Essays on Internal Migration in Developing Countries

A Dissertation presented

by

Tamara Gurevich

to

The Graduate School

in Partial Fulfillment of the

Requirements

for the Degree of

Doctor of Philosophy

in

Economics

Stony Brook University

May 2016

Stony Brook University

The Graduate School

Tamara Gurevich

We, the dissertation committee for the above candidate for the

Doctor of Philosophy degree, hereby recommend

acceptance of this dissertation

Mark R. Montgomery - Dissertation Advisor
Professor, Economics Department

Hugo Benitez-Silva - Chairperson of Defense
Associate Professor, Economics Department

Warren Sanderson
Professor, Economics Department

Partha Deb
Professor, Economics Department
Hunter College, CUNY

This dissertation is accepted by the Graduate School

Charles Taber
Dean of the Graduate School

Abstract of the Dissertation

Essays on Internal Migration in Developing Countries

by

Tamara Gurevich

Doctor of Philosophy

in

Economics

Stony Brook University

2016

This thesis investigates the determinants and implications of migration decisions made by individuals in households, using Indonesia as a case study. The thesis consists of two chapters. In each chapter I study respectively the effects of local recent flood events on individuals' and households' decision to leave their origin community, and the effects such migration decisions may have on subsequent health of migrant household members.

In chapter 2 of this dissertation, I quantify the effect of migration on subsequent health of migrants using a potential outcomes framework design that exploits exogenous impacts of floods on migration to reduce concerns regarding potential endogeneity of migration decisions. I focus on six often-used measurements of physical and general health that are potentially modifiable over short periods of time. I construct a latent class model of joint probabilities of the six health measures in which individuals are assumed to belong to one of two health classes: healthy or unhealthy. I estimate the model using data from the Indonesian Family Life Survey, an ongoing longitudinal survey of households and individuals in Indonesia. I find that migration last year has no effect on health, and that individuals who migrated two or more years ago as a result of a flood are 20 percent more likely to be in poor health than their non-migrant counterparts.

In chapter 3, I investigate the effects of recent local floods on probability of out-migration from affected communities. Using the dataset described above, I construct a 16-year panel to examine migration decision-making of individuals and households. I employ logistic modeling technique to find that individuals are six percentage points less likely to leave a community that has recently experienced a flood. Households

residing in affected communities are eight percentage points less likely to send out at least one migrant following a flood. This result is important to individuals and policy-makers when directing disaster recovery efforts.

Chapter 2 is a joint work with Partha Deb, who originally proposed the project and provided research guidance. The execution of the project, including data cleaning, computation and interpretation of the results, and writing of the final draft of the paper are all mine.

Table of Contents

List of Figures

List of Tables

Acknowledgements

First and foremost, I would like to thank my dissertation advisor Mark R. Montgomery, my dissertation committee members Hugo Benítez-Silva and Warren Sanderson, and outside reader Partha Deb. I am most grateful for their immense help and support throughout my graduate student career at Stony Brook University. I would also like to acknowledge organizers and participants of graduate microeconometrics workshop series for their helpful comments and suggestions. I appreciate the effort Samuele Centorrino put into organizing and running the workshop which played a vital role in advancing my research and presentation skills. Additionally, I would like to thank macroeconomics faculty, in particular Eva Cárceles-Poveda and Alexis Anagnostopoulos for tolerating me as long as they did, and Marina Azzimonti for providing help and guidance during the job search.

I have greatly benefited from discussions of research with my fellow graduate students. I am forever indebted to Ryan McKenna for his willingness to help me with exam preparations. My officemates, Anju Bhandari and Zahra Ebrahimi, have become my close friends and graduate school survival partners. I am grateful to Xin Tang for keeping me grounded and focused on research. I am also thankful for all my friends in the program for fun extracurriculars that made the graduate school so much better.

Finally, I'm thankful to my family for love and support they have provided me over the years. My mom has always been a great believer in quality education, and it is her effort throughout my entire educational career that made it possible for me to accomplish as much as I did. And of course, my wonderful husband, Mikhail, who suffered with me, supported and comforted me in the times of need, and made this possible. Thank you!

