destination (rural, urban, international) between the two IHDS rounds. The coefficients can be interpreted as the rate of change in probability of sending out a migrant separately for literate and illiterate households. The p-values indicate significant difference in the effects. Other household-specific characteristics are controlled for, but are not reported. The weather variables are constructed using ERA5 data. Dependent variable uses information from both IHDS rounds. Household-level controls use information from IHDS-I. The sample is composed of rural households in India. Reported fixed effects are at the state-level. Clustered standard errors are displayed in parentheses.* p<0.10, ** p<0.05, *** p<0.01.

Table B.15: *Heterogeneous effects of weather extremes on the probability of out-migration conditional on education: No state trends*

	Δ *Migration*		
	Rural	Urban	International
ΔTemp. anomaly (+) $\times$ Head illiterate	-0.000756***	0.00115**	0.000222*
	(0.000275)	(0.000569)	(0.000133)
ΔTemp. anomaly (+) $\times$ Head literate	-0.000281	0.000637	0.000377***
	(0.000226)	(0.000424)	(0.0000901)
p diff.	0.0691	0.2394	0.2867
ΔTemp. anomaly (-) $\times$ Head illiterate	-0.000107	0.00125	-0.0000532
	(0.000448)	(0.00121)	(0.000345)
ΔTemp. anomaly (-) $\times$ Head literate	0.000306	0.00126	0.000291
	(0.000449)	(0.00121)	(0.000274)
p diff.	0.4064	0.9928	0.2553
ΔPrecip. anomaly (+) $\times$ Head illiterate	-0.000429*	0.00101*	0.000112
	(0.000234)	(0.000604)	(0.000139)
ΔPrecip. anomaly (+) $\times$ Head literate	-0.000599***	0.000549	0.00000386
	(0.000210)	(0.000560)	(0.000107)
p diff.	0.4877	0.2751	0.5093
ΔPrecip. anomaly (-) $\times$ Head illiterate	-0.000130	0.00429**	-0.000159
	(0.000703)	(0.00173)	(0.000500)
ΔPrecip. anomaly (-) $\times$ Head literate	-0.000913	0.00217	-0.000565
	(0.000569)	(0.00163)	(0.000372)
p diff.	0.3075	0.1107	0.4024
N		24845	
Fixed effects		No	
Clustering		District	

The outcomes correspond to a multinomial logit model, where the dependent variable indicates an increase in households' migration by destination (rural, urban, international) between the two IHDS rounds. The coefficients can be interpreted as the rate of change in probability of sending out a migrant separately for literate and illiterate households. The p-values indicate significant difference in the effects. Other household-specific characteristics are controlled for, but are not reported. The weather variables are constructed using ERA5 data. Dependent variable uses information from both IHDS rounds. Household-level controls use information from IHDS-I. The sample is composed of rural households in India. Clustered standard errors are displayed in parentheses.* p<0.10, ** p<0.05, *** p<0.01.

Appendix C

Appendix to Chapter 3

C.1 Assembling the sample of original studies: A detailed description

To build the initial sample of original studies, we drew on a series of prominent literature reviews on environmental migration (Millock (2015); Berlemann and Steinhardt (2017); Cattaneo *et al.* (2019); Neumann and Hermans (2017); Piguet *et al.* (2011)) and an additional literature review conducted by a research assistant.[1] Next, following Ringquist (2013), we developed a search profile by using keywords related to the outcome variable (migration), focal predictor (climat*, environment*, natural disasters) and methodology (regression, econometric). We tested different types of boolean connectors and developed the following final query: migration AND (climat* OR environment* OR natural disaster) AND (regression OR econometric). The last search was carried out on October 31st, 2018 using a scoping review helper developed by the Mercator Research Institute on Global Commons and Climate Change (MCC) (Callaghan *et al.*, 2020) and Google Scholar. Via MCC's scoping helper, we accessed the database of Web of Science and Scopus and identified 1,157 studies. Further, we reviewed the first 50 pages of results returned by Google Scholar. We also conducted a backward search and analyzed Google Scholar profiles and (if existing) other personal or professional websites of corresponding authors of every acceptable study in our sample and contacted them for the approval of the final list of studies.

Applying the approach suggested by Ringquist (2013), after the analysis of the titles of the original studies applying generous inclusion criteria, we narrowed down 457 potentially relevant studies. A closer examination of abstracts, summaries and in some cases of full texts enabled us to refine the sample to 176 relevant studies. At this stage we excluded studies that i) do not apply econometric methods, ii) do not measure effect of climatic events[2] on migration,[3] iii) only reported interactions/polynomials, or iv) we were not able to access.[4] We then conducted a full text analysis of the relevant studies to further exclude 60 papers based on the duplication and relevance criteria,[5] or if studies do not report minimum information such as sample size, or significance. This left us with a final sample of 116 original studies. The main unit of analysis in our study is at

[1] This literature review is summarized in a Masters' thesis "On the empirical evidence on environmental. migration -a systematic literature review" by our research assistant at the time, Ms. Ramlah Abbas.

[2] Some studies examined effects of other environmental disasters (e.g. landslides) or geological disasters (e.g. Tsunami) rather than climatic events.

[3] In some cases, it was not clear from the title of the study what the outcome variable was.

[4] In these cases, study authors were contacted but were not responsive.

[5] We excluded studies based on the relevance criteria, if they perceived climate migration through the amenity channel. In such settings, climatic factors attract in-migration (thus are not the push factors) enabling populations, e.g. to escape hotter summers or experience warmer winters. Further, we also excluded studies where, the dependent variable only captures intention to migrate and not actual migration, or independent variables do not capture focal predictors of interest (i.e. climatic effects).

the effect-level, corresponding to 3,625 estimated effects.

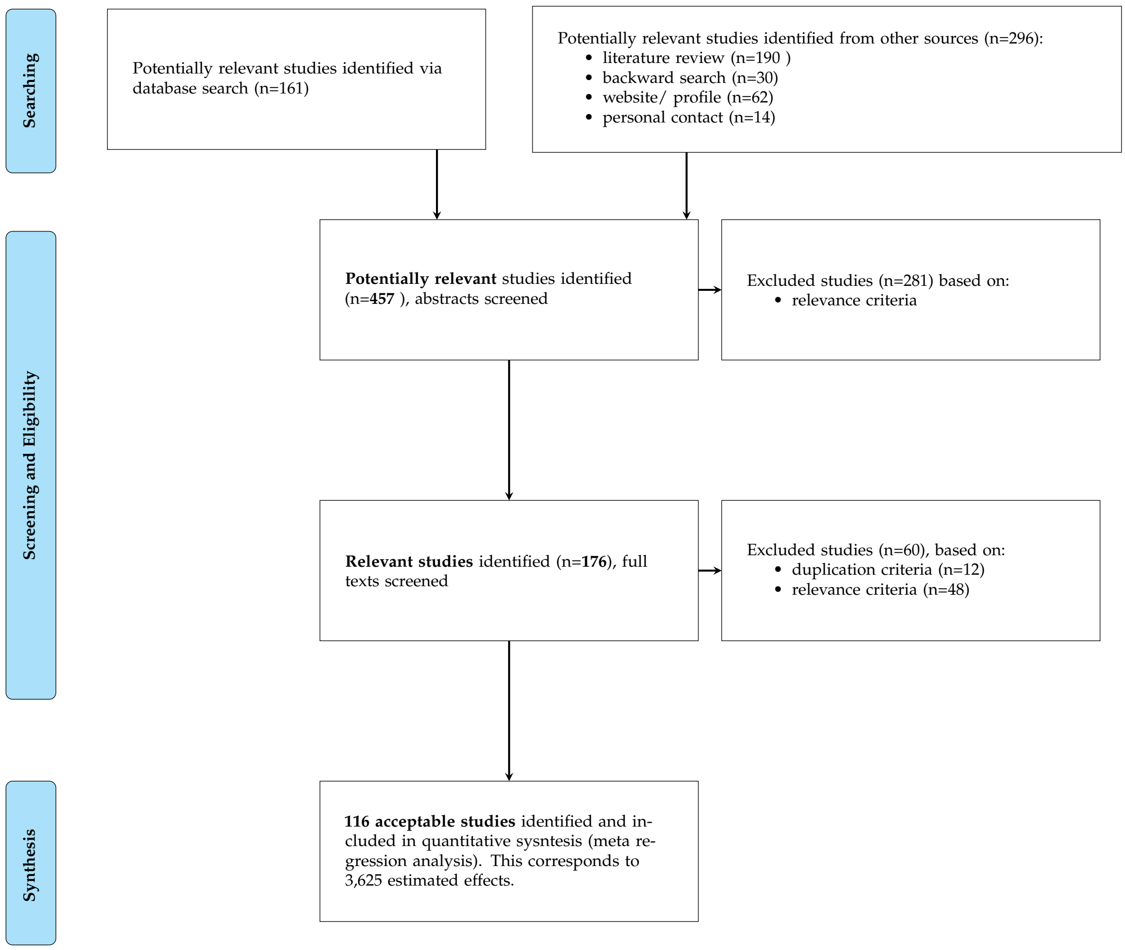


Figure C.1: *ROSES flow diagram for systematic reviews*

C.2 List of original studies

Table C.1: *Summary statistics: List of original studies*

	Number of estimates	Author female	Published
Adoho and Wodon (2014)	32	0	0
Afifi *et al.* (2014)	1	0	0
Alem *et al.* (2016)	6	0	0
Asrat (2017)	4	0	0
Backhaus *et al.* (2015)	18	0	1
Badiani and Abla (2008)	2	1	0
Baez *et al.* (2017a)	2	1	1
Bakar and Jin (2018)	21	0	1
Barassi *et al.* (2018)	60	0	1
Baronchelli and Ricciuti (2018)	25	1	0
Barrios *et al.* (2006)	4	0	1
Bazzi (2017)	15	0	1
Beine and Parsons (2014)	55	0	1
Beine and Parsons (2017)	48	0	1
Bettin and Nicolli (2012)	36	1	0
Bhattacharya and Innes (2008)	32	1	1
Bohra-Mishra *et al.* (2014)	60	1	1
Bohra-Mishra *et al.* (2017)	40	1	1
Bosetti *et al.* (2020)	4	1	0
Bylander (2016)	3	1	0
Cai *et al.* (2016)	5	0	1
Call *et al.* (2017)	15	1	1
Carvajal and Medalho Pereira (2009)	1	1	0
Castañer *et al.* (2017)	2	1	1
Cattaneo and Peri (2016)	50	1	1
Chen and Mueller (2018)	94	1	0
Chen *et al.* (2017)	32	1	1
Chort and De La Rupelle (2016)	58	1	1
Chort and De La Rupelle (2017)	281	1	0
Coniglio and Pesce (2015)	27	0	1
Curran and Meijer-Irons (2014)	8	1	1
Dallmann and Millock (2017)	94	1	0
Deschênes and Moretti (2009)	1	0	1
Dillon *et al.* (2011)	9	0	1
Drabo and Mbaye (2014)	106	0	1
Duda *et al.* (2018)	2	1	1
Feng *et al.* (2015)	32	0	0
Fussell *et al.* (2017)	32	1	1
Gao and Sam (2017)	24	1	1
Goldbach (2017)	42	1	1
Grace *et al.* (2018)	16	1	1
Gray (2009)	3	0	1
Gray (2010)	4	0	1
Gray and Bilsborrow (2013)	72	0	1
Gray and Mueller (2012a)	116	0	1
Gray and Mueller (2012b)	141	0	1
Gray and Wise (2016)	125	0	1
Gröger and Zylberberg (2016)	12	0	1
Gröschl and Steinwachs (2017)	53	1	1
Gutmann *et al.* (2005)	28	0	1
Henderson *et al.* (2017)	10	0	1
Henry *et al.* (2004)	109	1	1
Henry *et al.* (2003)	2	1	1
Hirvonen (2016b)	74	0	1
Hornbeck and Naidu (2014)	39	0	1
Hunter *et al.* (2013)	47	1	1
Iqbal and Roy (2015)	50	0	1
Jennings and Gray (2015)	128	1	1
Jessoe *et al.* (2016)	21	1	1
Joseph *et al.* (2014)	34	0	0
Khamis and Li (2018)	12	1	0
Kleemans (2015)	20	1	0
Kleemans and Magruder (2018)	16	1	1
Koubi *et al.* (2012)	18	1	0
Koubi *et al.* (2016a)	14	1	1
Koubi *et al.* (2016c)	18	1	1
Koubi *et al.* (2016b)	28	1	1
Koubi *et al.* (2018)	18	1	0

Continue on the next page

Summary statistics: List of original studies (cont.).

	Number of estimates	Author female	Published
Kubik (2016)	62	1	0
Kubik and Maurel (2016)	21	1	1
Kumar and Viswanathan (2013)	24	0	1
Lewin *et al.* (2012)	5	0	1
Loebach (2016)	2	0	1
Mahajan and Yang (2018)	11	0	0
Marchiori *et al.* (2012)	12	0	1
Mastrorillo *et al.* (2016)	81	1	1
Matera (2014)	12	1	0
Maurel and Tuccio (2016)	20	1	1
Maystadt *et al.* (2016)	2	0	1
Missirian and Schlenker (2017)	102	1	1
Mueller *et al.* (2014)	248	1	1
Munshi (2003)	4	0	1
Naudé (2010)	3	0	1
Nawrotzki and Bakhtsiyarava (2016)	10	0	1
Nawrotzki *et al.* (2016)	28	0	1
Nawrotzki and DeWaard (2018)	54	0	1
Nawrotzki *et al.* (2013)	6	0	1
(Nawrotzki *et al.*, 2015a)	18	0	1
Nawrotzki *et al.* (2015b)	34	0	1
Nawrotzki *et al.* (2015c)	8	0	1
Nawrotzki *et al.* (2016)	20	0	1
Nawrotzki *et al.* (2016)	10	0	1
Nawrotzki *et al.* (2017)	4	0	1
Ouattara and Strobl (2014)	9	0	1
Pei and Zhang (2014)	2	0	1
Pei *et al.* (2016)	2	0	1
Pei *et al.* (2018)	4	0	1
Poston *et al.* (2009)	4	0	1
Reuveny and Moore (2009)	3	0	1
Riosmena *et al.* (2018)	6	0	1
Robalino *et al.* (2015)	38	0	1
Ruiz (2017)	43	0	0
Ruyssen and Rayp (2014)	5	1	1
Saldaña-Zorrilla and Sandberg (2009b)	7	0	1
Šedová and Kalkuhl (2018)	78	1	0
Shiva and Molana (2018)	8	0	0
Simon (2018)	24	0	0
Smith (2012)	4	0	0
Spencer and Urquhart (2018)	16	1	1
Strobl and Valfort (2015)	3	0	1
Tan *et al.* (2015)	4	1	1
Thiede and Gray (2017)	26	0	1
Thiede *et al.* (2016)	42	0	1
Tse (2012)	36	0	0
Viswanathan and Kumar (2015)	12	1	1
Wodon *et al.* (2014)	16	0	0
N	3625		

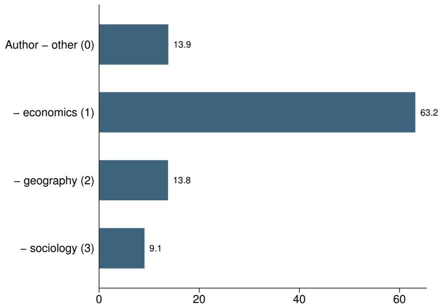
C.3 Descriptive statistics: All variables

Table C.2: *Summary statistics: Coded variables*

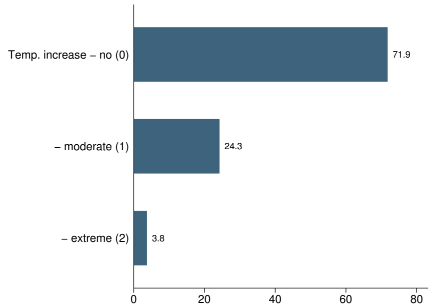
Variable	Mean	Std. Dev.	Min.	Max.	Description
Dependent variable					
Migration (binary)	0.3992	0.4898	0	1	binary
Migration (categorical)	2.0792	0.6269	1	3	categorical
Climatic variables					
Slow	0.7418	0.4377	0	1	binary
Temperature increase	0.3194	0.5419	0	2	categorical
Precipitation decrease	0.363	0.5099	0	2	categorical
Drought	0.0709	0.2567	0	1	binary
Sea-level rise	0.0262	0.1598	0	1	binary
Flood	0.1062	0.3081	0	1	binary
Hurricane/cyclone/typhoon	0.083	0.276	0	1	binary
Self-reported	0.1164	0.3208	0	1	binary
Direct effect	0.4844	0.4998	0	1	binary
Study-level variables					
Author - female	0.5561	0.4969	0	1	binary
Author - discipline	1.1815	0.78	0	3	categorical
Year of publication/ latest draft	2014.9354	2.9738	2003	2018	continuous
Peer-reviewed	0.7302	0.4439	0	1	binary
Sample characteristics					
Micro	0.5663	0.4956	0	1	binary
Multiple countries	0.2047	0.4035	0	1	binary
Low-income included	0.3942	0.4887	0	1	binary
Lower-middle income included	0.5972	0.4905	0	1	binary
Upper-middle income included	0.5484	0.4977	0	1	binary
1960s	0.0604	0.2383	0	1	binary
1970s	0.1404	0.3475	0	1	binary
1980s	0.2866	0.4522	0	1	binary
1990s	0.6681	0.4709	0	1	binary
2000s	0.4154	0.4929	0	1	binary
2010s	0.3763	0.4845	0	1	binary
Migration-related variables					
Origin	1.1526	0.9797	0	2	categorical
Destination 1	0.7167	0.7572	0	2	categorical
Destination 2	1.8086	0.5313	0	2	categorical
Temporary	0.0298	0.17	0	1	binary
Measurement	0.2756	0.4469	0	1	binary
Migrants	2.2789	1.1515	0	4	categorical
Econometric modeling variables					
Approach	1.8651	1.099	0	3	
Clustered std. errors	0.6152	0.4866	0	1	binary
Nr. of climatic variables	3.7807	2.7441	0	15	count
Controls	14.4246	10.0084	0	45	count
Income-related controls	0.6513	0.4766	0	1	binary
Polit. stability-related controls	0.2251	0.4177	0	1	binary
Main model	0.2814	0.4497	0	1	binary
N		3625			