Chapter 1

INTRODUCTION

The United Nations estimates that over one billion people in the world live outside the immediate region of their birth (UNDP, 2009). Of those, nearly 750 million – 75% – are internal migrants, relocating to other regions of their native countries (ibid). Lifetime migration estimates for developed countries state that some 255 million people live of outside their region of birth; nearly twice as many people – 505 million – migrated in the developing world (Bell and Charles-Edwards, 2013). Furthermore, these numbers are expected to rise reflecting increases in future voluntary migration and displacement.

On a macroeconomic level, integrating an increasing number of migrants may present social and economic challenges for governments and policy-makers in both developing and developed countries, however, the developing countries will face a greater difficulty since the number of migrants is large and available resources are relatively scarce. On the microeconomic side of things, individuals and households will likely encounter problems adopting to their new surroundings.

One of the reasons for the projected increase in migration in developing countries is population displacement due to climate change. This is a complex process already affecting millions of people worldwide, disproportionally so the poor in developing countries.[1] Climate change can be described by increased average temperatures and increased rainfall variability. Increased temperature and decreased rainfall can adversely affect agricultural incomes in the rural areas (Bohra-Mishra et al., 2014), while increased rainfall can lead to flood-induced displacement of rural and urban populations residing in lowlands. Additionally, increased frequency of extreme weather events such as hurricanes and cyclones will affect residents of both rural and urban areas (Ghimire et al., 2015).

There is a vast literature on the relationship between climate change and migration. Researches look at displacement following unexpected "sudden onset" extreme weather events such as the Indian Ocean Tsunami and Hurricane Katrina, and a multitude of research questions surrounding these events (Halliday (2006), Stal (2011),

[1] Hunter et al. (2015) provide a review of the most recent literature on the subject.

Gray et al. (2014)). Another strand of literature focuses on "slow onset" disasters such as droughts (Findley (1994), Gray (2010)). While the former events are immediately life threatening in nature, the latter take time to develop, potentially leaving households with time to adapt. Both of these event types are often found to lead to increased out-migration from affected areas, thought this effect may be group-specific.[2]

A particular type of weather events that can be associated with climate change is local flooding. In comparison with the body of literature studying other types of natural hazard events, the literature on this topic is relatively sparse. In this dissertation I investigate two integral questions related to floods and internal migration in developing countries, using Indonesia as a case study. I select Indonesia because of its large population size, high rates of internal migration, geographic and social diversity, and high prevalence of flood events.[3]

Indonesia, a former Dutch colony, is the fourth most populous country in the world, located in Southeaster Asia.[4] The country is an archipelago consisting of over 17,500 islands, of which about 6,000 are inhibited by some 300 ethnic groups speaking more than 700 different languages.

Indonesia is subdivided into 34 provinces and special regions consisting of regencies *(Kabupaten)*. Each *Kabupaten* is further subdivided into districts *(Kecamatan)*, which are further divided into villages and urban communities *(Desa)*. Indonesia is a relatively poor country. GDP per capita, adjusted to purchasing power parity, is \$5,200, which places Indonesia 158^{th} in the world countries' rating. Almost 40% of the labor force is employed in agriculture, with agriculture share of GDP at 14%.

The most common natural hazards threatening inhabitants of Indonesian islands are floods, droughts, tsunamis, earthquakes, volcanic eruptions and forest fires. In addition, Indonesians are exposed to environmental issues of water and air pollution in urban areas, and smoke and haze from forest fires. Major health risks come from waterborne and vectorborne diseases: bacterial diarrhea, hepatitis A, typhoid fever, dengue fever, and malaria. All of these diseases can, to some extent, be associated with recent floods (World Health Organization, 2016).

In chapter 2, I study how recent local floods affect internal out-migration in Indonesia. I use a panel dataset spanning the period of 1993–2007 that is administered by RAND Corporation, the Indonesian Family Life Survey (IFLS), a representative sample of over 33,000 individuals residing in more than 7,000 households. The unique feature of this dataset is that it provides detailed retrospective migration histories of

---

[2]Many researchers find differential effects of droughts based on individuals' gender, household wealth and other socio-economic characteristics.