Table C.3: *Weighted summary statistics: Coded variables*

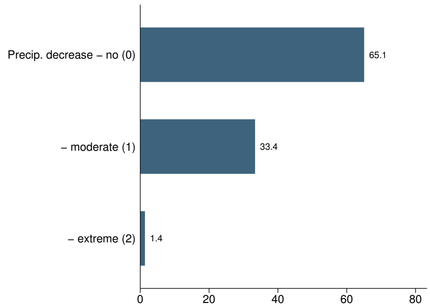
Variable	Mean	Std. Dev.	Min.	Max.
Dependent variable				
Migration (binary)	0.4007	0.4901	0	1
Migration (categorical)	2.0779	0.6283	1	3
Climatic variables				
Slow	0.7595	0.4274	0	1
Temperature increase	0.3296	0.5605	0	2
Precipitation decrease	0.3779	0.5244	0	2
Drought	0.0664	0.2491	0	1
Sea-level rise	0.0391	0.1939	0	1
Flood	0.109	0.3116	0	1
Hurricane/cyclone/typhoon	0.0656	0.2477	0	1
Self-reported	0.1085	0.311	0	1
Direct effect	0.4736	0.4994	0	1
Study-level variables				
Author - female	0.5496	0.4976	0	1
Author - discipline	1.2162	0.8308	0	3
Year of publication/ latest draft	2014.897	3.0527	2003	2018
Peer-reviewed	0.7419	0.4377	0	1
Sample characteristics				
Micro	0.6321	0.4823	0	1
Multiple countries	0.2097	0.4072	0	1
Low-income included	0.3955	0.4890	0	1
Lower-middle income included	0.6009	0.4898	0	1
Upper-middle income included	0.547	0.4979	0	1
1960s	0.0621	0.2414	0	1
1970s	0.148	0.3551	0	1
1980s	0.3154	0.4647	0	1
1990s	0.6547	0.4755	0	1
2000s	0.4188	0.4934	0	1
2010s	0.3603	0.4801	0	1
Migration-related variables				
Origin	1.1359	0.9828	0	2
Destination 1	0.7198	0.7592	0	2
Destination 2	1.8083	0.5341	0	2
Temporary	0.0314	0.1743	0	1
Measurement	0.2505	0.4334	0	1
Migrants	2.3011	1.1297	0	4
Econometric modeling variables				
Approach	1.9624	1.0987	0	3
Clustered std. errors	0.5978	0.4904	0	1
Nr. of climatic variables	3.8717	2.845	0	15
Controls	15.396	10.4082	0	45
Income-related controls	0.6515	0.4766	0	1
Polit. stability-related	0.195	0.3963	0	1
Main model	0.3005	0.4585	0	1
N		3625		



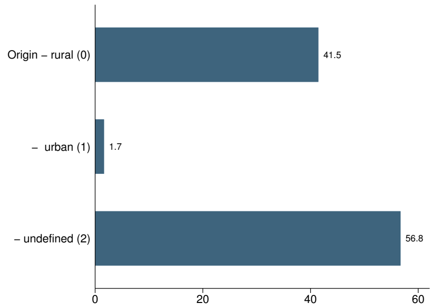
(a) *Authors' discipline*



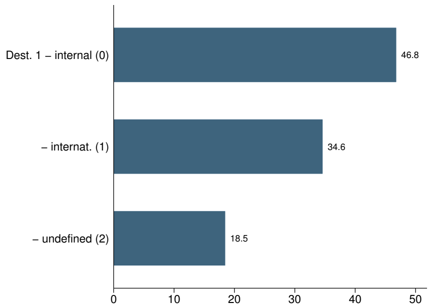
(b) *Temperature increase*



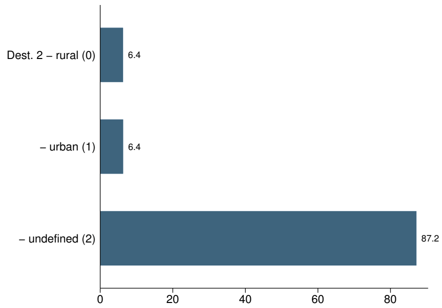
(c) *Precipitation decrease*



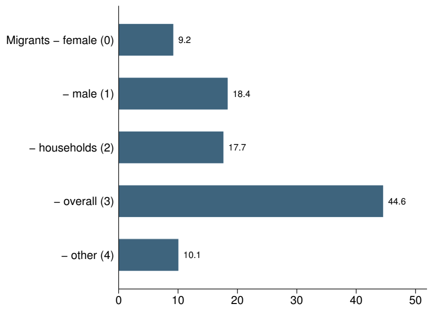
(d) *Origin*



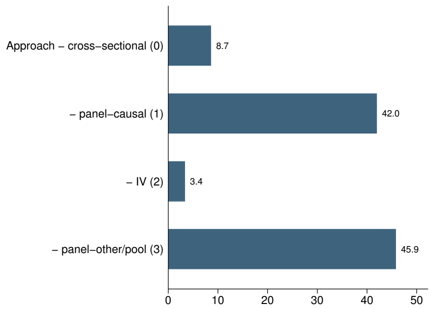
(e) *Destination 1*



(f) *Destination 2*



(g) *Migrants*



(h) *Approach*

Figure C.2: *Categorical variables: Distribution of specific categories (percent)*

C.4 Aggregate MRA: Main outcomes

Table C.4: *Meta-analytic probit (1) and multinomial probit (2) models*

	(1)	(2)		
	Significant effect	Decrease	No effect	Increase
Climatic variables				
Temp. increase - moderate (1) / ref.: no temp. (0)	0.015	-0.050	-0.009	0.059
	(0.17)	(-1.16)	(-0.10)	(0.69)
- extreme (2)	0.037	-0.134***	-0.064	0.198
	(0.31)	(-3.88)	(-0.51)	(1.60)
Precip. decrease - moderate (1) / ref.: no precip. (0)	-0.109	-0.092**	0.111	-0.019
	(-1.37)	(-1.98)	(1.41)	(-0.27)
- extreme (2)	-0.048	-0.131***	0.044	0.087
	(-0.38)	(-2.88)	(0.33)	(0.68)
Drought (1)	-0.023	-0.140***	-0.023	0.163
	(-0.25)	(-5.45)	(-0.24)	(1.64)
Sea level rise (1)	-0.282***	-0.149***	0.249***	-0.100
	(-4.67)	(-7.90)	(3.42)	(-1.46)
Flood (1)	-0.192***	-0.075**	0.208***	-0.133**
	(-2.95)	(-2.21)	(3.29)	(-2.55)
Hurricane/cyclone/typhoon (1)	-0.133	-0.092**	0.127	-0.034
	(-1.52)	(-2.57)	(1.39)	(-0.40)
Self-reported event (1)	-0.056	-0.001	0.041	-0.040
	(-0.98)	(-0.01)	(0.69)	(-0.83)
Direct effect (1)	-0.036	-0.074***	0.034	0.040
	(-1.03)	(-3.25)	(0.99)	(1.15)
Study-level variables				
Author: female (1)	0.026	-0.037	-0.022	0.060
	(0.60)	(-1.53)	(-0.52)	(1.50)
Author - economics (1)/ref.: other (0)	0.085	-0.076	-0.071	0.147***
	(1.34)	(-1.55)	(-1.09)	(3.10)
- geography (2)	-0.042	-0.171***	0.027	0.144**
	(-0.54)	(-3.22)	(0.34)	(2.18)
- sociology (3)	-0.098	-0.083	0.095	-0.012
	(-1.12)	(-1.25)	(1.09)	(-0.23)
Year of publication/ latest draft	-0.021**	-0.013***	0.021***	-0.008
	(-2.51)	(-2.85)	(2.58)	(-1.25)
Peer-reviewed: yes (1)	-0.002	0.045*	0.009	-0.054
	(-0.06)	(1.65)	(0.25)	(-1.58)
Sample characteristics				
Micro-level analysis (1)	-0.040	0.012	0.045	-0.057
	(-0.69)	(0.35)	(0.74)	(-0.97)
Multiple countries (1)	-0.022	-0.037	0.032	0.005
	(-0.38)	(-1.02)	(0.56)	(0.09)
Low income included (1)	-0.000	-0.014	0.001	0.013
	(-0.01)	(-0.79)	(0.07)	(0.61)
Lower-middle income included (1)	-0.052*	-0.052**	0.049	0.003
	(-1.65)	(-2.53)	(1.55)	(0.09)
Higher-middle income included (1)	0.066**	0.006	-0.065**	0.058**
	(2.02)	(0.32)	(-1.97)	(1.98)
1960s (1)	-0.013	0.080	-0.002	-0.078
	(-0.19)	(1.61)	(-0.03)	(-1.39)
1970s (1)	-0.176***	-0.097***	0.183***	-0.085*
	(-3.17)	(-3.89)	(3.32)	(-1.69)
1980s (1)	0.028	0.006	-0.031	0.026
	(0.60)	(0.18)	(-0.65)	(0.57)
1990s (1)	0.029	-0.019	-0.019	0.038
	(0.65)	(-0.63)	(-0.43)	(0.92)
2000s (1)	0.057	0.168***	-0.055	-0.113***
	(1.44)	(5.72)	(-1.41)	(-2.75)
2010s (1)	0.039	0.026	-0.043	0.017
	(0.80)	(0.78)	(-0.88)	(0.37)
Migration-related variables				
Origin - urban (1)/ ref.: rural (0)	-0.199**	-0.119***	0.198**	-0.080
	(-2.14)	(-3.54)	(2.19)	(-1.16)
- undefined (2)	0.021	-0.000	-0.010	0.011
	(0.61)	(-0.02)	(-0.30)	(0.29)
Dest. 1 - internat. (1)/ ref.: internal (0)	-0.010	-0.021	-0.003	0.023
	(-0.14)	(-0.56)	(-0.03)	(0.30)
- undefined (2)	-0.001	-0.000	0.002	-0.002
	(-0.03)	(-0.01)	(0.05)	(-0.04)
Dest. 2 - urban (1)/ ref.: rural (0)	-0.069	-0.091	0.081	0.010
	(-0.77)	(-0.92)	(0.89)	(0.19)

Continue on the next page

Table C.4: *Meta-analytic probit (1) and multinomial probit (2) models (cont.).*

	(1)	(2)		
	Significant effect	Decrease	No effect	Increase
- undefined (2)	-0.014	-0.074	0.019	0.055
	(-0.20)	(-0.85)	(0.27)	(1.03)
Temporary (1)	0.097	0.010	-0.088	0.077
	(1.08)	(0.26)	(-0.91)	(0.94)
Measurement - bilateral (1)	-0.107**	-0.001	0.106**	-0.105***
	(-2.43)	(-0.02)	(2.38)	(-2.69)
Migrants - male (1)/ ref.: female (0)	0.057	0.044	-0.056	0.012
	(1.37)	(0.99)	(-1.41)	(0.48)
- households (2)	0.216***	0.146***	-0.205***	0.059
	(3.33)	(3.09)	(-3.31)	(1.17)
- overall (3)	0.198***	0.073*	-0.198***	0.125***
	(3.32)	(1.69)	(-3.41)	(2.85)
- other (4)	0.269***	0.081*	-0.267***	0.186***
	(4.48)	(1.69)	(-4.57)	(4.48)
Econometric modelling variables				
Approach - panel-causal (1)/ref.: cross-section (0)	-0.076	0.020	0.066	-0.087*
	(-1.09)	(0.33)	(1.01)	(-1.77)
- IV (2)	0.071	0.106	-0.097	-0.009
	(0.63)	(1.23)	(-0.86)	(-0.12)
- panel-other/pool (3)	0.034	0.034	-0.038	0.004
	(0.53)	(0.65)	(-0.59)	(0.07)
Clustered std. errors (1)	0.033	0.002	-0.019	0.017
	(0.91)	(0.09)	(-0.53)	(0.52)
Nr. of climatic variables	-0.016**	-0.004	0.015**	-0.011*
	(-2.51)	(-1.02)	(2.32)	(-1.82)
Nr. of controls	-0.002	-0.003**	0.002	0.001
	(-1.13)	(-2.12)	(1.11)	(0.26)
Income-related controls (1)	-0.038	0.041*	0.037	-0.078**
	(-0.93)	(1.68)	(0.92)	(-2.19)
Polit. stability-related controls (1)	-0.009	0.072*	0.004	-0.076*
	(-0.19)	(1.68)	(0.09)	(-1.92)
Main model (1)	0.015	0.005	-0.011	0.006
	(0.63)	(0.28)	(-0.48)	(0.28)
Observations	3625	3625	3625	3625

C.5 Aggregate MRA: Sensitivity tests

Here, we present a series of sensitivity tests. First, in Table C.5, we analyze whether there is generally a difference in implications of slow- and sudden-onset climatic events (summarized by a binary variable *Slow*). Models 1 and 2 display average marginal effects from probit models and model 3 from a multinomial probit. Model 1 applies study-specific fixed effects to account for observable and possible unobservable effects at the study-level.[6] Models 2 and 3 are fully specified, accounting for all moderator variables, but the fixed effects. Coefficients of the moderator variables provide further evidence for the results from the main analysis, but are not reported in the interest of space.[7] The outcomes suggest that slow events are by approximately 9-12 percentage points (p.p.) more likely to significantly affect and by 8 p.p. to increase migration compared to sudden-onset events. This further underlines conclusions derived in the main analysis that migration strategy is more likely to serve as an adaptation to slow-onset events.

Second, in Tables C.6, C.7 and C.8 we employ alternative weighting strategies (recall that in the main analysis we apply log-transformation of the sample size square root as weights). When using a log-transformation of the sample size (Table C.6) or no weights (Table C.8), the estimated results largely provide further evidence for the main findings. In Table C.7, we use a square root of the sample size and obtain coefficients with generally larger magnitudes, likely due to the wide range of weight values. For most coefficients, the direction and significance levels remain unchanged, with some notable exceptions. Most prominently, we find a clear positive association between extremely high temperatures and extremely dry conditions (extreme precipitation decrease or droughts) and migration. This importantly complements the outcomes from the main analysis, where we only find a weak indication of this positive relationship. We also find that if applying an instrumental variable approach, researchers are less likely to find an insignificant effect. Generally, if coefficients have become insignificant at the conventional levels as compared to the main analysis, the effect direction remains unchanged. An exception is the variable *Low-income included*, which now explicitly indicates that if low income countries are included in the sample, it is less likely to find evidence of climate migration.

Third, in Table C.9 we meta-analyze a sub-sample of effects derived from panel analyses. These studies produce coefficients that can be interpreted causally and thus are established as a quality standard in the literature. Largely, we find additional evidence for the main outcomes. If coefficients loose their significance at conventional levels, they nevertheless largely maintain the same effect direction as in the main analysis. There

[6] Since we have several studies with only one estimate, and a lot of explanatory variables are at the study-level, we lose numerous observations and explanatory power when using the fixed effects approach. Therefore, this MRA model is only applied for a robustness check.

[7] The full set of coefficients from models 2 and 3 in Appendix C.5, Table C.5 is available upon request.

are two new noteworthy findings, compared to the main analysis. First, we find explicit evidence that international migration is less likely to increase in response to adverse climatic events compared to internal. Second, the destination of climate migration are likely to be urban areas. Overall, this evidence implies that including studies, which are not quasi-experiments does not bias evidence from this meta-analysis. [8]

Fourth, in Table C.10 we meta-analyze a sub-sample of effects with focus on international migration to understand whether there are different climatic drivers of internal and international moves. We only report climatic effects as these are of main interest.[9] We find evidence that only a moderate temperature increase likely reduces international migration; the remaining coefficients of climatic events are insignificant. This suggests that climate migration mostly takes place internally, likely due to the costly nature of migration and stricter budgetary constraints imposed by adverse climatic events.[10]

Table C.5: *Meta-analytic probit (1 and 2) and multinomial probit (3) models*

	(1)	(2)	(3)		
	Significant effect	Significant effect	Decrease	No effect	Increase
Slow (1)	0.115*	0.091**	0.015	-0.091**	0.077*
	(0.064)	(0.042)	(0.027)	(0.041)	(0.042)
N	3500	3625	3625	3625	3625
Study FE	Yes	No	No	No	No
Full model	No	Yes	Yes	Yes	Yes

Coefficients in models 1 and 2 capture the rate of change in probability of finding a significant effect of adverse climatic events on migration. Coefficients in model 3 capture the rate of change in probability of finding a significantly negative (1), no (2) or significantly positive (3) effect of adverse climatic events on migration. Std. errors are clustered at the study-level. Both models also control for decade-specific dummies. In the interest of space the coefs. of the moderator variables are not reported. * p<0.10, ** p<0.05, *** p<0.01. The full set of results is available upon request.
* p<0.10, ** p<0.05, *** p<0.01.

[8]Due to problems with multicollinearity, in models presented in Appendix, Table C.9, several variables are dropped including *Sea-level rise*, *Author*, *Temporary*, *Origin* or *Approach*. We generated a few binary variables to capture some of the feature in this more restricted environment, including *Author: economics*, *Precipitation decrease* or *Origin - rural*.

[9]The full set of results from Table C.10 is available upon request.

[10]Due to problems with multicollinearity, in models presented in Appendix, Table C.10, several variables are dropped including *Sea-level rise*, and sudden-onset events.

Table C.6: *Meta-analytic probit (1) and multinomial probit (2) models: Alternative weights (log. sample size)*

	(1)	(2)		
	Significant effect	Decrease	No effect	Increase
Climatic variables				
Temp. increase - moderate (1) / ref.: no temp. (0)	0.015	-0.050	-0.009	0.059
- extreme (2)	0.037	-0.134***	-0.064	0.198
Precip. decrease - moderate (1) / ref.: no precip. (0)	-0.109	-0.092**	0.111	-0.019
- extreme (2)	-0.048	-0.131***	0.044	0.087
Drought (1)	-0.023	-0.140***	-0.023	0.163
Sea level rise (1)	-0.282***	-0.149***	0.249***	-0.100
Flood (1)	-0.192***	-0.075**	0.208***	-0.133**
Hurricane/cyclone/typhoon (1)	-0.133	-0.092**	0.127	-0.034
Self-reported event (1)	-0.056	-0.001	0.041	-0.040
Direct effect (1)	-0.036	-0.074***	0.034	0.040
Study-level variables				
Author: female (1)	0.026	-0.037	-0.022	0.060
Author - economics (1)/ref.: other (0)	0.085	-0.076	-0.071	0.147***
- geography (2)	-0.042	-0.171***	0.027	0.144**
- sociology (3)	-0.098	-0.083	0.095	-0.012
Year of publication/ latest draft	-0.021**	-0.013***	0.021***	-0.008
Peer-reviewed: yes (1)	-0.002	0.045*	0.009	-0.054
Sample characteristics				
Micro-level analysis (1)	-0.040	0.012	0.045	-0.057
Multiple countries (1)	-0.022	-0.037	0.032	0.005
Low income included (1)	-0.000	-0.014	0.001	0.013
Lower-middle income included (1)	-0.052*	-0.052**	0.049	0.003
Higher-middle income included (1)	0.066**	0.006	-0.065**	0.058**
Migration-related variables				
Origin - urban (1)/ ref.: rural (0)	-0.199**	-0.119***	0.198**	-0.080
- undefined (2)	0.021	-0.000	-0.010	0.011
Dest. 1 - internat. (1)/ ref.: internal (0)	-0.010	-0.021	-0.003	0.023
- undefined (2)	-0.001	-0.000	0.002	-0.002
Dest. 2 - urban (1)/ ref.: rural (0)	-0.069	-0.091	0.081	0.010
- undefined (2)	-0.014	-0.074	0.019	0.055
Temporary (1)	0.097	0.010	-0.088	0.077
Measurement - bilateral (1)	-0.107**	-0.001	0.106**	-0.105***
Migrants - male (1)/ ref.: female (0)	0.057	0.044	-0.056	0.012
- households (2)	0.216***	0.146***	-0.205***	0.059
- overall (3)	0.198***	0.073*	-0.198***	0.125***
- other (4)	0.269***	0.081*	-0.267***	0.186***
Econometric modelling variables				
Approach - panel-causal (1)/ref.: cross-section (0)	-0.076	0.020	0.066	-0.087*
- IV (2)	0.071	0.106	-0.097	-0.009
- panel-other/pool (3)	0.034	0.034	-0.038	0.004
Clustered std. errors (1)	0.033	0.002	-0.019	0.017
Nr. of climatic variables	-0.016**	-0.004	0.015**	-0.011*
Nr. of controls	-0.002	-0.003**	0.002	0.001
Income-related controls (1)	-0.038	0.041*	0.037	-0.078**
Polit. stability-related controls (1)	-0.009	0.072*	0.004	-0.076*
Main model (1)	0.015	0.005	-0.011	0.006
Observations	3625	3625	3625	3625

Coefficients in model 1 capture the rate of change in probability of finding a significant effect of adverse climatic events on migration. Coefficients in model 2 capture the rate of change in probability of finding a significantly negative (1), no (2) or significantly positive (3) effect of adverse climatic events on migration. Std. errors are clustered at the study-level (not reported). Both models also control for decade-specific dummies. In the interest of space and because we do not find strong results the coefs. are not reported. The full set of results is available upon request. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table C.7: *Meta-analytic probit (1) and multinomial probit (2) models: Alternative weights (square root of sample size)*

	(1)	(2)		
	Significant effect	Decrease	No effect	Increase
Climatic variables				
Temp. increase - moderate (1) / ref.: no temp. (0)	0.142	0.014	-0.157	0.144
- extreme (2)	0.402***	-0.018	-0.409***	0.427***
Precip. decrease - moderate (1) / ref.: no precip. (0)	-0.021	-0.094*	-0.008	0.102
- extreme (2)	0.114	-0.124**	-0.103	0.227**
Drought (1)	0.086	-0.126***	-0.169	0.294***
Sea level rise (1)	-0.286***	-0.123***	0.217**	-0.094
Flood (1)	-0.052	-0.039	0.100	-0.061
Hurricane/cyclone/typhoon (1)	0.036	-0.079**	-0.102	0.181
Self-reported event (1)	-0.028	-0.010	-0.034	0.044
Direct effect (1)	0.007	-0.056	-0.015	0.071
Study-level variables				
Author: female (1)	0.070	-0.014	-0.075	0.089*
Author - economics (1)/ref.: other (0)	0.229***	-0.015	-0.237***	0.252***
- geography (2)	0.069	-0.081	-0.099	0.180*
- sociology (3)	-0.046	-0.006	0.022	-0.016
Year of publication/ latest draft	-0.026**	-0.025***	0.024**	0.001
Peer-reviewed: yes (1)	0.025	0.041	-0.020	-0.021
Sample characteristics				
Micro-level analysis (1)	-0.049	0.006	0.070	-0.076
Multiple countries (1)	-0.007	-0.042	0.008	0.034
Low income included (1)	-0.051*	-0.057***	0.050	0.007
Lower-middle income included (1)	-0.013	-0.033	0.009	0.024
Higher-middle income included (1)	0.025	-0.001	-0.036	0.037
Migration-related variables				
Origin - urban (1)/ ref.: rural (0)	-0.108	-0.045*	0.132	-0.087
- undefined (2)	0.090	0.070*	-0.054	-0.016
Dest. 1 - internat. (1)/ ref.: internal (0)	0.129	0.047	-0.140	0.094
- undefined (2)	0.005	0.051	-0.011	-0.040
Dest. 2 - urban (1)/ ref.: rural (0)	-0.120*	-0.259*	0.182*	0.078
- undefined (2)	-0.070	-0.284**	0.143	0.141***
Temporary (1)	0.070	0.049	-0.061	0.012
Measurement - bilateral (1)	-0.113**	-0.039	0.119**	-0.080
Migrants - male (1)/ ref.: female (0)	0.034	0.049	-0.015	-0.034
- households (2)	0.104	0.113***	-0.084	-0.029
- overall (3)	0.100	0.073**	-0.090	0.017
- other (4)	0.296***	0.058	-0.287***	0.230***
Econometric modelling variables				
Approach - panel-causal (1)/ref.: cross-section (0)	-0.050	0.018	0.032	-0.050
- IV (2)	0.273*	0.151	-0.286**	0.136
- panel-other/pool (3)	0.056	0.000	-0.068	0.068
Clustered std. errors (1)	0.021	-0.017	-0.020	0.037
Nr. of climatic variables	-0.019***	-0.008**	0.021***	-0.012***
Nr. of controls	0.002	-0.003	-0.003	0.006***
Income-related controls (1)	-0.121**	0.025	0.126**	-0.151***
Polit. stability-related controls (1)	-0.040	0.030	0.024	-0.054
Main model (1)	-0.016	-0.011	0.024	-0.013
Observations	3625	3625	3625	3625

Coefficients in model 1 capture the rate of change in probability of finding a significant effect of adverse climatic events on migration. Coefficients in model 2 capture the rate of change in probability of finding a significantly negative (1), no (2) or significantly positive (3) effect of adverse climatic events on migration. Std. errors are clustered at the study-level (not reported). Both models also control for decade-specific dummies. In the interest of space and because we do not find strong results the coefs. are not reported. The full set of results is available upon request. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table C.8: *Meta-analytic probit (1) and multinomial probit (2) models: No weights*

	(1)	(2)		
	Significant effect	Decrease	No effect	Increase
Climatic variables				
Temp. increase - moderate (1) / ref.: no temp. (0)	-0.016	-0.054	0.025	0.030
- extreme (2)	-0.025	-0.140***	-0.003	0.143
Precip. decrease - moderate (1) / ref.: no precip. (0)	-0.138*	-0.087**	0.143*	-0.056
- extreme (2)	-0.083	-0.137***	0.077	0.060
Drought (1)	-0.048	-0.140***	0.011	0.129
Sea level rise (1)	-0.283***	-0.149***	0.252***	-0.103
Flood (1)	-0.234***	-0.080**	0.246***	-0.166***
Hurricane/cyclone/typhoon (1)	-0.146*	-0.094***	0.147*	-0.053
Self-reported event (1)	-0.064	0.010	0.050	-0.060
Direct effect (1)	-0.031	-0.069***	0.030	0.039
Study-level variables				
Author: female (1)	0.024	-0.037	-0.018	0.055
Author - economics (1)/ref.: other (0)	0.054	-0.077	-0.040	0.117***
- geography (2)	-0.065	-0.177***	0.051	0.126*
- sociology (3)	-0.121	-0.089	0.120	-0.031
Year of publication/ latest draft	-0.017**	-0.010**	0.017**	-0.007
Peer-reviewed: yes (1)	-0.005	0.047*	0.012	-0.059*
Sample characteristics				
Micro-level analysis (1)	-0.032	0.008	0.032	-0.040
Multiple countries (1)	-0.009	-0.041	0.022	0.019
Low income included (1)	0.002	-0.003	-0.002	0.004
Lower-middle income included (1)	-0.058*	-0.055***	0.056*	-0.001
Higher-middle income included (1)	0.069**	0.009	-0.068**	0.059**
Migration-related variables				
Origin - urban (1)/ ref.: rural (0)	-0.214**	-0.131***	0.212**	-0.081
- undefined (2)	0.006	-0.012	0.000	0.012
Dest. 1 - internat. (1)/ ref.: internal (0)	-0.048	-0.034	0.034	-0.000
- undefined (2)	-0.004	-0.009	0.001	0.008
Dest. 2 - urban (1)/ ref.: rural (0)	-0.084	-0.086	0.096	-0.010
- undefined (2)	-0.004	-0.051	0.007	0.044
Temporary (1)	0.113	0.003	-0.102	0.100
Measurement - bilateral (1)	-0.115***	0.005	0.112***	-0.117***
Migrants - male (1)/ ref.: female (0)	0.054	0.038	-0.054	0.016
- households (2)	0.244***	0.145***	-0.232***	0.087*
- overall (3)	0.196***	0.066	-0.197***	0.131***
- other (4)	0.270***	0.086*	-0.267***	0.181***
Econometric modelling variables				
Approach - panel-causal (1)/ref.: cross-section (0)	-0.072	0.019	0.064	-0.083*
- IV (2)	0.015	0.087	-0.040	-0.047
- panel-other/pool (3)	0.025	0.036	-0.028	-0.008
Clustered std. errors (1)	0.030	0.006	-0.015	0.009
Nr. of climatic variables	-0.015**	-0.001	0.013*	-0.012*
Nr. of controls	-0.003	-0.003*	0.003	-0.001
Income-related controls (1)	-0.024	0.031	0.020	-0.051
Polit. stability-related controls (1)	-0.001	0.081**	-0.002	-0.078**
Main model (1)	0.014	0.002	-0.011	0.009
Observations	3625	3625	3625	3625

Coefficients in model 1 capture the rate of change in probability of finding a significant effect of adverse climatic events on migration. Coefficients in model 2 capture the rate of change in probability of finding a significantly negative (1), no (2) or significantly positive (3) effect of adverse climatic events on migration. Std. errors are clustered at the study-level (not reported). Both models also control for decade-specific dummies. In the interest of space and because we do not find strong results the coefs. are not reported. The full set of results is available upon request. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table C.9: *Meta-analytic probit (1) and multinomial probit (2) models: Panel studies only*

	(1)	(2)		
	Significant effect	Decrease	No effect	Increase
Climatic variables				
Temp. increase - moderate (1) / ref.: no temp. (0)	-0.025	-0.141**	0.061	0.079
- extreme (2)	-0.167*	-0.231***	0.108	0.123
Precipitation decrease (1)	-0.085	-0.135**	0.121	0.013
Drought (1)	-0.083	-0.193***	-0.009	0.201
Flood (1)	-0.208***	-0.134***	0.212***	-0.078
Hurricane/cyclone/typhoon (1)	-0.188*	-0.168***	0.200*	-0.033
Direct effect (1)	-0.029	-0.079	0.041	0.038
Study-level variables				
Author: female (1)	-0.010	-0.078*	0.023	0.055
Author: economics (1)	0.120	0.025	-0.088	0.063
Year of publication/ latest draft	-0.012	0.002	0.020	-0.022
Peer-reviewed: yes (1)	-0.085	-0.001	0.122**	-0.121*
Sample characteristics				
Micro-level analysis (1)	-0.088	-0.015	0.058	-0.043
Multiple countries (1)	0.045	-0.059	-0.062	0.121
Low income included (1)	0.020	-0.028	-0.016	0.044
Lower-middle income included (1)	0.008	0.020	-0.026	0.006
Higher-middle income included (1)	0.113*	0.026	-0.085	0.059
Migration-related variables				
Origin - rural (1)	0.052	0.003	0.010	-0.013
Dest. 1 - internat. (1)/ ref.: internal (0)	-0.138	0.047	0.163	-0.210**
- undefined (2)	0.112	0.014	-0.110	0.096
Dest. 2 - urban (1)/ ref.: rural (0)	0.160***	-0.025	-0.144*	0.169**
- undefined (2)	0.181*	0.050	-0.180*	0.129**
Measurement - bilateral (1)	-0.117***	-0.042	0.117***	-0.076
Migrants - male (1)/ ref.: female (0)	0.211***	0.112***	-0.180***	0.068
- households (2)	0.323	0.255*	-0.213	-0.042
- overall (3)	0.355***	0.158***	-0.294***	0.136
- other (4)	0.499***	0.307***	-0.471***	0.164*
Econometric modelling variables				
Nr. of climatic variables	-0.012	0.000	0.009	-0.009
Income-related controls (1)	-0.077	0.057*	0.072	-0.129***
Main model (1)	0.016	0.019	-0.031	0.011
Observations	1524	1524	1524	1524

Coefficients in model 1 capture the rate of change in probability of finding a significant effect of adverse climatic events on migration. Coefficients in model 2 capture the rate of change in probability of finding a significantly negative (1), no (2) or significantly positive (3) effect of adverse climatic events on migration. Std. errors are clustered at the study-level (not reported). Both models also control for decade-specific dummies. In the interest of space and because we do not find strong results the coefs. are not reported. The full set of results is available upon request. * p<0.10, ** p<0.05, *** p<0.01.

Table C.10: *Meta-analytic probit (1) and multinomial probit (2) models: International migration*

	(1)	(2)		
	Significant effect	Decrease	No effect	Increase
Climatic variables				
Temp. increase - moderate (1) / ref.: no temp. (0)	0.153*	0.074*	-0.160*	0.086
- extreme (2)	0.124	-0.072	-0.120	0.192
Precip. decrease - moderate (1) / ref.: no precip. (0)	0.115	0.025	-0.114	0.089
- extreme (2)	0.093	0.063	-0.107	0.045
Drought (1)	0.077	0.016	-0.087	0.072
Observations	1256	1256	1256	1256

Coefficients in model 1 capture the rate of change in probability of finding a significant effect of adverse climatic events on migration. Coefficients in model 2 capture the rate of change in probability of finding a significantly negative (1), no (2) or significantly positive (3) effect of adverse climatic events on migration. Std. errors are clustered at the study-level (not reported). Both models also control for decade-specific dummies. In the interest of space and because we do not find strong results the coefs. are not reported. The full set of results is available upon request. * p<0.10, ** p<0.05, *** p<0.01.

C.6 Differences in model specifications

Section 3.5.1, sub-sample for **temperature-related effects**: In this more restricted sample, the following variables were causing multicollinearity problems: *Origin*, *Destination 2*. Thus, they were omitted from the analysis. The meta-analytic model also includes decade-specific dummies that cover the time dimension of the sample analyzed. In the interest of space, these dummies are not reported.

Section 3.5.1, sub-sample for **precipitation-related effects**: In this more restricted sample, the following variables were causing multicollinearity problems: *Nr. of controls*, *Self-reported*, *Micro-level analysis*, *Temporary* and *Measurement*. Thus, we did not include these variables in the analysis. The meta-analytic model also includes decade-specific dummies, which do not show any strong results. In the interest of space, these dummies are not reported.

Section 3.5.1, sub-sample for **drought-related effects**: In this more restricted sample, the following variables were causing multicollinearity problems: *Year of publication/latest draft*, *Low income included*, *Upper-middle income included*, decadal dummies, *Measurement - bilateral*, *Temporary*, *Destination 2*, *Nr. of climatic variables*, *Nr. of controls*, *Main model*, *Income-related controls* and *Polit. stability controls*. Thus, we did not include these variables in the analysis. Further, since the categorical variable capturing authors' disciplines was causing multicollinearity problems, we generated a binary variable capturing whether the lead author is an economist (*Author: economist*) or not. Similarly, the categorical variable capturing migration origin, destinations, domain and approach, as used in the main analysis, were causing multicollinearity problems, so we generated binary variables capturing whether the migration origin is rural (*Origin - rural*); migration destination is internal (*Dest. - internal*), whether the migration variable captures women (*Migrants - female*) and whether an effect is derived from a model using causal inference *Panel-causal*.

Section 3.5.1, sub-sample for **flood-related effects**: In this more restricted sample, the following variables were causing multicollinearity problems: decadal dummies, *Lower-middle income included*, *Destination 2*, *Measurement - bilateral*, *Clustered std. errors*, *Nr. of controls*, *Income-related controls* and *Polit. stability controls*. Thus, we did not include these variables in the analysis. Further, the categorical variable capturing authors' disciplines was causing multicollinearity problems, so we generated a binary variable capturing whether the lead author is an economist (*Author: economist*) or not. Similarly, categorical variables capturing migration origin, destinations and domain, as well as variable *Approach* used in the main analysis, were causing multicollinearity problems, so we generated binary variables capturing whether the migration origin is rural (*Origin - rural*); whether the migration variable captures women (*Migrants - female*); and whether a coefficient is derived from a model using causal inference (*Panel - causal*).

Appendix D

Appendix to Chapter 4

D.1 Overview of studies used in the meta-analyses

Table D.1: *Summary information on studies considered in the two meta-analyses*

Study	N	Geographical focus	Climate measure	Migration measure	Analytical method
Afifi and Warner (2008)	4	World	desertification/sea-level rise, binary, Source not provided; flood/hurricane, cyclone, typhoon, storm, binary, Source not provided	international, bilateral, count, log, Migration DRC - Development Research Centre on Migration, Globalisation and poverty	country-level, Cross-section, OLS
Badiani and Safir (2008)	2	India	precipitation, deviation, Indian Meteorological Department	internal, unilateral, count, level, ICRISAT	household-level, Panel - causal, OLS
Barrios et al. 2006	5	Africa	precipitation, level, IPCC	internal, unilateral, fraction, log, UN World Urbanization Prospects	country-level, panel-analysis, OLS
Bhattacharya and Innes (2008)	32	India	precipitation/temperature, deviation/level, Source not provided	internal, bilateral, fraction, level, Registrar General's Offce of India	district-level, Cross-section/IV, GMM/OLS
Bohra-Mishra et al. (2014)	12	Indonesia	flood, deaths/losses/nr. of houses destroyed/nr. of injured, DesInventar database	internal, bilateral, binary, level, Indonesia Family Life Survey	household-level/province-level, Panel - causal, LPM
Carvajal and Pereira (2009)	1	Nicaragua	precipitation, deviation, Instituto Nicaragüense de Estudios Territoriales	undefined (internal/internat.), unilateral, binary, level, Nicaraguan Living Standard Measurement Studies	household-level, Cross-section, Probit
Coniglio and Pesce (2015)	168	World	precipitation/temperature, anomaly/coef. of variation/deviation/level, CRU	international, bilateral, count, level, OECD	country-level, panel-analysis, OLS
Dallman and Millock (2016)	94	India	drought/precipitation/temperature, SPI/anomaly/duration/nr. of events, CRU; flood/hurricane, cyclone, typhoon, storm, SPI/duration/hazard index/level/nr. of events, CRU/Dartmouth Flood Observatory	internal, bilateral, fraction, log, Indian Census	state-level, Panel - causal/Panel-other/pool, OLS/PPML
Dillon et al. (2011)	9	Nigeria	temperature, degree days, NASA/Surface Meteorology and Solar Energy (NASA)	internal, bilateral, binary, level, Nothern Nigeria Survey, +tracking survey of authors	household-level, Panel-other/pool, LPM
Gray (2009)	3	Ecuador	precipitation, level, Author's own collection	internal/international, unilateral, binary, level, Original survey of authors	individual-level, Panel-other/pool, Logit
Gray and Mueller (2012)a	116	Ethiopia	drought/precipitation, Index/fraction of affected people, Ethiopian Rural Household Survey/NASA; flood, fraction of affected people, Ethiopian Rural Household Survey	internal, unilateral, binary, level, Ethiopia Rural Household Survey	individual-level, Panel-other/pool, Logit
Gray and Mueller (2012)b	129	Bangladesh	flood, binary/fraction of affected people/losses, International Food Policy Research Institute	internal/undefined (internal/internat.), unilateral, binary, level, International Food Policy Research Institute	individual-level, Panel-other/pool, Logit
Gröschl and Steinwachs (2017)	53	World	drought/precipitation/temperature, SPEI/deviation, CRU/Climate Prediction Center of the National Centers for Environmental Prediction/Ifo Game Databse/NASA/NOAA; hurricane, cyclone, typhoon, storm/multiple fast, hazard index/speed, Ifo Game Databse/International Best Track Archive for Climate Stewardship v03r07	international, bilateral, fraction, level, World Bank (GBMD)/World Bank - Global Migrant Origin Database	country-level, Panel - causal, OLS/PPML
Gutmann et al. (2005)	28	USA	precipitation/temperature, deviation/level, VEMAP	internal, bilateral, fraction, level, US Census	county-level, Panel-other/pool, OLS
Henry et al. (2004)	109	Burkina Faso	precipitation, deviation/level, CRU	internal/international/undefined (internal/internat.), unilateral, binary, level, University of Ouagadougou	individual-level, Panel-other/pool, Logit
Lewin et al. (2011)	5	Malawi	drought/precipitation, binary/coef. of variation/fraction of long-run mean, Malawai Meteorological Services/Malawi Integrated Household Survey; flood, binary, Malawi Integrated Household Survey	internal, unilateral, binary, level, Malawi Integrated Household Survey	individual-level, Cross-section, FIML

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Summary information on studies considered in the two meta-analyses (cont.).