[3]An estimated 10% of population of Indonesia (about 23 million people) were inter-provincial migrants as of 2010 (van Lottum and Marks, 2012); floods are the most common natural disasters in Indonesia, accounting for 70% of all natural disasters (Mulyana et al., 2013).

[4]Here and further the background information on Indonesia is provided by the CIA World Fact Book last accessed on May 1, 2016 at `https://www.cia.gov/library/publications/the-world-factbook/geos/print/country/countrypdf_id.pdf`

all respondents age 12 and older, as well as a very high precision of post-migration follow-ups.

I build a conditional fixed effects logit model to examine the "push" effects floods have on probability of leaving an affected community in the following year. My model includes individual and household socio-economic characteristics, as well as a limited set of controls for conditions at origin communities that are generally associated with migration. While such "push" model may be somewhat naive, it provides a baseline for an empirical assessment of factors that lead to individuals migration decisions in the aftermath of floods. I find that recent local floods significantly reduce the probability of out-migration by 5 percentage points, from 18% to 13%.

While this finding is not initially intuitive, it is not unique to the literature. Gray and Mueller (2012b) and Mueller et al. (2014) show that in some instances floods can be associated with reduced migration. In particular, migration following floods could be reduced due to decline of financial assets required for migration or due to a desire of household members to remain in the affected community to help with recovery effort. Another explanation comes through a high prevalence of flood relief programs that may incentivize people to remain in the affected communities. I discuss preliminary evidence as to which channel may dominate in the results section of chapter 2.

In chapter 3, I investigate and quantify the effect of internal migration on subsequent health of Indonesian migrants. Given the large scope of internal migration, if migrants have specialized health needs, understanding health consequences of migration is important both to migrants and policy makers. Using the same dataset as in chapter 2, IFLS, I estimate a latent class probability model where each individual is assumed to belong to one of two latent health classes: "good" or "poor" health. In order to reduce concern about voluntary nature of migration, I use floods in potential outcomes framework of Athey and Imbens (2006). I find that migration has a negative effect on health and this effect becomes pronounced two or more years after a migration: migrants are 20% more likely to be in poor health two or more years following a move, compared to non-migrants at origin locations.

Previous literature on the effects of migration on subsequent health is inconclusive. In one paper, Lu (2010) finds that health of the same individuals may improve, deteriorate, or remain unchanged depending on how the author measures health.[5] I depart from the existing literature on the effects of migration on health in the way I model health outcomes. In order to preserve the richness of health information available in the data and to allow for potential correlation among different measures of health of the same individual, I assign individuals to two health classes — "good" and "poor" health — using Grade of Membership framework of Manton and Woodbury (1982) that allows for estimation of probability an individual is "healthy" given the individual's health measures as well as other individual, household, and community characteristics. In doing so, I am able to quantify the effect of migration on a more comprehensive measure of health.

[5] Lu (2010) is just one example of many with similar approach and findings.

In chapter 4, I connect the two preceding chapters and provide a discussion for further avenues of research. At the first glance, the findings from chapters 2 and 3 are at odds with each other. On one hand, migration in the aftermath of floods declines. On the other hand, people who migrate, even though migration is now less likely, end up in worse health than if they were to stay put.

However, these two findings can be consistent. As noted in the discussion of results of chapter 2, communities that receive outside help for flood recovery and reconstruction tend to send out more migrants. Communities that do not receive any help may have to deal with the aftermath of floods on their own, thus increasing labor demands for the younger and healthier residents that otherwise could have moved away. Therefore, it is plausible that the individuals who move out following floods are on average different along the health dimensions from those who migrate under ordinary, non-flood circumstances. The concluding chapter of this dissertation provides some descriptive evidence to support this hypothesis.

Chapter 2

THE EFFECTS OF RECENT LOCAL FLOODS ON MIGRATION

2.1 Introduction

In recent years, a growing body of research has turned to examining migration as a response to natural disasters and climate change. Researchers have looked at climate change as a driver of migration (Massey et al. (2010); Bohra-Mishra et al. (2014)), tried to to assess meaning and magnitude of environmental displacement (Hugo (1996); Myers (2002); Hunter et al. (2015)), examined responses to sudden devastating events (Halliday (2006); Gray et al. (2014)) and adaptation to slow-onset disasters such as droughts (Rosenzweig and Stark (1989); Henry et al. (2004); Gray and Mueller (2012a) among many others). Meanwhile, floods received considerably less attention.

However, floods are different from other natural disasters. Unlike disasters such as earthquakes and tsunamis, floods are a periodic, and in that sense expected occurrence. At the same time, floods are rapid-onset, a stark difference with slowly developing droughts that affect agriculture and impoverish many households, but rarely cause additional bodily and property damages inherent to floods, which often render people injured, homeless and jobless. Furthermore, the United Nations estimates that more than 30% of all natural disasters worldwide in 1970–2005 were floods, making them the most commonly occurring natural disasters in the world.[1]

Thus, it's important to understand floods separately from other types of disasters, as the effects on population mobility due to flooding and policies required to mitigate these effects could be different from other disasters. This study contributes to literature on migration in response to natural disasters by empirically investigat-

[1] `http://www.unisdr.org/disaster-statistics/pdf/isdr-disaster-statistics-occurrence.pdf`

ing the effects of recent floods on out-migration probabilities both on individual and household level.

We select Indonesia because of high frequency of flood events. Table 2.1 shows details of occurrences, deaths and damages for eight most common major natural disasters in Indonesia in 1993–2007.[2] Flood is the most common disaster, affecting nearly five million people in sixteen years. Floods cause over two billion dollars worth of damages, kill, injure and displace more people than most disasters other than earthquakes.[3] In addition to major disasters listed in EM-DAT, many lesser local floods affect Indonesians every year. Mulyana et al. (2013) estimate that there were over 750 floods in Indonesia in 2003–2005 alone.

We investigate the effects of flood on migration using data from Indonesian Family Life Survey, a four-wave panel spanning the period of 1993–2007, collecting data on over 33,000 respondents in 7000 households residing in 312 communities in Indonesia. We use variation in timing of local floods and migration decisions of community residents to estimate the effects of recent floods on out-migration probability both on individual and household level.

We build a conditional fixed effects logit model to examine the "push" effects floods have on out-migration probability. We find that recent floods have a negative and significant effect on probability of out-migration. On average, individuals are six percentage points less likely to leave a community that has experienced a flood in a year leading up to migration decision. Households are eight percentage points less likely to send out a migrant following a last year's flood.

The remainder of the paper is organized as follows. In section 2, we review previous literature. Section 3 discusses data and background on Indonesia. Section 4 presents model and identification strategy, section 5 discusses results, and section 6 concludes.

2.2 Literature Review

2.2.1 General Theory of Migration

Early literature on theory of migration emphasized on migration as means to increase individual income. Much of literature was focused on rural-urban migration and migration across country borders. Individuals were viewed as comparing expected future discounted wages across locales, weighting costs and benefits of a move and making a decision in line with general neoclassical economic theory (Todaro and Maruszko, 1987).

[2]A disaster has to be large enough in terms of damages and bodily harm in order to be listed in the database. Source: "EM-DAT: The OFDA/CRED International Disaster Database. www.em-dat.net — Universit Catholique de Louvain — Brussels — Belgium.

[3]Another source, Dartmouth Flood Observatory, reports 107 flooding incidents in 1993–2007 that caused nearly $2,5 billion U.S. dollars worth of damages, killing 2,505 people, and displacing over three million. http://www.dartmouth.edu/~floods/Archives/index.html

In their seminal 1985 paper, Stark and Bloom point out the importance of looking at a migration decision through prism of a household, rather than an individual. In this context, migration is viewed not only as a way to increase household income, but also minimize household income risks and accumulate capital. This new economic theory of labor migration suggests that households make migration decisions in order to diversify household income and self-insure against various risks in an economic environment with limited access to credit and insurance markets.