Study	N	Geographical focus	Climate measure	Migration measure	Analytical method
Marchiori et al. (2012)	48	Africa	precipitation/temperature, anomaly, IPCC	international, undefined (unilat./bilat.), fraction, level, US Census Bureau and UNHCR (2009)	country-level, panel-analysis, OLS/POLS
Munshi (2003)	4	Mexico	precipitation, level, Source not provided	international, unilateral, fraction, level, Mexican Migration Project	individual-level, Panel - causal, OLS
Poston et al. (2009)	4	USA	temperature, Index, US National Climatic Data Center	undefined (internal/internat.), bilateral/unilateral, fraction, level, Source: not specified	state-level, Cross-section, OLS
Reuveny and Moore (2009)	3	World	multiple fast, fraction of affected people, Geo Data portal	international, bilateral, count, log, OECD, US Citizen and Immigration Services	country-level, non-panel-analysis, OLS/Robust regression/Tobit
Viswanathan and Kavi Kumar (2015)	8	India	precipitation/temperature, anomaly/level, Indian Meteorological Department	internal, bilateral, fraction, level, Indian Census	state-level, IV/Panel - causal, 2SLS/LIML/OLS
Backhaus et al. (2015)	20	World	precipitation/temperature, level, University of Delaware	international, bilateral, count, log, OECD, Eurostat	country-level, panel-analysis, OLS
Beine and Parsons (2017)	48	World	precipitation/temperature, anomaly/deviation, CRU; multiple fast, nr. of events, Ifo Game Databse/International Disaster Database	international, bilateral, fraction, log, World Bank (GBMD)	country-level, Panel - causal, Poisson-pseudo maximum likelihood
Cai et al.(2016)	545	World	precipitation/temperature, duration/level, NASA MERRA	international, bilateral, fraction, log, National statistical offices	country-level, panel-analysis, OLS
Cattaneo and Peri (2016)	275	World	precipitation/temperature, anomaly/level, Dell et al. (satellite + stations); multiple fast, nr. of events, EM-DAT	internal/international, bilateral, fraction, level/log, Ozden et al. (2011), UN World Urbanization Prospects	country-level, panel-analysis, OLS
Drabo and Mously Mbaye (2014)	106	Developing world	drought/precipitation/temperature, binary/level, Centre for Research on the Epidemiology of Disasters (CRED); flood/hurricane, cyclone, typhoon, storm/multiple fast, binary, Centre for Research on the Epidemiology of Disasters (CRED)	international, bilateral, fraction, level, World Bank (GBMD)	country-level, Panel - causal, GMM/OLS
Goldbach (2017)	42	Ghana/Indonesia	flood/hurricane, cyclone, typhoon, storm/multiple fast, nr. of events, Author's own collection/Community's flood risk - Indonesia National Agency for Disaster Management (BNPB)/Tropical Marine Research Bremen ZMT	internal/undefined (internal/internat.), unilateral, binary, level, Original survey of authors	household-level/individual-level, Cross-section, Logit
Gray and Bilsborrow (2013)	72	Ecuador	precipitation, coef. of variation/deviation/level, WorldClim; INAMHI	internal/international, unilateral, categorical, level, Original survey of authors	individual-level, Panel-other/pool, Multinomial logit
Gröger and Zylberberg (2016)	12	Vietnam	flood, duration, NASA MODIS	internal, unilateral, fraction, level, Vulnerability to Poverty in Southeast Asia	household-level, Panel - causal, Difference-in-differences
Koubi et al. (2016a)	14	Vietnam	multiple slow, binary, Survey responses; multiple fast, binary, Survey responses	internal, unilateral, binary, level, Original survey of authors	individual-level, Cross-section, Logit
Mastrorillo et al. (2016)	81	South Africa	drought/precipitation/temperature, VIC drought index/anomaly, African Drought and Flood Monitor project	internal, unilateral, count, level, South African Census	district-level, IV/Panel - causal, 2SLS/PPML
Mueller et al. (2014)	248	Pakistan	precipitation/temperature, level, NASA Power; flood, deaths, Dartmouth Flood Observatory	internal/undefined (internal/internat.), unilateral, binary/categorical, level, Pakistan Panel Survey	individual-level, Panel-other/pool, Logit/Multinomial logit
Naudé (2010)	3	Africa	multiple fast, nr. of events, Centre for Research on the Epidemiology of Disasters (CRED)	international, bilateral, count, level, UN Population Division	country-level, panel-analysis, GMM
Robalino et al. (2015)	38	Costa Rica	flood/multiple fast, deaths/losses/nr. of events, DesInventar database	internal, unilateral, fraction, level, Costa Rica Census	canton-level, Panel-other/pool, GLM/OLS
Ruyssen and Rayp (2014)	5	Africa	temperature, deviation, IPCC	international, bilateral, fraction, level, World Bank (GBMD), US Census	country-level, Panel-other/pool, Spatial Durbin

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Summary information on studies considered in the two meta-analyses (cont.).

Study	N	Geographical focus	Climate measure	Migration measure	Analytical method
Saldana-Zorilla and Sandberg (2009)	7	Mexico	multiple fast, nr. of events, CENAPRED; DesInentar-La ed	international, unilateral, fraction, log, National Institute of Statistics and Informatics of Mexico	municipality-level, Cross-section, ML/OLS/Spatial Durbin
Strobl and Valfort (2015)	3	Uganda	precipitation, SPI, IPCC	internal, bilateral/unilateral, fraction, level, 2002 Uganda Census	district-level/individual-level, Cross-section, OLS
Thiede et al. (2016)	42	South America	precipitation/temperature, Z-score/anomaly/level, CRU	internal, unilateral, binary, level, Census data via IPUMS	individual-level, Panel-other/pool, Logit
Bazzi (2017)	15	Indonesia	precipitation, deviation, NOAA	international, unilateral, binary/fraction, level/log, Suenas household survey/Village Potential (Podes)	household-level/village-level, Panel - causal/Panel-other/pool, Logit/OLS/Probit/SU-LPM/Tobit
Chort and de la Rupelle (2017)	281	Mexico	precipitation/temperature, anomaly/dry season /rainy season , NOAA; hurricane, cyclone, typhoon, storm, intensity/nr. of events, NOAA	international, unilateral, fraction, cube root/log, EMIF survey	state-level, Panel - causal, OLS
Henry et al. (2003)	2	Burkina Faso	drought/precipitation, deviation/nr. of events, Direction nationale de la Meteorologie au Burkina Faso	internal, unilateral, count, level, INSD 1985	province-level, Cross-section, Poisson regression
Jessoe et al. (2016)	21	Mexico	precipitation/temperature, degree days/level, Mexican National Water Commission	internal/international, unilateral, binary, level, Mexico National Rural Household Survey	individual-level, Panel - causal, LPM
Kleemans (2015)	20	Indonesia	precipitation, level, University of Delaware	internal, unilateral, binary, level, Indonesia Family Life Survey	individual-level, Panel - causal, LPM
Bosetti et al. (2018)	4	World	precipitation/temperature, diff. between origin and dest., GLDAS	international, bilateral, count, log, Ozden et al. (2011)	country-level, Panel - causal, OLS/PPML
Chen et al. (2017)	32	Bangladesh	flood, quintile, Bangladesh Meteorological Department/NASA MODIS/Tropical Rainfall Measuring Mission/University of Delaware	undefined (internal/internat.), unilateral, binary, level, Bangladesh Bureau of Statistics	household-level, Panel-other/pool, LPM
Baez et al. (2017)	2	North America	drought, intensity, CRU; hurricane, cyclone, typhoon, storm, intensity, NASA TRMM	internal, unilateral, binary, level, Costa Rica (2000, 2011), Dominican Republic (2002, 2010), El Salvador (1992, 2007), Haiti (1982, 2003), Jamaica (1991, 2001), Mexico (2000, 2010), Nicaragua (1995, 2005), and Panama (2000, 2010)	individual-level, Panel - causal, LPM
Missirian and Schlenker (2017)	66	World	temperature, level, Berkeley Earth/University of Delaware	international, unilateral, count, log, UNHCR	county-level, Panel - causal, OLS
Kubik (2016)	62	Tanzania	precipitation, SPEI, Vincente-Serrano et al. (2010)	internal, unilateral, categorical, level, Tanzania National Panel Survey	household-level, Cross-section, Multinomial logit
Maurel and Tuccio (2016)	32	Non-OECD countries	precipitation/temperature, anomaly/coef. of variation, Tyndall Centre for Climate Change Research	international, bilateral, count, log, Ozden et al. (2011)	country-level, panel-analysis, 2SLS/OLS
Kubik and Maurel (2016)	21	Tanzania	multiple slow/precipitation, SPEI/level, CRU/NOAA	internal, unilateral, binary, level, Tanzania National Panel Survey	household-level, Cross-section/IV, Probit
Chort and de la Rupelle (2016)	58	North America	precipitation, Z-score, Tropical Rainfall Measuring Mission; hurricane, cyclone, typhoon, storm, intensity/nr. of events, NOAA	international, bilateral/unilateral, count/fraction, level/log, EMIF survey	state-level, Panel - causal, OLS/PPML
Pei and Zhang (2014)	2	China	precipitation/temperature, Z-score, Reconstructed from 13 published references/Yang et al. (2002)	internal, unilateral, count, level, Zhong Guo Yi Min Shi (The History of Migration in China)	sub-national-level, Panel-other/pool, OLS
Gray and Wise (2016)	125	Burkina Faso/ Kenya/ Nigeria/ Senegal/ Uganda	precipitation/temperature, anomaly/duration/level, CRU/NASA MERRA	internal/international/undefined (internal/internat.), bilateral, count, level, African Migration and Remittances Surveys (AMRS)	household-level, Panel-other/pool, Negative binomial regression
Tan et al. (2014)	4	China	multiple fast, binary, Tan et al. (2014)	undefined (internal/internat.), unilateral, binary, level, Tan et al. (2014)	household-level, IV, 2SLS
Pei et al. (2015)	2	China	precipitation, anomaly, Reconstructed - precipitation reconstruction by Pei et al. (2014) and temperature reconstruction by Yang et al. (2002).	internal, unilateral, count, level, Zhong Guo Yi Min Shi (The History of Migration in China)	province-level, Panel-other/pool, OLS/Poisson regression

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Summary information on studies considered in the two meta-analyses (cont.).

Study	N	Geographical focus	Climate measure	Migration measure	Analytical method
Nawrotzki and Bakhtsiyarava (2016)	10	Burkina Faso/Senegal	drought/precipitation/temperature, nr. of events, ; multiple fast, nr. of events,	international, unilateral, binary, level,	household-level, Cross-section, Logit
Alem et al. (2016)	6	Ethiopia	drought/precipitation, binary/coef. of variation, Ethiopian meteorology agency	undefined (internal/internat.), unilateral, binary, level, Ethiopia Rural Household Survey	household-level, IV/Panel-other/pool, Probit
Nawrotzki et al. (2017)	4	Mexico	drought/temperature, deviation, CRU	internal, unilateral, binary, log, Mexican Census	individual-level, Panel-other/pool, Logit
Wodon et al. (2014)	16	Morocco	drought/precipitation, reduction in agricultural yield, Morocco Household and Youth Survey (World bank); multiple, binary/losses, Morocco Household and Youth Survey (World bank)	undefined (internal/internat.), unilateral, binary, level, Morocco Household and Youth Survey (World bank)	household-level, Panel-other/pool, Probit
Adoho and Wodon (2014)	32	MENA-countries	drought, Index, Household survey (2011) - World Bank and the Agence Française de Développement; flood, hazard index, Household survey (2011) - World Bank and the Agence Française de Développement; multiple, losses, Household survey (2011) - World Bank and the Agence Française de Développement	undefined (internal/internat.), unilateral, binary, level, Household survey (2011) - World Bank and the Agence Française de Développement	individual-level, Cross-section, Probit
Joseph et al. (2014)	14	Yemen	precipitation/temperature, anomaly/coef. of variation/level/tercile, BIOCLIM	internal, bilateral, binary, level, Yemen 2004 census	district-level, Cross-section, Logit
Henderson et al. (2017)	10	Africa	precipitation, level/precipitation divided by potential evapotranspiration, University of Delaware	internal, unilateral, fraction, level, US Census	country-level/district-level, Panel - causal, OLS
Thiede and Gray (2017)	10	Indonesia	precipitation/temperature, deviation/duration, NASA MERRA	internal, unilateral, categorical, log, Indonesia Family Life Survey	individual-level, Panel-other/pool, Multinomial logit
Iqbal and Roy (2015)	50	Bangladesh	precipitation/temperature, anomaly, Thana Statistics and Upazila Statistics; flood/multiple fast, binary/ratio of damaged cropped area, Bangladesh Agricultural Research Council (BARC), DFO GlobalArchive/Thana Statistics and Upazila Statistics	internal, bilateral, fraction, level, Bangladesh Bureau of Statistics	district-level, IV/Panel - causal/Panel-other/pool, 2SLS/OLS
Hirvoven (2016)	74	Tanzania	precipitation/ temperature, degree days/level, NASA MERRA/Tanzanian Meteorological Agency	internal, unilateral, binary/categorical, log, Kagera Health & Development Survey (KHDS)	individual-level, Panel - causal, LPM/ Logit/ Multinomial logit
Nawrotzki et al. (2013)	4	Mexico	precipitation, binary, Mexican National Institute for Statistics and Geography - Mexican Migration Project	international, unilateral, binary, log, 2000 Mexican General Population and Housing Census long form (MGPHC)	household-level, Panel-other/pool, Logit
Nawrotzki et al. (2015a)	18	Mexico	precipitation/temperature, Z-score/level, NOAA	international, unilateral, binary, level, Mexican Migration Project	household-level, Panel-other/pool, Logit
Nawrotzki et al. (2015b)	34	Mexico	precipitation/temperature, days above/below a treshold/duration/level/max value of daily max/max value of night max/min value of daily min, NOAA	international, unilateral, binary, level, Mexican Migration Project	household-level, Panel-other/pool, Logit
Nawrotzki and DeWaard (2016)	28	Mexico	precipitation/temperature, Z-score/duration/level, NOAA	international, unilateral, binary, level, Mexican Migration Project	household-level, Panel-other/pool, Logit
Nawrotzki et al. (2015c)	8	Mexico	precipitation/temperature, Z-score/level,	international, unilateral, binary, level,	household-level, Panel-other/pool, Logit
Nawrotzki et al. (2016a)	20	Mexico	precipitation/temperature, days above/below a treshold/duration/level, NOAA	internal/international, unilateral, binary, level, Mexican Migration Project	household-level, Panel-other/pool, Logit
Nawrotzki et al. (2016b)	10	Burkina Faso/Senegal	drought/multiple slow/precipitation/temperature, anomaly, CRU	international, unilateral, binary, level, Burkina Faso (2006 census) via Terra Populus/Senegal (2002 census) via Terra Populus	household-level, Panel-other/pool, Logit

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Summary information on studies considered in the two meta-analyses (cont.).

Study	N	Geographical focus	Climate measure	Migration measure	Analytical method
Nawrotzki and DeWaard (2018)	42	Zambia	drought/temperature, deviation/duration/intensity, CRU	internal, bilateral/unilateral, count, log, Zambian Census	district-level, Panel - causal/Panel-other/pool, Negative binomial regression/OLS
Koubi et al. (2016b)	18	Vietnam	multiple slow, binary, Author's own collection; multiple fast, binary, Author's own collection	internal, unilateral, binary, level, Original survey of authors	individual-level, Cross-section, Logit
Koubi et al. (2012)	18	Developing world	drought/multiple slow, binary, EACH-FOR program/EM-DAT; flood/multiple fast, binary, EACH-FOR program/EM-DAT; multiple, binary, EACH-FOR program	internal, unilateral, binary, level, EACH-FOR program	individual-level, Cross-section, Logit
Koubi et al. (2016c)	28	Cambodia/Multiple/Nicaragua/Peru/Uganda/Vietnam	multiple slow, binary, Author's own collection; multiple fast, binary, Author's own collection	internal, unilateral, binary, level, Original survey of authors	individual-level, Panel-other/pool, Logit
Gray (2010)	4	Ecuador	precipitation, level, Author's own collection	internal/international, unilateral, categorical, log, Gray (2008)	individual-level, Panel-other/pool, Multinomial logit
Maystadt et al. (2016)	2	Nepal	drought, binary, NASA; flood, binary, NASA	internal, unilateral, fraction, level, Nepal Living Standards Survey	district-level, Panel - causal, OLS
Feng et al. (2015)	16	USA	temperature, degree days, Schlenker & Roberts (2009), which are extended beyond 2005 in Berry, Roberts & Schlenker (2013).	internal, bilateral, fraction, level, US Census	county-level, Panel - causal, OLS
Smith (2012)	4	Burkina Faso	precipitation, quintile, University of Delaware	undefined (internal/internat.), unilateral, binary, level, Migration Dynamics, Urban Integration and Environment Survey of Burkina Faso	individual-level, Cross-section, Logit
Chen and Mueller (2018)	94	Bangladesh	sea-level rise, fraction of water pixels/percentage of total land area affected, NASA MODIS/Soil Resource Development Institute, an agency of Bangladesh's Ministry of Agriculture	internal/international/undefined (internal/internat.), unilateral, binary/count, level, Bangladesh Bureau of Statistics	household-level, Panel-other/pool, LPM/Negative binomial regression
Tse (2012)	36	Indonesia	flood, nr. of events, DesInventar database	internal, unilateral, binary/count, level, Indonesia Family Life Survey	household-level, Panel - causal/Panel-other/pool, LPM/OLS
Kumar and Viswanathan (2013)	24	India	precipitation/temperature, anomaly/level, Indian Meteorological Department	internal, unilateral, binary, level, National Sample Survey	individual-level, Cross-section, Probit
Deschenes and Moretti (2009)	1	USA	temperature, diff. between origin and dest., US National Climatic Data Center	internal, unilateral, binary, level, US Census	individual-level, Cross-section, LPM
Kleemans and Magruder (2018)	16	Indonesia	precipitation, Z-score/level, CRU	internal, unilateral, fraction, level, Indonesia Family Life Survey	individual-level, Panel - causal, OLS
Bettin and Nicolli (2012)	54	Africa/Asia/Multiple	precipitation/temperature, anomaly, Mitchell et al. (2004, 2005); multiple, binary, Mitchell et al. (2004, 2005)	international, bilateral, count, level, World Bank (GBMD)	country-level, panel-analysis, Negative binomial regression
Hunter et al. (2013)	47	Mexico	drought/precipitation, deviation, Source not provided	international, unilateral, binary, level, Mexican Migration Project	household-level, Panel-other/pool, Logit
Jennings and Gray (2015)	128	Netherlands	precipitation/temperature, cold days/hot days/level, Royal Netherlands Meteorological Institute; flood, binary, Royal Netherlands Meteorological Institute	internal/international, unilateral, binary, level, HSN Data Set Life Course Release	individual-level, Panel-other/pool, Logit
Mahajan and Yang (2018)	13	World	hurricane, cyclone, typhoon, storm, hazard index, Unisys and the Joint Typhoon Warning Centre	international, unilateral, fraction, level, US Census, Yearbook of Immigration Statistics, Statistical Yearbook of the Immigration and Naturalization Service	country-level, panel-analysis, OLS
Ruiz (2017)	43	Mexico	drought/precipitation, SPI/duration/nr. of events, Source not provided; hurricane, cyclone, typhoon, storm, nr. of events, Source not provided	internal, bilateral, count, log, Inegi	state-level, Panel - causal, PPML

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Summary information on studies considered in the two meta-analyses (cont.).