Migration as an income diversification strategy has been widely studied in the context of migration from Mexico and Latin America to the United States. Massey and Espinosa (1997) discuss the links between Mexico–U.S. migration and a plethora of different migration determinants. In particular, the authors discuss migration as "part of conscious strategy of risk diversification and capital accumulation". According to this study, migration is, in part, necessary because of economic and political insecurity facing many Mexican households.

The new theory of labor migration is particularly well suited for studying migration as a risk diversification strategy in preparation for *(ex-ante)* or in the aftermath of *(ex-post)* natural disasters. Some notable examples of research in this area include Halliday (2006), Dillon et al. (2010) and Kleemans (2014). The first study focuses on migrant-sending behavior of households in El Salvador. While households engage in ex-post migration as risk mitigation behavior, the 2001 earthquake is found to reduce out-migration, possibly due to households' liquidity constraints.

Dillon et al. (2010) investigate the role of migration in both ex-ante and ex-post agricultural risk insurance. The authors find that households with higher ex-ante risk are more likely to send migrants, though some households tend to keep their male migrants in relatively close proximity. Furthermore, there is evidence that households use migration as means of ex-post risk mitigation, though the effects are gender specific. Kleemans (2014) shows that migration increases following a negative contemporaneous income shock and after a period of accumulated positive income shocks. She further distinguishes between mitigation migration — a short-term rural migration following a negative shock, and investment migration — a long-distance, urban, and more permanent migration.

More recently, Martin et al. (2014) look at behavioral aspects of migration decision-making. The authors rely on the framework of Stark and Bloom (1985), but collect their own data using focus groups in farming communities in Bangladesh. In this paper households make a migration decision, maximizing expected income or minimizing perceived risks. Overall, if household members believe rainfall to be insufficient for agriculture, irregular or unpredictable, they send out more migrants as a method of insurance against crop failures and floods.

2.2.2 Climate Change

Hugo (1996) pioneered the discussion of migration due to environmental changes. He looked at theory of environmentally induced migration and emphasized the importance of preventative policy response to reduce out-migration and resulting environmental stress to the destination communities, however, this work focused on international migration only. Myers (2002) took the discussion a step further, reviewing literature on both internal and international migration due to climate change. The prediction was grim: global warming — with its sea-level rise, coastal flooding and droughts — would displace as many as 200 million people. Myers (2002) predicted that by as early as 2010 climate change and global warming would double the number of environmental refugees from the contemporary estimate of 25 million. While UNHCR estimates fall short of this prediction, the number went up to about 36 million in 2008.[4]

Many researchers have argued that Myers' (2002) gloomy predictions had been based on a simplistic approach to understanding the relationship between climate change and resulting population movement. For example, Black et al. (2011a) critique Myers (2002), stating that evidence to support major population movement in response to climate change is weak at best, often "largely based on "common sense" rather than insights from theory or evidence."[5] Instead, Black et al. (2011a) proposed a conceptual framework of migration that consists of five different drivers that induce people to move. Environmental change — one of those drivers — was proposed to have direct and indirect effect on migration. The authors argue that the direct effect of climate change on migration is through hazardousness of the climate change, while indirect effect comes through economic (productivity) and political (conflict over scarce resources) channels.

More recently, a number of researchers attempted to address the question of environmentally induced migration empirically.[6] Climate change was found to induce migration through various channels such as reduction in expected income, decline in land availability and agricultural productivity. But more importantly, not everyone was affected in similar fashion. Massey et al. (2010) found that while decline in agricultural productivity had a positive effect on out-migration probability, the effect differed by gender, ethnicity and distance of move. Drabo and Mbaye (2011) showed that more educated people were more likely to migrate, thus creating brain drain from already declining communities.[7]

Saldaña-Zorrilla and Sandberg (2009) look at the effects of recurrent natural disasters on out-migration in Mexico. In particular, the authors focus on vulnerable regions, where natural disasters together with decreasing income levels and lower access to credit disproportionately affect the poor. As a result, migration is viewed

[4] `http://www.un.org/en/globalissues/briefingpapers/refugees/nextsteps.html`

[5] See Hunter et al. (2015) for further critique of Myers (2002) and subsequent literature on the subject.

[6] See Saldaña-Zorrilla and Sandberg (2009), Massey et al. (2010), Drabo and Mbaye (2011), Mulyana et al. (2013), Bohra-Mishra et al. (2014).

[7] Kleemans (2014) produces similar findings for households that invest in long-term urban migration of household members.

as a product of altered income expectations. Using spatial econometrics techniques, the authors estimate an OLS model at municipality level averages. While poor municipalities that are frequently affected by natural disasters are found to have higher out-migration rates, individual and household heterogeneities are obscured in aggregation.

Furthermore, environmental changes such as declining land cover, increased time to gather inputs, increasing population density and decline in agricultural productivity lead to increased out-migration from affected areas. In one particular study, Massey et al. (2010) find that deforestation and declining access to livestock pastures lead to increased rural out-migration in Nepal. On the other hand, Gray (2010) shows that in Ecuador, lack or degradation of natural capital that stems from environmental change may lead to lower level of international migration, though this result is only significant for men. The author argues that land-rich households are more likely to send out international male migrants because they use their land income to facilitate migration.

Hunter et al. (2014) show that natural capital matters for temporary out-migration. The authors argue that access to environmental capital provides households with means to support temporary relocation of household members. The permanent migration is not affected by access to capital. Authors propose that temporary migration is "economic" in nature, but permanent migration is more likely to be for marriage and household formation, and as a result wouldn't be direclty affected by household resources.

The importance of capital endowments in migration decisions is also underlined in McLeman and Smit (2006). In some instances, landless farmers in rural Eastern Oklahoma during 1930s were forced to migrate due to repeated crop failure as a result of droughts and flooding, though this migration was not entirely voluntary. While land-owning households could decide to remain on their land following a year of bad crop, tenant farmers were forced out by landlords.

Mulyana et al. (2013) show that climate change has negative effects not only on agricultural, rural communities, but on urban communities as well. In a case study from Semarang, Indonesia, the authors show that as many as 200 thousand mostly poor households were at risk of moderate to severe flooding, with poorest being the most vulnerable.

Black et al. (2011c) propose a new approach to understanding the links between climate change and migration that recognizes the complexities of migration decision-making. The authors suggest that future researchers should not try to estimate the total number of climate migrants, but rather focus on specific locations, as well as "push" and "pull" factors inherent in these locations. This approach, the authors suggest, will prove of use in climate adaptation planning to policy-makers.

2.2.3 Sudden Disasters

Migration in response to sudden disasters — large and devastating events such as earthquakes and hurricanes — has received considerable attention in the literature. Not surprisingly, studies show that out-migration increases in the wake of a disaster. Sudden unexpected events do not leave household with many options to adapt. The survivors must move out, at least temporarily. However, not everyone can.

Halliday (2006) finds that households use migration as ex-post risk management strategy. The author shows that the El Salvador earthquake of 2001 is a significant and positive determinant of out-migration to the U.S., but only for households that are not cash-constrained. The poorest and most vulnerable are excluded from using migration to help recover from a devastating earthquake. This finding is supported by later work by Yang (2008).

Groen and Polivka (2008), Sastry and Gregory (2009) and Stringfield (2010) use Hurricane Katrina to study the effects of devastating events on migration and return probability, looking at race, gender and education as determinants of return. All three studies find that blacks, young adults, and poor are less likely to return home. Furthermore, the non-returnees are less likely to be employed and are shown to fair worse in terms of income than the returnees.

Gray et al. (2014) investigate the effects of the Indian Ocean Tsunami on population mobility in Indonesia. The authors find that households are 12 times more likely to leave a heavily damaged area than an undamaged area, and this effect is similar across socio-demographic characteristics. However, those with more liquid assets were found to be more likely to move.

Stal (2011) studies the effects of extreme flooding and tropical cyclones on migration patterns in Mozambique. Respondents in that study report loss of crops and farmland due to natural disasters, though they view permanent relocation as a last resort. Instead, they use periodic, semi-permanent relocation as an adaptive strategy.