Study	N	Geographical focus	Climate measure	Migration measure	Analytical method
Ouattara and Strobl (2014)	9	USA	hurricane, cyclone, typhoon, storm, hazard index, Strobl (2011)	internal, bilateral, fraction, level, Internal Revenue Service County-to-County Migration Data	county-level, Panel - causal/Panel-other/pool, OLS/VAR
Khamis and Li (2018)	12	Mexico	multiple fast, nr. of events, DesInventar database	internal, unilateral, count, level, Mexican Census	state-level, Panel-other/pool, PPML
Sedova and Kalkuhl (2018)	78	India	precipitation/temperature, anomaly/level, ERA5	internal/international/undefined (internal/internat.), unilateral, binary/categorical, level, IHDS	household-level, Cross-section/Panel - causal, LPM/Logit/Multinomial logit
Bohra-Mishra et al. (2017)	40	Philippines	precipitation/temperature, level, University of Delaware; hurricane, cyclone, typhoon, storm, deaths, DesInventar database	internal, unilateral, fraction, level, Philippines Census of Population IPUMS	province-level, Panel - causal, OLS
Call et al. (2017)	3	Bangladesh	flood, binary, Dartmouth Flood Observatory	undefined (internal/internat.), unilateral, binary, level, Matlab Demographic Surveillence System MDSS	individual-level, Panel-other/pool, Logit
Beine and Parsons (2015)	132	World	drought/precipitation/temperature, anomaly/deviation/nr. of events, CRU/International Disaster Database; flood/hurricane, cyclone, typhoon, storm, nr. of events, International Disaster Database	internal/international, bilateral, fraction, log, Ozden et al. (2011)	individual-level, panel-analysis, PPML
Riosmena et al. (2018)	6	Mexico	temperature, anomaly/deviation, CRU	international, unilateral, binary, level, Mexican Census	household-level, Panel-other/pool, Logit
Spencer and Urquhart (2018)	16	Central America and Caribbean	hurricane, cyclone, typhoon, storm, hazard index, Strobl 2010(HURDAT, Eastern North Pacific Track Files)	international, unilateral, fraction, log, American Community Survey, US Census	country-level, panel-analysis, OLS
Koubi et al. (2018)	18	Cambodia/ Multiple/ Nicaragua/ Peru/ Uganda/ Vietnam	multiple slow, binary, Author's own collection; multiple fast, binary, Author's own collection	internal, unilateral, binary, level, Koubi et al (2016)	individual-level, Cross-section/Panel-other/pool, Logit
Hornbeck and Naidu (2014)	39	USA	flood, fraction of affected area, US Coast and Geodetic Survey (1927)	internal, unilateral, count/fraction, level/log, Census of Agriculture and the Census of Population (Haines 2010)	county-level/individual-level, Panel - causal, OLS
Pei et al. (2018)	4	China	precipitation/temperature, anomaly, Reconstructed - precipitation reconstruction by Pei et al. (2014) and temperature reconstruction by Yang et al. (2002).	undefined (internal/internat.), unilateral, count, level, Ge et al., 1997 - Chinese Migration History	country-level, Panel-other/pool, OLS/Poisson regression
Shiva and Molana (2018)	8	Iran	precipitation/temperature, deviation/level, Iranian National Climate Change Office	internal, bilateral, count, log, Iranian National Census	province-level, Panel - causal, OLS
Duda et al. (2018)	2	Tanzania	precipitation, binary, Author's own collection; multiple fast, binary, Author's own collection	internal, unilateral, binary, log, Original survey of authors	household-level, Cross-section, Logit
Simon (2018)	24	Mexico	drought/temperature, duration, CRU	international, unilateral, binary, level, Mexican Migration Project	household-level, Panel-other/pool, Logit
Bakar and Jin (2018)	21	Australia	precipitation/temperature, days above/below a treshold/level/max, Australian Bureau of Meteorology	internal, bilateral/unilateral, fraction, level, Australian Bureau of Statistics	district-level, Panel-other/pool, Bayesian spatio-temporal
Baronchelli and Ricciuti (2018)	25	Vietnam	temperature, deviation, CRU	undefined (internal/internat.), unilateral, binary, level, VARHS household data	household-level, IV/Panel-other/pool, 2SLS/LPM
Fussell et al. (2017)	32	USA	hurricane, cyclone, typhoon, storm, losses/nr. of events, SHELDUS - Spatial Hazard Events and Losses Database for the United States	undefined (internal/internat.), unilateral, fraction, level, US Census	county-level, Panel-other/pool, OLS
Castañer (2017)	2	Mexico	precipitation/temperature, level, UNAM's Atmospheric and Environmental Sciences Information Unit	undefined (internal/internat.), unilateral, binary, log, 2010 Population and Housing Census	individual-level, Cross-section, LPM

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Summary information on studies considered in the two meta-analyses (cont.).

Study	N	Geographical focus	Climate measure	Migration measure	Analytical method
Curran and Meijer-Irons (2014)	8	Thailand	multiple slow, duration, National Weather Service's Climate Prediction Center	internal, unilateral, binary, level, Nang Rong Survey - conducted by the Carolina Population Center at the University of North Carolina and the Institute for Population and Social Research at Mahidol University in Thailand	individual-level, Panel-other/pool, Logit
Bylander (2016)	3	Cambodia	drought/precipitation, binary, Cambodia Socio-Economic Survey (CSES) - National Institute of Statistics at the Cambodian Ministry of Planning; flood, binary, Cambodia Socio-Economic Survey (CSES) - National Institute of Statistics at the Cambodian Ministry of Planning	international, unilateral, binary, level, Cambodia Socio-Economic Survey	household-level, Panel-other/pool, Logit
Loebach (2016)	2	Nicaragua	hurricane, cyclone, typhoon, storm, binary, Question in survey (if respondent from disaster affected municipality)	international, unilateral, binary, level, Nicaraguan Living Standard Measurement Studies	household-level, Panel-other/pool, Logit
Matera (2014)	12	World	drought/temperature, fraction of affected people/nr. of events, EM-DAT; flood, fraction of affected people/nr. of events, EM-DAT	international, bilateral, fraction, level, UN World Population Prospects	country-level, Panel-other/pool, OLS
Barassi et al. (2018)	60	China	precipitation/temperature, anomaly, China Statistical Yearbook	internal, unilateral, fraction, level/log, Chinese Census	province-level, Panel - causal, OLS/PPML
Grace et al. (2018)	16	Mali	precipitation, Index (Good)/Index (Normal), CHIRPS	undefined (internal/internat.), unilateral, binary, level, SLAM	individual-level, Panel-other/pool, LPM/Logit
Asrat (2017)	4	Tanzania	precipitation/temperature, level, CRU	undefined (internal/internat.), unilateral, binary, level, LSMS-ISA	household-level, Cross-section, Logit
Gao and Sam (2017)	24	China	precipitation/temperature, level, National Meteorological Information Center (NMIC), China	undefined (internal/internat.), bilateral, fraction, log, National Bureau of Statistics of China	prefecture-level, Panel-other/pool, OLS/correlated random effects model
Alexeev et al. (2010)a	10	World	rapid-onset events, number/share of affected/number of occurances and fatalities of weather and non-weather related disasters, EM-DAT	international, flow from origin to destination (thousand), OECD, SOPEMI and USINS	country-level, longitudinal, OLS, loglog
Brückner (2012)a	11	Africa	rainfall/precipitation, annual levels, Terrestrial Air Temperature 1.01 (Matsuura and Willmott, 2007)	internal, share of population living in urban areas, WDI	country-level, longitudinal, OLS, linlin
Cattaneo and Bosetti (2017)a	30	World	temperature & precipitation, mean levels, Dell et al. (2012); rapid-onset, occurence of floods, storms, droughts, EM-DAT	international, net emigration flows as differences between stocks of foreigners (divided by 1000), Özden et al. (2011)	country-level, longitudinal, OLS, linlin
Ghimire et al. (2015)a	2	World	precipitation, rainfall variability, TYN CY 1.11 University of East Anglia	flood-induced displacement, Dartmouth Flood Observatory	country-level, longitudinal, Random Effects, linlin
Gröschl (2012)a	78	World	rapid-onset, number occurrence of different type of disasters, EMDAT	international, bilateral decennial migration rates, World Bank	country-level, longitudinal, OLS, loglin
Hanson & McIntosh (2012)a	8	LAC	rapid-onset, disaster occurrence, EMDAT	international, census data, birth cohorts by origin countries, WDI	country-level, longitudinal, FE, linlin
Naude (2009)a	2	SSA	rapid-onset, disaster occurrence, EMDAT	international, net migration rate, UN Population Division	country-level, longitudinal, FD GMM, llinlin
Peri and Sasahara (2019)a	62	World	temperature, temperature change, UDEL Terrestrial Air Temperature and Precipitation: 1900-2006 Gridded Monthly Time Series, Version 1.01	international, net migration per one-kilometer grid cell, aggregated to country level, de Sherbinin et al., 2015	country-level, longitudinal, OLS/FE, linlin
Wesselbaum and Aburn (2019)a	32	World	temperature, anomaly, Berkeley Earth Database; rapid-onset, disaster occurrence, EMDAT	international, net migration flow, UN Population Division	country-level, longitudinal, FE, loglin
Damette & Gittard (2017)a	12	SSA	temperature & precipitation, deviation from long-run mean, IPCC	international, net migration rate corrected for refugee movement, US Census Bureau	country-level, longitudinal, FE2SLS, linlin

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Summary information on studies considered in the two meta-analyses (cont.).

Study	N	Geographical focus	Climate measure	Migration measure	Analytical method
Marchiori et al. (2017)	32	Africa	precipitation/temperature, anomaly, IPCC	international, undefined (unilat./bilat.), fraction, level, US Census Bureau and UNHCR (2009)	country-level, panel-analysis, OLS/POLS

D.2 Overview of data sources for climate migration research

Table D.2: *Overview of common data sources used in climate migration research*

Name	Institution/Provider	Description	Link
International migration data			
Global Bilateral Migration Database	World Bank	Global matrices of bilateral migrant stocks spanning the period 1960-2000, disaggregated by gender and based primarily on the foreign-born concept	https://datacatalog.worldbank.org/dataset/-global-bilateral-migration-database
OECD Migration Database	OECD	Provides tables with recent annual series on migration flows and stocks of foreign-born or foreigners in OECD countries as well as on acquisitions of nationality.	https://www.oecd.org/migration/-mig/oecdmigrationdatabases.htm
European Union Migration Data	IOM's Global Migration Data Analysis Centre	High quality, harmonized migration data comparable across countries	https://migrationdataportal.org/-regional-data-overview/europe
IPUMS International	The University of Minnesota, National Statistical Offices, international data archives, and other international organizations.	IPUMS provides census and survey data from around the world integrated across time and space. Harmonized international census data for social science and health research. 102 countries, 473 censuses and surveys, over 1 million person records.	https://international.ipums.org/-international/
IPUMS TERRA	The University of Minnesota, NSF	IPUMS Terra provides global-scale data on human population characteristics, land use, land cover, climate and other environmental characteristics.	https://terra.ipums.org/
Global Internal Displacement Database	Norwegian Refugee Council	Provides country-specific historical data on internal displacement by cause(i.e. either conflict or natural disasters).	https://www.internal-displacement.org/database/displacement-data
Asylum applications	UNHCR	Global database with historical bilatreral flows of asylum applications.	https://www.unhcr.org/-refugee-statistics/download/
Illegal border crossings	Frontex	Data reported on a monthly basis by Member States and Schengen Associated Countries on detections of illegal border-crossings to Member States of the EU and Schengen Associated Countries.	https://frontex.europa.eu/along-eu-borders/migratory-map/
Longitudinal migration survey data			
India Human Development Survey	The University of Maryland, the National Council of Applied Economic Research (NCAER), Indiana University, the University of Michigan	A nationally representative, multi-topic panel survey of 41,554 households in 1503 villages and 971 urban neighborhoods across India.	https://ihds.umd.edu/
India National Sample Survey	Ministry of Statistics & Programme Implementation	Large scale sample surveys in diverse fields on All India basis. Primarily data are collected through nation-wide household surveys on various socio-economic subjects, Annual Survey of Industries (ASI), etc. NSS additionally collects data on rural and urban prices.	http://mospi.nic.in/national-sample-survey-nss
Indonesia Family Life Survey (IFLS)	The RAND Corporation	An on-going longitudinal survey in Indonesia. The sample is representative of about 83% of the Indonesian population and contains over 30,000 individuals living in 13 of the 27 provinces in the country.	https://www.rand.org/well-being/social-and-behavioral-policy/data/FLS/IFLS.html
Peru Encuesta Nacional de Hogares sobre Condiciones de Vida (ENAHO)	Instituto Nacional de Estadística e Informática (INEI)	A survey conducted at the national level, in urban and rural areas in the 24 departments and the Constitutional Province of Callao. It is a continuous statistical research that generates quarterly indicators on the evolution of poverty, well-being and livelihood conditions, measures the scope of social programs.	http://iinei.inei.gob.pe/microdatos/
Brazil National Household Sample Survey (PNAD)	Brazilian Institute of Geography and Statistics (IBGE)	PNAD started in the second quarter of 1967 and was finished in 2016, with the release of information for 2015. It surveyed, on an ongoing basis, general characteristics of the population, education, labor, income and housing, and, according to the information needs for Brazil, having the household as its unit of survey.	https://www.ibge.gov.br/en/-statistics/social/-social-protection/20293-supplements-pnad4.html?=&t=o-que-e
Mexico Panel Study	Massachusetts Institute of Technology (MIT)	A major survey research project on Mexico's election campaigns (1997 Federal District; National in 2000, 2006, and 2012). It is intended to be a resource for scholars working on campaigns, public opinion, voting behavior, and political communication, whether they focus on Mexico or not.	https://mexicopanelstudy.mit.edu/-mexico-panel-studies

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Overview of common data sources used in climate migration research (cont.).

Name	Institution/Provider	Description	Link
USA Panel Study of Income Dynamics	The University of Michigan	The study began in 1968 with a nationally representative sample of over 18,000 individuals living in 5,000 families in the United States. Information on these individuals and their descendants has been collected continuously, including data covering employment, income, wealth, expenditures, health, marriage, childbearing, child development, philanthropy, education, and numerous other topics.	https://psidonline.isr.umich.edu/
Tanzania National Panel Survey	Tanzania National Bureau of Statistics (NBS)	Series of nationally representative household panel surveys that collect information on a wide range of topics including agricultural production, non-farm income generating activities, consumption expenditures, and a wealth of other socioeconomic characteristics.	https://www.nbs.go.tz/index.php/en/census-surveys/poverty-indicators-statistics/national-panel-survey
Uganda National Panel Survey	Uganda Bureau of Statistics	A multi-topic household survey.	https://www.ubos.org/uganda-national-panel-survey/
Demographic and Health Surveys (DHS)	The Demographic and Health Surveys (DHS) Program	Nationally representative surveys are designed to collect data on monitoring and impact evaluation indicators important for individual countries and for cross-country comparisons.	https://dhsprogram.com/
Multiple Indicator Cluster Survey (MICS)	UNICEF	Over two decades, more than 300 Multiple Indicator Cluster Surveys have been carried out in more than 100 countries, generating data on key indicators on the well-being of children and women, and helping shape policies for the improvement of their lives.	https://www.unicef.org/-statistics/index_24302.html
Google's dataset search engine			
Google Dataset Search Engine	Google	Search engine for datasets. Using a simple keyword search, users can discover datasets hosted in thousands of repositories across the Web.	https://datasetsearch.research.-google.com/
Historical climate data			
CRU climate data	University of East Anglia Climate Research Unit (CRU)	Instrumental climate data, palaeoclimate data, reanalysis climate data, climate model data and future climate projections.	https://sites.uea.ac.uk/cru/data
NCEI environmental data	NOAA NCEI	Comprehensive oceanic, atmospheric, and geophysical data.	http://www.ncdc.noaa.gov/oa/ncdc.html
NWS ASOS program	NOAA National Weather Service	US primary surface weather observing network.	https://www.weather.gov/asos/
US Climate Reference Network	NOAA NCEI	Systematic and sustained network of climate monitoring stations with sites across the conterminous U.S., Alaska, and Hawaii.	https://www.ncdc.noaa.gov/crn/
U.S. Historical Climatology Network (USHCN)	NOAA NCEI	USHCN data are used to quantify national- and regional-scale temperature changes in the contiguous United States.	https://www.ncdc.noaa.gov/data-access/land-based-station-data/land-based-datasets/us-historical-climatology-network-ushcn
Netherlands Meteorological Institute (KNMI) Climate Explorer	WMO	A tool to explore monthly mean climate time series and the relationships between them.	http://climexp.knmi.nl/start.cgi
Atmospheric River Archive (ARA version 2.0)	Santander Meteorology Group	Archive of atmospheric-river arrivals along the European Atlantic sea-board and the West Coast of North America.	http://www.meteo.unican.es/en/-atmospheric-rivers
PRISM Climate Group (USA gridded & point data)	PRISM Climate Group	Climate observations from a wide range of monitoring networks, sophisticated quality control measures, and spatial climate datasets that reveal short- and long-term climate patterns. The datasets incorporate a variety of modeling techniques and are available at multiple spatial/temporal resolutions, covering the period from 1895 to the present.	https://prism.oregonstate.edu/
Climate Impacts Group dataset	Center for Science in the Earth System (CSES), University of Washington	Hydro-climatic data at various spatial scales for historical and projected conditions in the Pacific Northwest and regions extending beyond the Pacific Northwest	https://cig.uw.edu/resources/data/
Global Historical Climatology Network (GHCN)	NOAA NCEI	Temperature datasets.	Monthly data: https://www.ncdc.noaa.gov/ghcn-monthly; Daily data: https://www.ncdc.noaa.gov/ghcnd-data-access

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Overview of common data sources used in climate migration research (cont.).