Penning-Roswell et al. (2013) look at push and pull factors affecting migration decisions in Bangladesh. In particular, they investigate the effects of cyclones and surge-induced flooding on migration. Findings are similar to those of Stal (2011). Migrants, primarily from the poorest households, use migration for safety and income recovery in the aftermath of a disaster, but there is little permanent out-migration from disaster prone areas. In other words, people leave their homes only temporarily with intent to return as soon as it is safe and feasible.

However, some studies find evidence against disaster-induced migration. Paul (2005) shows that out-migration did not increase in the aftermath of 2004 tornado in Bangladesh. He attributes this result to government and non-government (NGO) help in disaster relief and recovery.

2.2.4 Slow-Onset Changes

While slow-onset changes could include temperature rise and rain variability, vast body of literature in this field is primarily concerned with droughts. Overall, researchers studying migratory response to droughts agree: prolonged decrease in rainfall increases out-migration from affected areas. The poor and rural households are the most severely affected, but often lack resources required to send migrants. There are also important gender differences. While men migrate for work, often to nearby or distant urban centers, women and children remain in the affected areas. The ability of households to smooth consumption in response to droughts is limited by lack of access to formal and informal credit and insurance markets, and not all communities are equally able to use migration as a risk-reducing and income-increasing mechanism.

Findley (1994) is one of the first studies on the effects of droughts on migration. Using Mali as a case study, the author finds that the effects of droughts on migration are gender and age-specific. In particular, while women and children moved in response to droughts, men did not; further, study respondents moved in circular pattern rather than leaving their homes to relocate permanently. This behavior is attributed to the fact that households could have sent migrants out prior to the beginning of the drought and relied on remittances to supplement their income during the drought years. In a way, this study supports the theory of migration as ex-ante risk mitigation strategy.

Henry et al. (2004) show that short-term droughts increase probability of short-term moves to distant, often foreign locations for men. Young women migrate primarily for marriage reasons, don't move across country borders and stay at their new locations permanently. In both cases, out-migration is higher from drier areas.

Gray (2010) and Gray and Mueller (2012a) look at the effects of droughts on probability of out-migration in Ecuador and Ethiopia. Both studies find that droughts have positive effect on population displacement, with men more likely to migrate in an event of a drought. Again, the poor and landless households are affected disproportionately, since land-owning households can use their assets to enable full or partial household migration.

Barrios et al. (2006) and Marchiori et al. (2012) set out to understand how weather variability affects migration in sub-Saharan Africa. Both studies look at decrease in rainfall, with Marchiori et al. (2012) also considering increase in temperature, as causes of droughts and drought-related displacement. Both studies find evidence that rural households react to droughts by sending migrants to rural areas, thus increasing urbanization in sub-Saharan Africa. Marchiori et al. (2012) also find that many households use internal rural-urban migration as a stepping stone for subsequent international migration.

Kazianga and Udry (2006) show that households looking for ways to smooth consumption during droughts may find it difficult to do so. Using rural Burkina Faso as a case study, the authors show that risk sharing and use of assets as buffer stocks are not effective during droughts. Hardship caused by a drought is then amplified by lack of access to formal and informal credit and insurance market, again primarily affecting the most vulnerable to the greatest extent.

Finally, Hunter et al. (2013) show that rainfall deficits increase migration, but only in communities that have strong ties with the outside world. In other words, communities that sent migrants out prior to droughts are more likely to be able to send migrants during droughts, while other communities would lack social capital to do so. In fact, communities that have smaller social networks see reduction in migration during periods of droughts.

2.2.5 Floods

Literature on the effects of floods on migration mainly considers flooding that was induced by a larger event, such as a tropical cyclone. This type of flooding is sudden and unexpected, and it often simultaneously affects large areas of a country or a state. Examples of this research include Stal (2011) and Penning-Roswell et al. (2013) discussed above, along with many others. The effects of smaller local flooding on migration receive considerably less attention in the literature. The two notable papers in this area are by Gray and Mueller (2012b) and Mueller et al. (2014)

Gray and Mueller (2012b) study the effects of flooding on migration in Bangladesh. The authors show that out-migration from affected communities following floods is reduced. They attribute this finding to two channels. On one hand, affected households may not have the means needed to finance migration. On the other hand, floods may be increasing labor demand at home. Young men, who would otherwise be the ones most likely to migrate, are now in high demand for recovery and rebuilding efforts at their origin communities.