Name	Institution/Provider	Description	Link
Standardized Precipitation-Evapotranspiration Index (gridded drought index data)	CSIC, IPE, EEAD	A multiscalar drought index based on climatic data. It can be used for determining the onset, duration and magnitude of drought conditions with respect to normal conditions in a variety of natural and managed systems such as crops, ecosystems, rivers, water resources, etc.	https://spei.csic.es/
Livneh daily CONUS near-surface gridded meteorological and derived hydrometeorological data	NOAA PSL	The CONUS daily dataset from 1915 to 2011 is 1/16 resolution. The dataset variables have been generated using the Variable Infiltration Capacity VIC hydrologic model v.4.1.2.c which was driven with the companion meteorological data.	https://psl.noaa.gov/-data/gridded/data.livneh.html
International Surface Pressure Databank (ISPDv2)	UCAR RDA	The world's largest collection of pressure observations. The ISPDv2 consists of three components: station, marine, and tropical cyclone best track pressure observations. The station component is a blend of many national and international collections.	https://rda.ucar.edu/datasets/ds132.0/
The Global Observing System for Climate (GCOS) Essential Climate Variable (ECV) Data Access Matrix	NOAA	Satellite and non-satellite data for atmosphere, ocean, and land	https://www.ncdc.noaa.gov/-gosic/gcos-essential-climate-variable-ecv-data-access-matrix
Global Precipitation Climatology Centre (GPCC)	NOAA PSL	Four datasets are provided. First is the monitoring product for the period 2007 to present, based on quality-controlled data from 7,000 stations. The second and third are the Full Data Product (V2018 and V7) for the period 1901 to 2016 and 1901 to 2013, based on quality-controlled data from 67,200 stations world-wide that feature record durations of 10 years or longer. This product contains the monthly totals on a regular grid with a spatial resolution of $0.5° \times 0.5°$, $1.0° \times 1.0°$, and $2.5° \times 2.5°$ latitude by longitude. Precipitation anomalies at the stations are interpolated and then superimposed on the GPCC Climatology V2011 in the corresponding resolution. The third is the first guess (1×1) which is most up-to-date but which has limited analyzed stations.	https://psl.noaa.gov/data/gridded/-data.gpcc.html
Centre for Environmental Data Analysis (includes Climate Research Unit (CRU) data; requires (free) user account set-up)	CEDA	The CEDA Archive is the national data centre for atmospheric and earth observation research that hosts over 15 Petabytes of atmospheric and earth observation data.	https://www.ceda.ac.uk/
Gridded climate data for spatial analyses	NOAA PSL	Various climate data products, including gridded climate data, reanalysis data, atmospheric/ocean timeseries	https://psl.noaa.gov/data/gridded/
PRISM Climate Data	PRISM Climate Group	The PRISM Climate Group gathers climate observations from a wide range of monitoring networks, applies sophisticated quality control measures, and develops spatial climate datasets to reveal short- and long-term climate patterns. The resulting datasets incorporate a variety of modeling techniques and are available at multiple spatial/temporal resolutions, covering the period from 1895 to the present.	https://prism.oregonstate.edu/
NCEP North American Regional Reanalysis: NARR	NOAA PSL	The NARR model uses the very high resolution NCEP Eta Model (32km/45 layer) together with the Regional Data Assimilation System (RDAS) which, significantly, assimilates precipitation along with other variables. The improvements in the model/assimilation have resulted in a dataset with substantial improvements in the accuracy of temperature, winds and precipitation compared to the NCEP-DOE Global Reanalysis 2. Current output includes 8 times daily data at 29 levels and most of the variables.	https://psl.noaa.gov/data/gridded/-data.narr.html
NOAA-CIRES-DOE Twentieth Century Reanalysis (V3)	NOAA PSL	Contains objectively-analyzed 4-dimensional weather maps and their uncertainty from the early 19th century to the 21st century.	https://psl.noaa.gov/data/gridded/-data.20thC_ReanV3.html
University of Delaware Air Temperature & Precipitation	NOAA PSL	A monthly climatology of precipitation and air temperature, both at the surface, and a time series, spanning 1900 to 2010, of monthly mean surface air temperatures, and monthly total precipitation.	https://psl.noaa.gov/data/gridded/-data.UDel_AirT_Precip.html

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Overview of common data sources used in climate migration research (cont.).

Name	Institution/Provider	Description	Link
ERA5	European Centre for Medium-Range Weather Forecasts	ERA5 offers hourly estimates of a number of atmospheric, land and oceanic climate-related variables. The data cover the Earth on a 30km grid and resolve the atmosphere using 137 levels from the surface up to a height of 80km. ERA5 includes information about uncertainties for all variables at reduced spatial and temporal resolutions.	https://www.ecmwf.int/en/forecasts/-datasets/reanalysis-datasets/era5
Climate-related GIS and Google Earth data			
Climate Engine for visualization of observational and remote sensing datasets	Desert Research Institute, University of Idaho	Climate Engine uses Google's Earth Engine for on-demand processing of satellite and climate data via a web browser.	https://app.climateengine.org/
NCAR GIS-based Climate Change Scenario tools	UCAR	Datasets of climate change projections.	http://gisclimatechange.ucar.edu/
Google Earth interface for CRUTEM4 land temperature data	University of East Anglia CRU	Gridded historical temperature, derived from air temperatures near to the land surface recorded at weather stations across all continents of Earth.	https://crudata.uea.ac.uk/cru/-data/crutem/ge/
NWS GIS Portal (also has KML files for GoogleEarth)	NOAA National Weather Service	Global and downscaled climate change projections from the Community Climate System Model (CCSM-3) available for download in a common GIS format.	http://www.nws.noaa.gov/gis/
Permafrost Zonation Index and map for Google Earth and ArcGIS	University of Zurich	The Permafrost Zonation Index (PZI) or a corresponding map color indicates, to what degree permafrost exists only in the most favorable conditions (yellow) or nearly everywhere (blue).	http://www.geo.uzh.ch/microsite/-cryodata/pf_global/
CPC GIS Data	NOAA National Weather Service Climate Prediction Center	Operational predictions of climate variability, real-time monitoring of climate and the required data bases, and assessments of the origins of major climate anomalies. The products cover time scales from a week to seasons, extending into the future as far as technically feasible, and cover the land, the ocean, and the atmosphere, extending into the stratosphere.	https://www.cpc.ncep.noaa.gov/-products/GIS/GIS_DATA/
Hydrology / water-related data			
USGS Water Data for the Nation	USGS	Water-resources data collected at approximately 1.9 million sites in all 50 States, the District of Columbia, Puerto Rico, the Virgin Islands, Guam, American Samoa and the Commonwealth of the Northern Mariana Islands.	https://waterdata.usgs.gov/nwis
USBR HYDROMET Data System	USBR	The HydroMet network of automated hydrologic and meteorologic monitoring stations located throughout the Missouri Basin Region collects remote field data and transmits it via satellite to provide real-time water management capability. HydroMet data is then integrated with other sources of information to provide streamflow forecasting and current runoff conditions for river and reservoir operations.	https://www.usbr.gov/gp/hydromet/
NRCS water and snow data	NRCS		https://www.wcc.nrcs.usda.gov/
Teleconnection Data			
Teleconnection time series (SOI, PDO, AMO, etc.)	NOAA PSL		https://psl.noaa.gov/data/-climateindices/list/
The Pacific Decadal Oscillation (PDO)	JISAO	The Pacific Decadal Oscillation (PDO) Index is defined as the leading principal component of North Pacific monthly sea surface temperature variability (poleward of 20N for the 1900-93 period).	http://research.jisao.-washington.edu/pdo/
Drought data			
US Drought Portal	NIDIS	A multi-agency partnership that coordinates drought monitoring, forecasting, planning, and information at national, tribal, state, and local levels.	https://www.drought.gov/
The Palmer Drought Severity Index (PDSI)	NOAA National Weather Service CPC	The Palmer Drought Severity Index (PDSI) and Crop Moisture Index (CMI) are indices of the relative dryness or wetness affecting water sensitive economies. The data is provided in graphical and tabular formats, for the contiguous United States.	https://www.cpc.ncep.noaa.gov/-products/monitoring_and_data/-drought.shtml
US Drought Monitor	University of Nebraska-Lincoln The National Drought Mitigation Cente	A map released every Thursday, showing parts of the U.S. that are in drought.	https://droughtmonitor.unl.edu-/Data.aspx
Multiple types of climate change-related data			
NASA data	NASA	Observational and simulated climatic data.	https://data.giss.nasa.gov/
NASA Giovanni	NASA	An application that allows to visualize selected geophysical parameters or download time series from satellite era.	https://giovanni.gsfc.nasa.gov/-giovanni/

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Overview of common data sources used in climate migration research (cont.).

Name	Institution/Provider	Description	Link
The US Climate Service	NOAA	A source of timely and authoritative scientific data and information about climate.	https://www.climate.gov/-#dataServices
IRI/LDEO Climate Data Library	Columbia University	A tool that offers access any number of datasets; create analyses of data ranging from simple averaging to more advanced EOF analyses using the Ingrid Data Analysis Language; monitor present climate conditions with maps and analyses in the Maproom; create visual representations of data, including animations; download data in a variety of commonly-used formats, including GIS-compatible formats.	http://iridl.ldeo.columbia.edu/
National Geophysical Data Center	NOAA	One of the largest archives of atmospheric, coastal, geophysical, and oceanic research in the world.	https://www.ngdc.noaa.gov/-ngdcinfo/onlineaccess.html
World Bank Climate Change Knowledge Portal	World Bank	The Portal provides an online platform for access to comprehensive global, regional, and country data related to climate change and development.	https://climateknowledgeportal.-worldbank.org/
Historical and future climate data for western North America	University of British Columbia	The freely available programs use historical weather station data and global circulation model regional predictions to project future seasonal and annual climate variables in BC, western North America and entire North America.	http://www.climatewna.com/
Climate change impact data			
Agricultural productivity	USDA	The data provides estimates of productivity growth in the U.S. farm sector for 1948-2017, and estimates of the growth and relative levels of productivity across U.S. States for 1960-2004.	https://www.ers.usda.gov/data-products/agricultural-productivity-in-the-us.aspx; https://quickstats.nass.usda.gov/
Biodiversity data	GBIF	Data on all types of life on Earth.	https://www.gbif.org/
Climate Vulnerability Monitor	DARA	The Monitor comprises 34 indicators of the economic, human and ecological effects of climate change and the carbon economy.	https://daraint.org/climate-vulnerability-monitor/climate-vulnerability-monitor-2012/data/
Hurricanes / Tropical cyclones NHC Data Archive	NOAA National Weather Service	Reports, graphical products and GIS data on tropical cyclones and hurricanes.	https://www.nhc.noaa.gov/data/
Data.gov – climate impact data	U.S. General Services Administration	Datasets containing various types of government data.	https://www.data.gov/about
Inter-Sectoral Impact Model Intercomparison Project (ISIMIP)	Potsdam Institute for Climate Impact Research (PIK) and the International Institute for Applied Systems Analysis (IIASA)	ISIMIP provides a quantitative and cross-sectoral synthesis of the differential impacts of climate change, including the associated uncertainties	https://www.isimip.org/
Climate model projection data			
Statistically downscaled data for the continental USA; NetCDF or ASCII format	University of California MERCED	The MACA dataset downscales a large set of variables (temperature, precipitation, humidity, wind, radiation) making it ideal for different kinds of modeling of future climate (i.e. hydrology, ecology, vegetation, fire, wind). It uses a statistical downscaling method for removing biases from global climate model outputs.	https://climate.-northwestknowledge.net/MACA/
IPCC AR5 CMIP5 model output data; NetCDF format	IPCC	Climate data provided for the IPCC 5th Assessment Report. AR5 Database is based on the status of CMIP5 data on March 15, 2013. https://portal.enes.org/data/enes-model-data/cmip5	http://www.ipcc-data.org/sim/-gcm_monthly/AR5/index.html
Gridded climate model data for the US and Canada	Government of Canada	Thin plate spline smoothing algorithms (ANUSPLIN), non-parametric, multi-dimensional curve fitting technique for application to noisy multi-variate data. It offers an operationally efficient means to develop spatially continuous climate models ("surfaces").	https://cfs.nrcan.gc.ca/-projects/3?lang=en_CA
Global and regional model data available, plus dynamical or statistical downscaling — ASCII and ESRI formats	CCAFS	Data portal providing global and regional future high-resolution climate datasets that serve as a basis for assessing the climate change impacts and adaptation in a variety of fields including biodiversity, agricultural and livestock production, and ecosystem services and hydrology.	http://www.ccafs-climate.org/

Continue on the next page

Overview of common data sources used in climate migration research (cont.).

Name	Institution/Provider	Description	Link
Climate model data	WorldClim	WorldClim is a set of global climate layers (gridded climate data in GeoTiff format) that can be applied for mapping and spatial modeling. WordlClim version 2 contains average monthly climatic gridded data for the period 1970-2000 with different spatial resolutions, from 30 seconds (1 km2) to 10 minutes (340 km2). The dataset contains the main climatic variables (monthly minimum, mean and maximum temperature, precipitation, solar radiation, wind speed and water vapour pressure) and 19 derived bioclimatic variables.	https://www.worldclim.org/
Western US & hydrology statistically downscaled data; NetCDF or ASCII format	Bureau of Reclamation, Climate Analytics Group, Lawrence Livermore National Laboratory, Santa Clara University, Scripps Institution of Oceanography, U.S. Army Corps of Engineers, U.S. Geological Survey, California-Nevada Climate Applications Program, Southwest Climate Adaptation Science Center, National Center for Atmospheric Research, and Cooperative Institute for Research in Environmental Sciences.	This archive contains fine spatial resolution translations of climate projections over the contiguous United States (U.S.) developed using three downscaling techniques (monthly BCSD Figure 1, daily BCCA Figure 2, and daily LOCA Figure 3), CMIP3 hydrologic projections over the western U.S., and two sets of CMIP5 hydrology projections, corresponding to monthly BCSD climate projections, and corresponding to daily LOCA climate projections, both over the contiguous U.S. as well as Canadian portions of the Columbia River and Missouri River Basins.	https://gdo-dcp.ucllnl.org/downscaled_cmip-_projections/#Welcome
MATLAB scripts to produce downscaled monthly precipitation and temperature data	Oregon State University	Global Climate Data distributes tools written in MATLAB related to climate, hydrology, and hydropower. These tools can be used to (a) create 30-arcsecond (approximately 1km) grids of hindcast (20th century) and projected (21st century) precipitation and temperature data for and global land area; (b) produce gridded surface runoff estimates, and; (c) evaluate the hydropower potential at any site of interest. These processes utilize globally available gridded data (terrain, climate, etc.) which allows the tools available here to be applied with equal ease for any global land area.	http://globalclimatedata.org/ and the associated paper Mosier, T., Hill, D. & Sharp, K. (2013). 30-Arcsecond monthly climate surfaces with global land coverage. International Journal of Climatology, 34(7), pp.2175-2188. https://doi.org/10.1002/joc.3829
High Resolution WRF Simulations of the Current and Future Climate of North America	UCAR NCAR RAP	The dataset is from a high resolution climate change simulation that permits convection and resolves mesoscale orography at 4 km grid spacing over much of North America using the Weather Research and Forecasting (WRF) model. Two 13 years simulations were performed, consisting of a retrospective simulation (October 2000 to September 2013) with initial and boundary conditions from ERA-Interim and a future climate sensitivity simulation with initial and boundary conditions derived from reanalysis and modified by adding the CMIP5 ensemble mean of the high emission scenario climate change.	https://rda.ucar.edu/datasets/ds612.0/
Climate model projection visualization tools			
CMIP5 Statistically Downscaled for Coterminous USA	University of California MERCED	The MACA dataset downscales a large set of variables (temperature, precipitation, humidity, wind, radiation) making it ideal for different kinds of modeling of future climate (i.e. hydrology, ecology, vegetation, fire, wind). A statistical downscaling method removes biases from global climate model outputs.	https://climate.-northwestknowledge.net/MACA/
NCAR Climate Inspector and other GIS-based Climate Change Scenario tools	UCAR	The Climate Inspector is an interactive web application which expands GIS mapping and graphing capabilities to visualize possible temperature and precipitation changes throughout the 21st century. The maps and graphs are generated from a large dataset of climate simulations that were prepared for the 5th Assessment Report of the Intergovernmental Panel on Climate Change (IPCC).	http://gisclimatechange.ucar.edu/; http://gisclimatechange.ucar.edu/-inspector
Both regional and global models	USGC	RegClim is a collaboration between the U.S. Geological Survey and the College of Earth, Ocean, and Atmospheric Sciences at Oregon State University to provide access to global and regional climate datasets produced by our research projects.	http://regclim.coas.oregonstate.edu/-visualization/
Conflict data			

Continue on the next page

Overview of common data sources used in climate migration research (cont.).

Name	Institution/Provider	Description	Link
Uppsala Conflict Data Program	Uppsala University	The Uppsala Conflict Data Program (UCDP) is the world's main provider of data on organized violence and the oldest ongoing data collection project for civil war, with a history of almost 40 years.	https://ucdp.uu.se/
Major Episodes of Political Violence Database	CSP	The table lists 334 episodes of armed conflict (including 36 ongoing cases) that comprise a comprehensive accounting of all forms of major armed conflicts in the world over the contemporary period: 1946-2019.	https://www.systemicpeace.org/warlist/-warlist.htm
The Armed Conflict Location & Event Data Project	ACLED	ACLED collects real-time data on the locations, dates, actors, fatalities, and types of all reported political violence and protest events across Africa, the Middle East, Latin America & the Caribbean, East Asia, South Asia, Southeast Asia, Central Asia & the Caucasus, Europe, and the United States of America.	https://acleddata.com/#/dashboard

Appendix E

Appendix to Chapter 5

E.1 Local weather

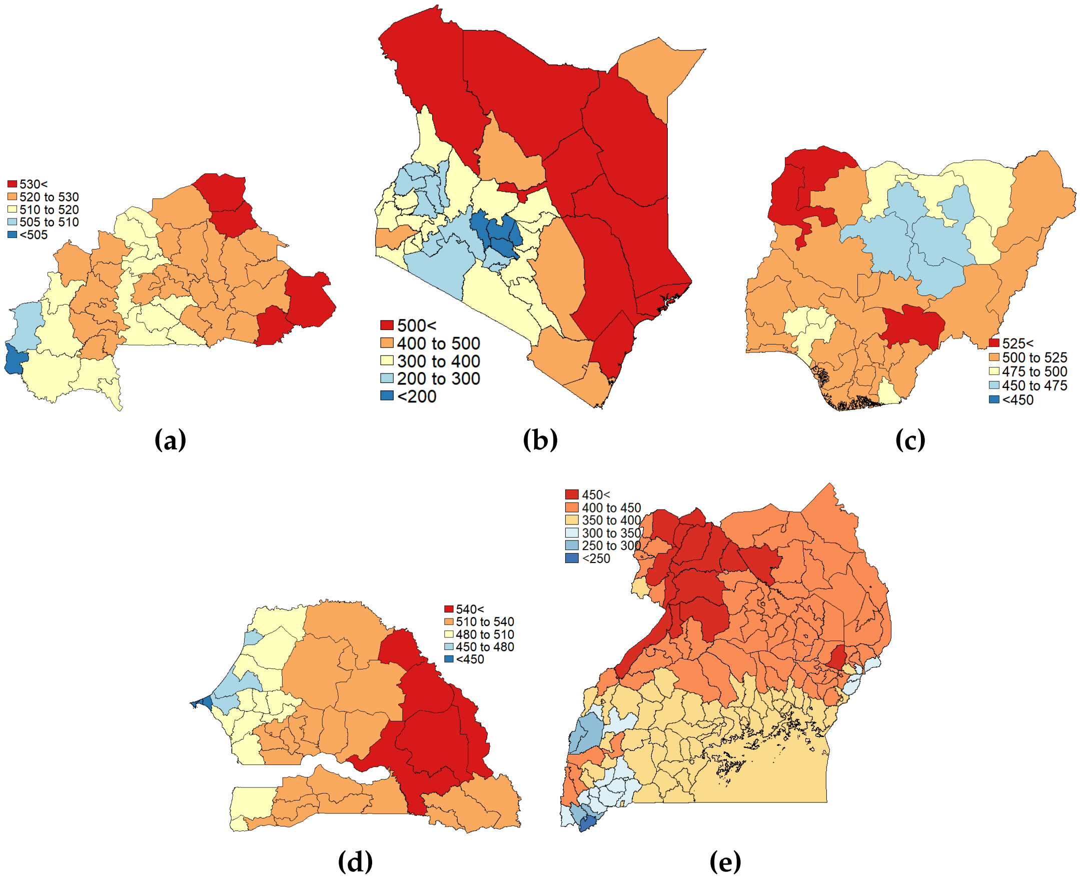


Figure E.1: *District-specific growing degree days (10–30 °): Average for 2000–2008 ((a) Burkina Faso, (b) Kenya, (c) Nigeria, (d) Senegal, (e) Uganda)*

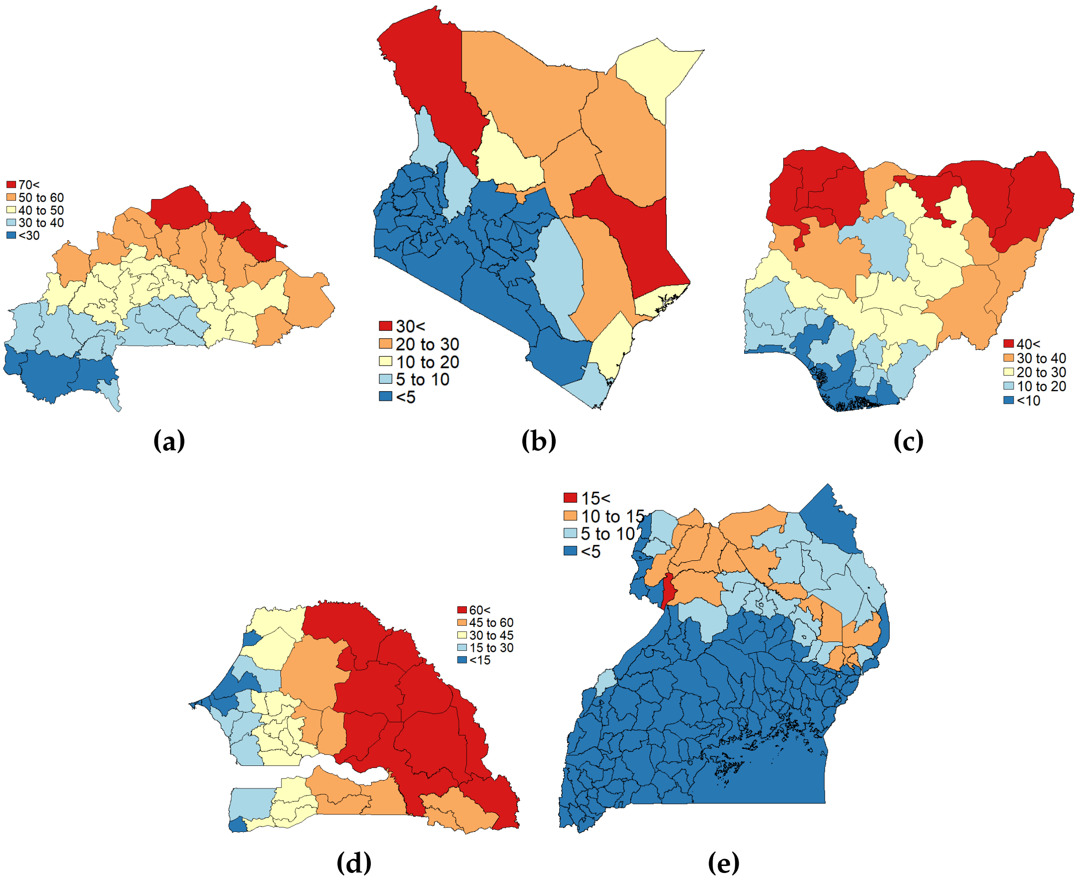
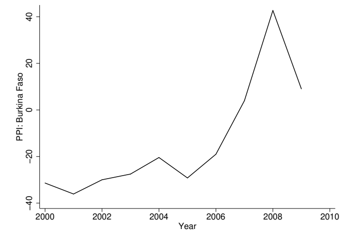


Figure E.2: *District-specific growing degree days (30 °): Average for 2000–2008 ((a) Burkina Faso, (b) Kenya, (c) Nigeria, (d) Senegal, (e) Uganda)*

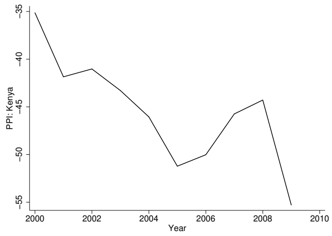
E.2 International food price index

Table E.1: *Commodity price data to generate PPI*

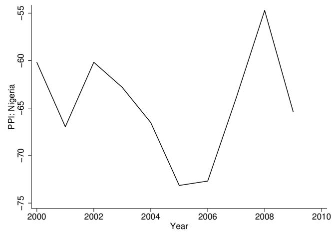
Commodity	Source	PPI
Cereals		
Maize	IMF	Yes (food)
Rice	IMF	Yes (food)
Wheat	IMF	Yes (food)
Fruits and vegetables		
Soybean	IMF	Yes (cash)
Tomatoes	IMF	Yes (cash)
Vegetable oils		
Palm oil	IMF	Yes (food)
Sugar		
Raw equivalent	IMF	Yes (food)
Refined	IMF	Yes (food)
Beverages & others		
Cocoa	IMF	Yes (cash)
Coffee	IMF	Yes (cash)
Tea	IMF	Yes (cash)
Tobacco	World Bank	Yes (cash)



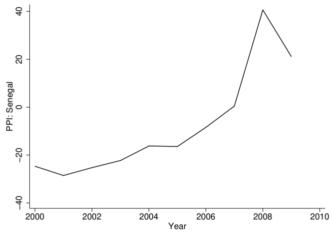
(a)



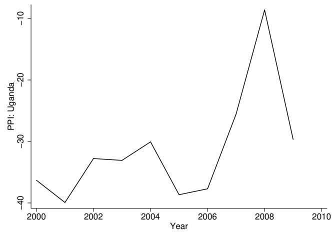
(b)



(c)



(d)



(e)

Figure E.3: *Country-specific PPI by year ((a) Burkina Faso, (b) Kenya, (c) Nigeria, (d) Senegal, (e) Uganda)*

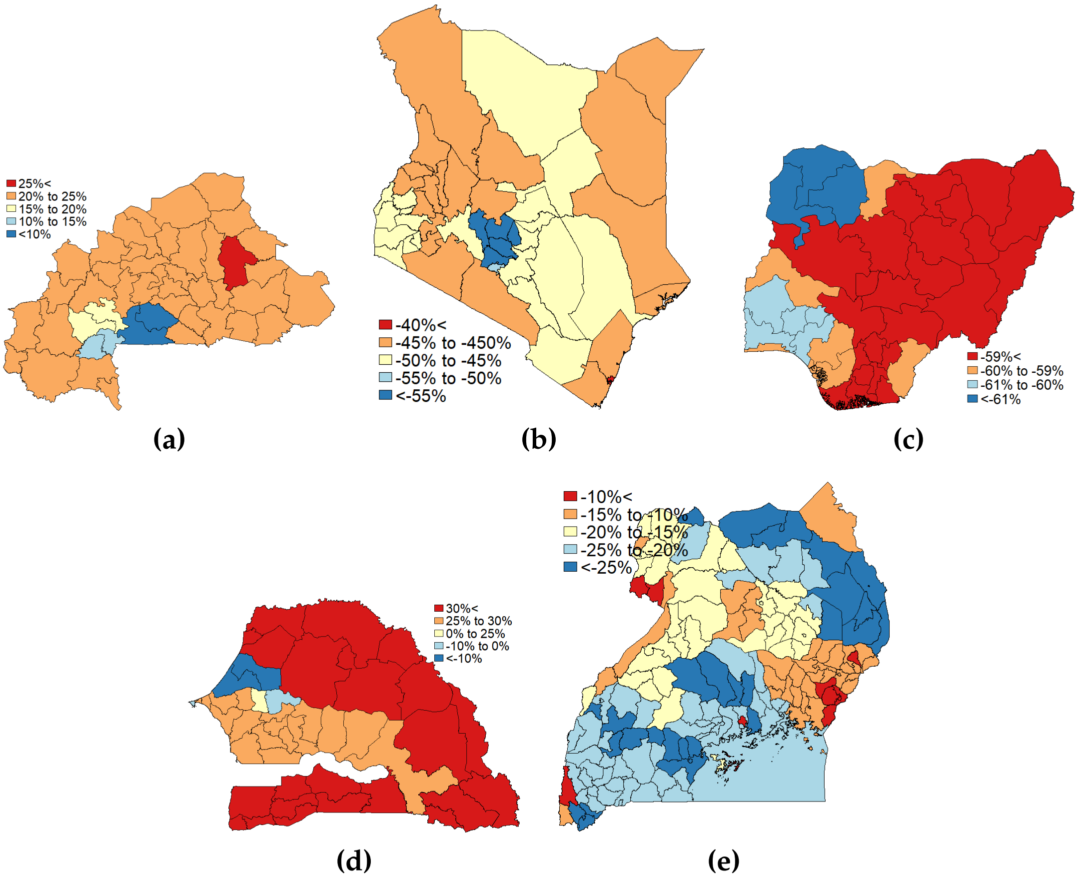


Figure E.4: *Average PPI (district-specific percentage change from the long-run average) during the 2007/08 food price crisis ((a) Burkina Faso, (b) Kenya, (c) Nigeria, (d) Senegal, (e) Uganda)*

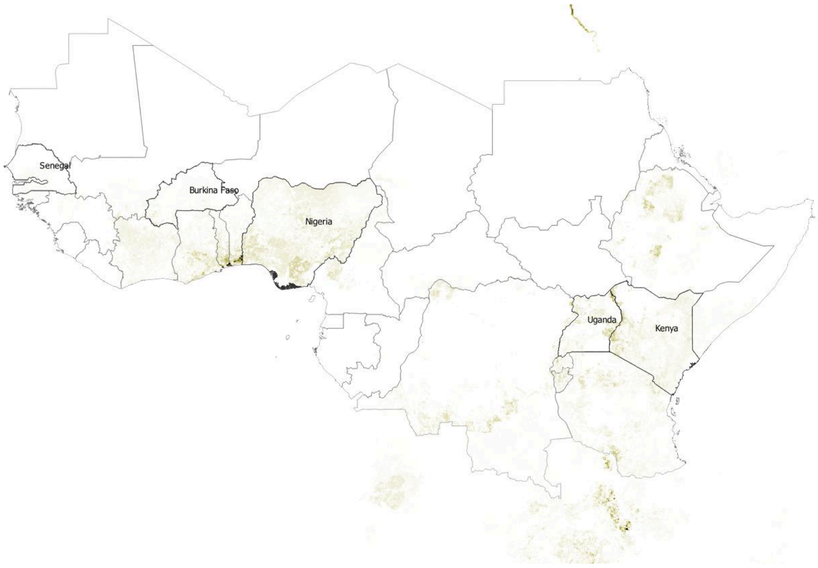


Figure E.5: *Fraction of harvested area of maize at the grid cell level (darker color indicates higher fraction)*

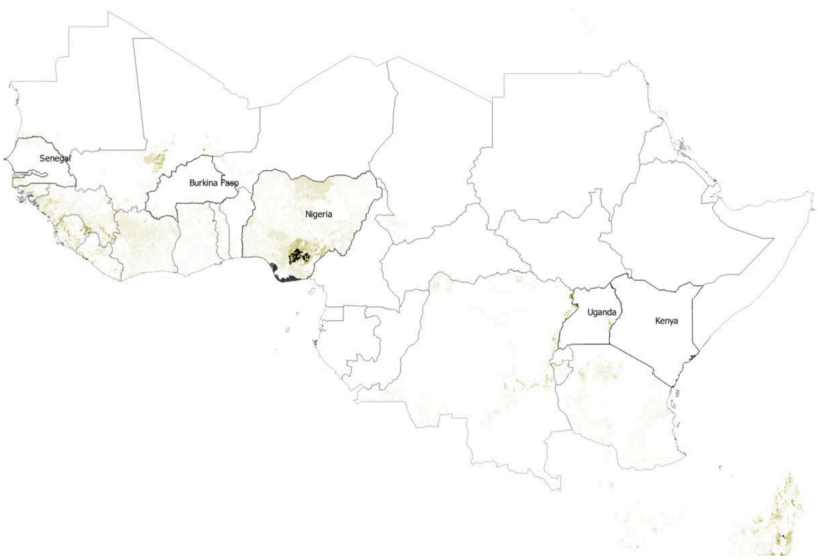


Figure E.6: *Fraction of harvested area of rice at the grid cell level (darker color indicates higher fraction)*

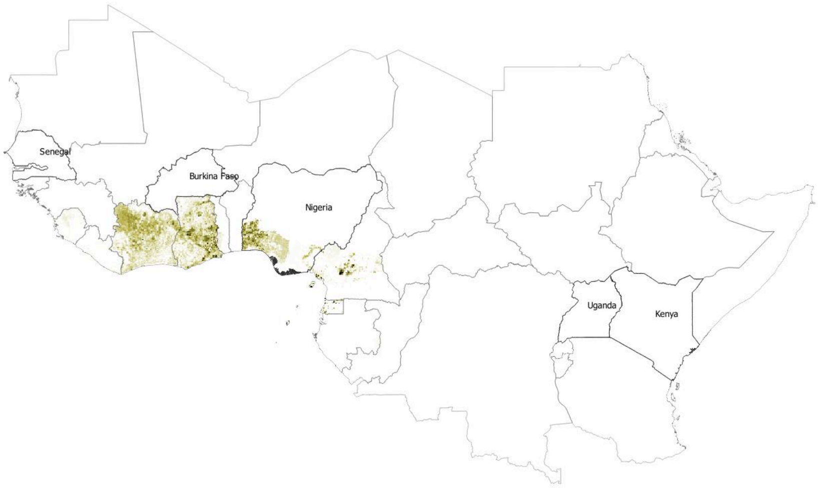


Figure E.7: *Fraction of harvested area of cocoa at the grid cell level (darker color indicates higher fraction)*

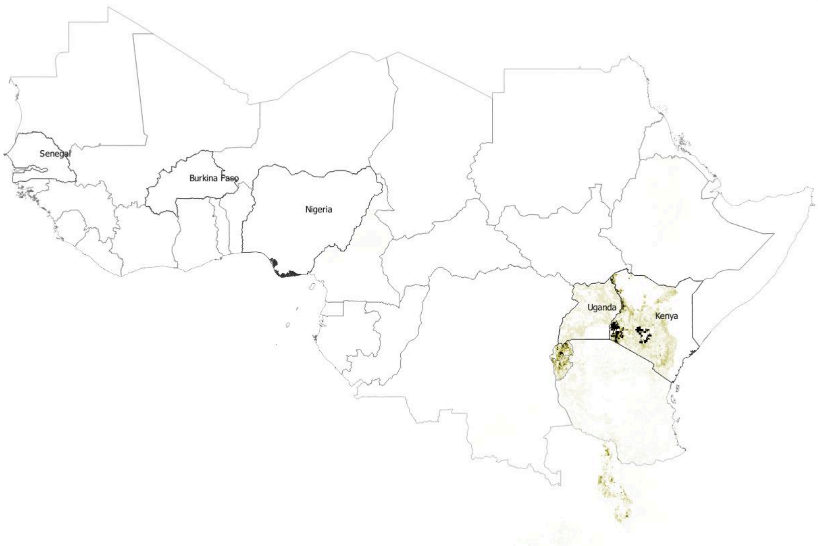


Figure E.8: *Fraction of harvested area of tea at the grid cell level (darker color indicates higher fraction)*

E.3 Sensitivity tests: Aggregate effects

As suggested in the main text, we further run the fully specified LPM model by distinguishing the PPI of cash and food crops. The outcomes are presented in Table E.2. For the **sub-sample of agricultural households**, we find that the estimated effects in Table 5.5 are mainly driven by price changes of food crops. Thus, in our sample covering the food price crisis, commodities that were both locally produced and consumed were more prominently to help producing households relax their budget constraints than cash crops. For the **sub-sample of non-agricultural households**, we find weak evidence that an increase in PPI of food crops reduces the probability that households send out a migrant. PPI of food crops better captures prices of locally consumed goods, suggesting that higher food prices impose a stricter budgetary constraint on net consumers, reducing their ability to move.

We then turn to robustness checks on the alternative definition of the growing season. In Tables E.3 and E.4 we present the outcomes for agricultural and non-agricultural households respectively. First, in models 1-2 we extend the definition of the growing season by one month in each direction. Second, in models 3-4 we look at the effects of annual weather conditions. As for the agricultural households, in models 1-3 the effect of 10 to 30 $^\circ$ degree days remains positive, but is only significant in model 1. In model 4 the effect stays insignificant but swaps the sign. The effect of degree days above 30 $^\circ$ is insignificant throughout the specifications and except of model 3 it remains negative. As for the non-agricultural households, the effect of 10 to 30 $^\circ$ degree days remains positive but insignificant throughout the specifications. These outcomes suggest that even though the direction of the local weather effects remain mostly unchanged when using alternative growing season definitions, migration reacts significantly particularly to weather conditions during the growing season as defined in the main analysis (June-August) and suggested by broader literature. For non-agricultural households, we find new evidence that degree days above 30 $^\circ$ outside the growing season drive out-migration. Even though analysis of weather-related migration from non-agricultural and urban households is an existing gap in the literature (Šedová *et al.*, 2021) this is beyond the scope of this paper and thus we abstract from the interpretation.

Table E.2: *Effect of PPI of cash and food crops on the probability of migration*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PPI (food)	0.0007***	0.0006**			0.0003	-0.0007*		
	(0.0002)	(0.0003)			(0.0003)	(0.0004)		
PPI (cash)			0.0001	0.0000			-0.0001	0.0007
			(0.0001)	(0.0003)			(0.0001)	(0.0007)
DD30	-0.0255*	-0.0460**	-0.0258	-0.0510***	0.0263	-0.0092	0.0358	-0.0039
	(0.0147)	(0.0178)	(0.0176)	(0.0193)	(0.0241)	(0.0265)	(0.0234)	(0.0265)
DD1030	0.0269**	0.0249*	0.0212*	0.0237*	0.0166	0.0247	0.0121	0.0258
	(0.0118)	(0.0142)	(0.0120)	(0.0141)	(0.0143)	(0.0159)	(0.0145)	(0.0159)
N	51075	51075	51075	51075	14427	14427	14427	14427
R^2	0.013	0.017	0.012	0.017	0.018	0.027	0.018	0.027
Time trend	Year	Country x Year	Year	Country x Year	Year	Country x Year	Year	Country x Year
Model	LPM	LPM	LPM	LPM	LPM	LPM	LPM	LPM
Precip. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Agri.	Agri.	Agri.	Agri.	Non-agri.	Non-agri.	Non-agri.	Non-agri.

The dependent variable is binary and captures household-level out-migration incidence in a given year. The producer price indexes (*PPI (food)* and *PPI (cash)*) are measured in percent and capture *PPI* change (%) compared to the long-run average (1990-1999) for food and cash crops separately. *DD1030* captures 100 degree days between 10 and 30 ° and *DD30* above 30 ° during the growing season (June-August). The migration variable is constructed using World Bank's African Migration and Remittances Surveys data. Weather variables are constructed using ERA5 data. PPI is constructed by combining crop-specific fraction of harvested area data by Monfreda *et al.* (2008) and annual global commodity prices from the IMF International Finance Statistics series and the World Bank Global Economic Monitor. Models 1-4 capture agricultural and models 5-8 non-agricultural households. All models further control for growing season precipitation and their squared terms and are estimated with LPM. Models 1, 3, 5 and 7 use a common and models 2, 4, 6 and 8 country-specific time trend. Standard errors clustered at the district level are displayed in parentheses.* $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table E.3: *Effects of PPI and local weather on the probability of migration of agricultural households: Alternative growing season definition*

	(1)	(2)	(3)	(4)
PPI	0.0006***	0.0005**	0.0006***	0.0005*
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
DD30 (May-Sep.)	-0.0103	-0.0213		
	(0.0121)	(0.0130)		
DD1030 (May-Sep.)	0.0154**	0.0127		
	(0.0076)	(0.0087)		
DD30 (Annual)			0.0037	-0.0131
			(0.0067)	(0.0082)
DD1030 (Annual)			0.0033	-0.0005
			(0.0036)	(0.0049)
N	52101	52101	52101	52101
R^2	0.013	0.017	0.012	0.017
Time trend	Year	Country x Year	Year	Country x Year
Model	LPM	LPM	LPM	LPM
Precip. controls	Yes	Yes	Yes	Yes
Sample	Agri.	Agri.	Agri.	Agri.

The dependent variable is binary and captures household-level out-migration incidence in a given year. The producer price index (*PPI*) is measured in percent and captures *PPI* change (%) compared to the long-run average (1990-1999). *DD1030 (May-Sep.)* and *DD1030 (Annual)* capture 100 degree days between 10 and 30 ° and *DD30 (May-Sep.) DD30 (Annual)* above 30 ° between May and September and annually. The migration variable is constructed using World Bank's African Migration and Remittances Surveys data. Weather variables are constructed using ERA5 data. PPI is constructed by combining crop-specific fraction of harvested area data by Monfreda *et al.* (2008) and annual global commodity prices from the IMF International Finance Statistics series and the World Bank Global Economic Monitor. The sample captures agricultural households only. All models further control for precipitation and their squared terms during the considered time frame. All models are estimated with LPM. Models 1 and 3 use a common and models 2 and 4 country-specific time trend. Standard errors clustered at the district level are displayed in parentheses.* $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table E.4: *Effects of PPI and local weather on the probability of migration of non-agricultural households: Alternative growing season definition*

	(1)	(2)	(3)	(4)
PPI	0.0003	0.0003	0.0004	0.0003
	(0.0003)	(0.0004)	(0.0003)	(0.0004)
DD30 (May-Sep.)	0.0443***	0.0361*		
	(0.0148)	(0.0206)		
DD1030 (May-Sep.)	0.0051	0.0078		
	(0.0051)	(0.0081)		
DD30 (Annual)			0.0233**	0.0082
			(0.0117)	(0.0157)
DD1030 (Annual)			0.0038	0.0010
			(0.0034)	(0.0046)
N	17307	17307	17307	17307
R^2	0.017	0.023	0.017	0.023
Time trend	Year	Country x Year	Year	Country x Year
Model	LPM	LPM	LPM	LPM
Precip. controls	Yes	Yes	Yes	Yes
Sample	Non-agri.	Non-agri.	Non-agri.	Non-agri.

The dependent variable is binary and captures household-level out-migration incidence in a given year. The producer price index (*PPI*) is measured in percent and captures *PPI* change (%) compared to the long-run average (1990-1999). *DD1030 (May-Sep.)* and *DD1030 (Annual)* capture 100 degree days between 10 and 30 ° and *DD30 (May-Sep.) DD30 (Annual)* above 30 ° between May and September and annually. The migration variable is constructed using World Bank's African Migration and Remittances Surveys data. Weather variables are constructed using ERA5 data. PPI is constructed by combining crop-specific fraction of harvested area data by Monfreda *et al.* (2008) and annual global commodity prices from the IMF International Finance Statistics series and the World Bank Global Economic Monitor. The sample captures non-agricultural households only. All models further control for precipitation and their squared terms during the considered time frame. All models are estimated with LPM. Models 1 and 3 use a common and models 2 and 4 country-specific time trend. Standard errors clustered at the district level are displayed in parentheses.* $p<0.10$, ** $p<0.05$, *** $p<0.01$.

E.4 Sensitivity tests: Household wealth

Table E.5: *Heterogeneous effects of PPI on migration by household wealth: Agricultural households*

	(1)	(2)	(3)	(4)	(5)	(6)
PPI	0.0057**	0.0059**	0.0110***	0.0007***	0.0007***	0.0005**
	(0.0027)	(0.0025)	(0.0025)	(0.0002)	(0.0002)	(0.0002)
PPI × Medium-Wealth	-0.0026	-0.0026	-0.0025	-0.0003*	-0.0003*	-0.0001
	(0.0016)	(0.0016)	(0.0017)	(0.0002)	(0.0002)	(0.0002)
PPI × Upper-Wealth	-0.0089**	-0.0088**	-0.0079**	-0.0009**	-0.0009**	-0.0004
	(0.0044)	(0.0044)	(0.0040)	(0.0003)	(0.0003)	(0.0003)
DD30		-0.3586	-0.2100		-0.0254*	-0.0438***
		(0.2265)	(0.1974)		(0.0145)	(0.0167)
DD1030		0.1783	0.0934		0.0215*	0.0204
		(0.1701)	(0.1479)		(0.0111)	(0.0135)
N	23742	23742	23742	52101	52101	52101
R^2				0.013	0.013	0.017
Time trend	Year	Year	Country x Year	Year	Year	Country x Year
Model	Logit	Logit	Logit	LPM	LPM	LPM
Precip. controls	No	Yes	Yes	No	Yes	Yes
Sample	Agri.	Agri.	Agri.	Agri.	Agri.	Agri.

The dependent variable is binary and captures household-level out-migration incidence in a given year. The wealth variable is categorical and takes on values for the year 2000: low wealth (0), medium wealth (1) upper wealth (2). The producer price index (*PPI*) is measured in percent and captures *PPI* change (%) compared to the long-run average (1990-1999). *DD1030* captures 100 degree days between 10 and 30 ° and *DD30* above 30 ° during the growing season (June-August). The migration and wealth variables are constructed using World Bank's African Migration and Remittances Surveys data. Weather variables are constructed using ERA5 data. PPI is constructed by combining crop-specific fraction of harvested area data by Monfreda *et al.* (2008) and annual global commodity prices from the IMF International Finance Statistics series and the World Bank Global Economic Monitor. The sample captures agricultural households only. Models 2-3 and 5-6 further control for growing season precipitation and their squared terms. Models 1-3 are estimated with fixed effects logit model and models 4-6 with LPM. Models 1-2 and 4-5 use a common and models 3 and 6 country-specific time trend. Model 5 corresponds to the preferred specification. Standard errors clustered at the district level are displayed in parentheses.* $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table E.6: *Heterogeneous effects of PPI on migration by household wealth: Non-agricultural households*

	(1)	(2)	(3)	(4)	(5)	(6)
PPI	0.0061	0.0059	0.0102**	0.0007	0.0007	0.0006
	(0.0043)	(0.0044)	(0.0049)	(0.0005)	(0.0005)	(0.0005)
PPI × Medium-Wealth	-0.0037	-0.0038	-0.0049	-0.0005	-0.0005	-0.0004
	(0.0034)	(0.0035)	(0.0036)	(0.0004)	(0.0004)	(0.0004)
PPI × Upper-Wealth	-0.0053	-0.0053	-0.0051	-0.0007	-0.0007	-0.0005
	(0.0078)	(0.0079)	(0.0081)	(0.0007)	(0.0007)	(0.0007)
DD30		0.3779	0.6080		0.0220	0.0042
		(0.3685)	(0.3776)		(0.0208)	(0.0196)
DD1030		0.2256	0.1854		0.0157*	0.0205*
		(0.1381)	(0.1379)		(0.0094)	(0.0112)
N	7443	7443	7443	17307	17307	17307
R^2				0.016	0.017	0.023
Time trend	Year	Year	Country x Year	Year	Year	Country x Year
Model	Logit	Logit	Logit	LPM	LPM	LPM
Precip. controls	No	Yes	Yes	No	Yes	Yes
Sample	Non-agri.	Non-agri.	Non-agri.	Non-agri.	Non-agri.	Non-agri.

The dependent variable is binary and captures household-level out-migration incidence in a given year. The wealth variable is categorical and takes on values for the year 2000: low wealth (0), medium wealth (1) upper wealth (2). The producer price index (*PPI*) is measured in percent and captures *PPI* change (%) compared to the long-run average (1990-1999). *DD1030* captures 100 degree days between 10 and 30 ° and *DD30* above 30 ° during the growing season (June-August). The migration and wealth variables are constructed using World Bank's African Migration and Remittances Surveys data. Weather variables are constructed using ERA5 data. PPI is constructed by combining crop-specific fraction of harvested area data by Monfreda *et al.* (2008) and annual global commodity prices from the IMF International Finance Statistics series and the World Bank Global Economic Monitor. The sample captures non-agricultural households only. Models 2-3 and 5-6 further control for growing season precipitation and their squared terms. Models 1-3 are estimated with fixed effects logit model and models 4-6 with LPM. Models 1-2 and 4-5 use a common and models 3 and 6 country-specific time trend. Model 5 corresponds to the preferred specification. Standard errors clustered at the district level are displayed in parentheses.* $p<0.10$, ** $p<0.05$, *** $p<0.01$.

E.5 Sensitivity tests: Destination choices

Table E.7: *The effect of PPI by destination choice: Non-agricultural households*

	(1) Total	(2) Internal	(3) Internal: rural	(4) Internal: urban	(5) Other African	(6) OECD
PPI	0.0004	0.0002	0.0000	0.0002	0.0000	0.0001
	(0.0003)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
DD1030	0.0156*	0.0165*	0.0059**	0.0106	0.0051	0.0050
	(0.0093)	(0.0094)	(0.0026)	(0.0095)	(0.0032)	(0.0071)
DD30	0.0205	-0.0186	-0.0082	-0.0106	0.0255**	0.0058
	(0.0214)	(0.0210)	(0.0073)	(0.0206)	(0.0103)	(0.0091)
N	17307	17307	17307	17307	17307	17307
R^2	0.016	0.023	0.006	0.018	0.003	0.002
Time trend	Year	Year	Year	Year	Year	Year
Model	LPM	LPM	LPM	LPM	LPM	LPM

The dependent variables are binary and capture household-level out-migration incidence by destination in a given year. The producer price index (*PPI*) is measured in percent and captures *PPI* change (%) compared to the long-run average (1990-1999). *DD1030* captures 100 degree days between 10 and 30 ° and *DD30* above 30 ° during the growing season (June-August). The migration variable is constructed using World Bank's African Migration and Remittances Surveys data. Weather variables are constructed using ERA5 data. PPI is constructed by combining crop-specific fraction of harvested area data by Monfreda *et al.* (2008) and annual global commodity prices from the IMF International Finance Statistics series and the World Bank Global Economic Monitor. All models capture non-agricultural households, control for growing season precipitation and their squared terms and are estimated with LPM. Standard errors clustered at the district level are displayed in parentheses.* p<0.10, ** p<0.05, *** p<0.01.

Table E.8: *PPI and destination choices: Agricultural households*

	(1) Total	(2) Internal	(3) Internal: rural	(4) Internal: urban	(5) Other African	(6) OECD
PPI	0.0004*	0.0001	0.0000	0.0000	0.0005***	-0.0000
	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
GDD1030	0.0198	0.0223**	0.0034	0.0189*	-0.0011	0.0038
	(0.0150)	(0.0102)	(0.0039)	(0.0102)	(0.0065)	(0.0060)
GDD30	-0.0473***	-0.0265**	0.0033	-0.0293***	-0.0166**	-0.0054
	(0.0167)	(0.0132)	(0.0062)	(0.0110)	(0.0070)	(0.0046)
N	54099	54099	54099	54099	54099	54099
R^2	0.017	0.018	0.005	0.014	0.009	0.002
Time trend	CountryXYear	CountryXYear	CountryXYear	CountryXYear	CountryXYear	CountryXYear
Model	LPM	LPM	LPM	LPM	LPM	LPM
Precip. controls	Yes	Yes	Yes	Yes	Yes	Yes

The dependent variables are binary and capture household-level out-migration incidence by destination in a given year. The producer price index (*PPI*) is measured in percent and captures *PPI* change (%) compared to the long-run average (1990-1999). *DD1030* captures 100 degree days between 10 and 30 ° and *DD30* above 30 ° during the growing season (June-August). The migration variable is constructed using World Bank's African Migration and Remittances Surveys data. Weather variables are constructed using ERA5 data. PPI is constructed by combining crop-specific fraction of harvested area data by Monfreda *et al.* (2008) and annual global commodity prices from the IMF International Finance Statistics series and the World Bank Global Economic Monitor. All models capture agricultural households, control for growing season precipitation and their squared terms and are estimated with LPM employing country-specific trends. Standard errors clustered at the district level are displayed in parentheses.* p<0.10, ** p<0.05, *** p<0.01.

Table E.9: *PPI and destination choices: Non-agricultural households*

	(1) Total	(2) Internal	(3) Internal:rural	(4) Internal:urban	(5) Other African	(6) OECD
PPI	0.0003	0.0003	0.0001***	0.0002	-0.0001	0.0001
	(0.0004)	(0.0003)	(0.0000)	(0.0003)	(0.0001)	(0.0002)
GDD1030	0.0186	0.0169	0.0106**	0.0073	0.0074	-0.0041
	(0.0121)	(0.0125)	(0.0047)	(0.0124)	(0.0049)	(0.0102)
GDD30	0.0142	-0.0072	-0.0124*	0.0039	0.0233**	0.0018
	(0.0244)	(0.0228)	(0.0073)	(0.0242)	(0.0113)	(0.0104)
N	18342	18342	18342	18342	18342	18342
R^2	0.024	0.031	0.009	0.026	0.006	0.005
Time trend	CountryXYear	CountryXYear	CountryXYear	CountryXYear	CountryXYear	CountryXYear
Model	LPM	LPM	LPM	LPM	LPM	LPM
Precip. controls	Yes	Yes	Yes	Yes	Yes	Yes

The dependent variables are binary and capture household-level out-migration incidence by destination in a given year. The producer price index (*PPI*) is measured in percent and captures *PPI* change (%) compared to the long-run average (1990-1999). *DD1030* captures 100 degree days between 10 and 30 ° and *DD30* above 30 ° during the growing season (June-August). The migration variable is constructed using World Bank's African Migration and Remittances Surveys data. Weather variables are constructed using ERA5 data. PPI is constructed by combining crop-specific fraction of harvested area data by Monfreda *et al.* (2008) and annual global commodity prices from the IMF International Finance Statistics series and the World Bank Global Economic Monitor. All models capture non-agricultural households, control for growing season precipitation and their squared terms and are estimated with LPM employing country-specific trends. Standard errors clustered at the district level are displayed in parentheses.* p<0.10, ** p<0.05, *** p<0.01.

E.6 Further tests on the link between producer prices and conflict

In this section, we present outcomes from a set of LPM regressions with and without state-specific trends, analyzing the association between PPI, local weather and the probability of conflict incidence. We conduct the analyses at the district level. In models 1-2 and 5-6 of Table E.10, we study the direct effects on output and factor conflict likelihoods, respectively. In models 3-4 and 7-8 of Table E.10 we then interact the PPI and local weather variables with a district-specific fraction of agricultural households, to study if the effect of international prices varies by districts' dependence on agricultural production.

From the theoretical perspective, the direct effect of higher food prices on conflict is a priori not clear. On the one hand, the predation (or rapacity) and deprivation theories imply that higher food prices can result in more violent events. The so-called predation effect suggests that higher prices increase the value of the appropriable surplus, leading to more conflicts (Besley and Persson, 2008; Dube and Vargas, 2013). The deprivation effect indicates that among consumers, an increase in prices can induce perceptions of relative deprivation in comparison to others and thus lead to public unrests (Hendrix and Haggard). On the other hand, the opportunity costs effect suggests that higher food prices reduce conflicts, by increasing the opportunity costs of insurrection for farmers as higher wages and revenues make it more attractive to work (Bazzi and Blattman, 2014; Dube and Vargas, 2013; De Winne and Peersman, 2019). Moreover, higher commodity prices can increase state revenues and so the capacity of the state to reduce conflicts

(Besley and Persson, 2008; De Winne and Peersman, 2019).

Our results reveal that a rise in producer commodity prices decreases the likelihood of output conflicts. This is in line with findings by Brückner and Ciccone (2010) or Berman and Couttenier (2015) and the opportunity cost theory (Bazzi and Blattman, 2014; Dube and Vargas, 2013). These findings contrast the evidence by Bellemare (2015); Hendrix and Haggard; Raleigh *et al.* (2015) or De Winne and Peersman (2019) in line with the predation (also called rapacity) and deprivation effects, both of which outline how higher food prices can increase violence. The magnitudes of the interaction terms between output conflict and agricultural dependence are very close to zero. We also do not find significant effect of producer prices on factor conflict.

The direct effect of yield decreasing temperatures (*DD30*) on the likelihood of factor conflict is negative and becomes significant only in models 3-4. When interacted with the agricultural dependence, the effect is positive suggesting that yield decreasing temperatures are more likely to increase the probability of output conflict in areas that are more dependent on agricultural production. This outcome is in line with the findings on PPI, namely that the opportunity costs of violence decrease with decreasing agricultural incomes (Koubi, 2019). We do not find a significant effect of yield decreasing temperatures on factor conflict.

The effect of yield enhancing temperatures (*DD1030*) on output conflict likelihood is positive in models 1 and 3 but looses its significance in model 2 and additionally swaps the sign in model 4. When it comes to factor conflict, the effect of yield enhancing temperatures is positive throughout specifications but it only becomes significant in model 5. These generally positive associations are in line with the predation theory and seem to be relevant primarily for net-consumers (the interaction with agricultural dependence is insignificant), for whom the increase in agricultural surplus increases the rewards from engaging in conflict.

Table E.10: *Effect of PPI on conflict*

	Output conflict				*Factor conflict*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PPI	-0.001233*	-0.000677	-0.002686*	-0.003222*	-0.000408	0.000377	0.000012	0.000603
	(0.000689)	(0.000967)	(0.001444)	(0.001782)	(0.000485)	(0.000638)	(0.000818)	(0.000926)
DD1030	0.131833***	0.005112	0.156017*	-0.079531	0.076543**	0.018637	0.077876	0.078093
	(0.049673)	(0.066760)	(0.087221)	(0.095586)	(0.038051)	(0.048522)	(0.091138)	(0.090370)
DD30	-0.092142	-0.106884	-1.235795***	-1.429446**	-0.112580	-0.102938	-0.354520	-0.398344
	(0.075057)	(0.143670)	(0.467423)	(0.591827)	(0.069739)	(0.088839)	(0.302292)	(0.259986)
PPI × Agricultural (%)			0.000021	0.000032*			-0.000005	-0.000003
			(0.000014)	(0.000017)			(0.000007)	(0.000007)
DD1030 × Agricultural (%)			-0.000295	0.001175			-0.000031	-0.000755
			(0.001240)	(0.001361)			(0.001167)	(0.001126)
DD30 × Agricultural (%)			0.012997***	0.014654**			0.002724	0.003311
			(0.004928)	(0.005820)			(0.003243)	(0.002746)
N	1260	1260	1260	1260	1260	1260	1260	1260
R^2	0.045	0.125	0.052	0.134	0.011	0.043	0.012	0.044
Time trend	Year	Country x Year	Year	Country x Year	Year	Country x Year	Year	Country x Year
Model	LPM	LPM	LPM	LPM	LPM	LPM	LPM	LPM
Precip. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Conflicts	Jul.-Dec.	Jul.-Dec.	Jul.-Dec.	Jul.-Dec.	Jul.-Dec.	Jul.-Dec.	Jul.-Dec.	Jul.-Dec.

The dependent variable is binary and captures district-level conflict incidence in a given year. The *Output conflict* variable is binary and measures smaller scale conflict incidence. The *Factor conflict* variable is binary and measures larger conflict incidence. The producer price index (*PPI*) is measured in percent and captures *PPI* change (%) compared to the long-run average (1990-1999). *DD1030* captures 100 degree days between 10 and 30 ° and *DD30* above 30 ° during the growing season (June-August). *Output conflict* is constructed using ACLED data. *Factor conflict* is constructed using UCDP data. Weather variables are constructed using ERA5 data. PPI is constructed by combining crop-specific fraction of harvested area data by Monfreda *et al.* (2008) and annual global commodity prices from the IMF International Finance Statistics series and the World Bank Global Economic Monitor. All models are estimated using LPM. Models 1, 3, 5 and 7 use a common and models 2, 4, 6 and 8 country-specific time trend. Standard errors clustered at the district level are displayed in parentheses.* p<0.10, ** p<0.05, *** p<0.01.