Mueller et al. (2014) look at the long-term permanent migration decisions in the aftermath of floods in rural Pakistan. The authors find that floods hare limited to no effect on out-migration, though poor and landless are more likely to migrate. They attribute their finding to high prevalence of flood relief programs that may incentivize people to stay put, while the private best response could have been to migrate out of flood-prone areas.

2.3 Background and Data

Indonesia is the fourth most populated country in the world, but it ranks 125th out of 187 in the IMF list of PPP adjusted GDP per capita.[8] In recent years Indonesia has experienced a high level of rural to urban migration, and current projections estimate that by 2025 nearly 70% of Indonesians will reside in urban areas.[9] Nearly 40% of population are employed in agriculture, the largest employment sector (von

[8] 101st in World Bank.

[9] `http://www.urbanknowledge.org/ur/docs/Indonesia_Report.pdf`

Rooij, 2012). Rice, corn and cassava remain the most important crops (Barbier, 1989). Indonesian population is growing at about 1.3% per year.[10] Java is the most populous island, home to 60% of population, but comprising only 7% of total area.

Floods are the most common natural disasters in Indonesia, and to some extent are expected.[11] Floods account for 70% of all most recent natural disasters in Indonesia, the remaining 30% are droughts, landslides, forest fires, heat waves, storms and other disasters (Mulyana et al., 2013). Starting in 2007, the Indonesian government has begun undertaking a flood management program that is designed for "risk reduction, either through physical construction or community's capacity building" (Permana et al., 2013). Yet floods continue to affect millions of Indonesians every year.

In this study, we use the Indonesian Family Life Survey (IFLS), a periodic panel survey administered by RAND. There are currently four waves available, spanning years 1993–2007. The sample spreads across 13 of 32 provinces in Indonesia, but represents about 83% of population. The 1993 wave has over 33,000 people living in 7,224 households in 312 sample communities. The sample grows to over 50,000 people in 13,536 households by 2007. Recontact rate in each wave of the the survey is over 90%.

The unique feature of the IFLS is that it provides retrospective annual migration histories for all respondents age 12 and older. Additionally, it follows migrants even after they move out of sample communities. This reduces attrition due to out-migration and allows us to investigate the effects of recent floods even in communities that are not in the IFLS sample. We build a person-year panel, spanning all sixteen years of the survey. There are over 26,000 migration instances during the survey years, 1.2% of which are out of a community that has experienced a flood in the previous calendar year. We restrict our sample to adults of age 15 and above, which results in an unbalanced panel for nearly 40 thousand individuals or 360 thousand person-year observations. Average migration rate of all respondents age 15 and older in the IFLS is 6.25%, which is nearly identical to the rate found by Gray et al. (2014) using different data sources.

Floods are highly localized, and can be treated as idiosyncratic community-specific shocks, rather than aggregate risks that affect multiple sample communities at a time.[12] Figure 2.1 shows number of disasters per year in the 16 years of data. On average, 10 communities in our sample experience a flood in a given year. In 2001 no community experienced a natural disaster of any kind, while in 2007 there were 41 floods.

Figure 2.2 shows number of floods a community experienced in the entire 16 years of our data. Nearly 65% of sample communities did not have any floods during the entire sample period, while around 35% experienced one or more flood. No community

[10] `http://data.worldbank.org/indicator/SP.POP.GROW`

[11] See Table 2.1 for details

[12] Here, we exclude hurricanes (typhoons) and hurricane-induced floods from the flood category, including them with other disasters.

has been hit by more than four floods. We use variation in timing and number of floods to investigate the effects floods have on likelihood of out-migration.

2.3.1 Variable Selection

Our model and variable selection are motivated by Angeles et al. (2005), Massey and Espinosa (1997), and VanWey (2005). The first study shows that community fixed-effects have an impact on individual-level outcomes, therefore, it's important to cluster at the community rather than the household level.[13] Massey and Espinosa (1997) test a wide array of controls that can theoretically determine migration outcomes, showing what variables are meaningful both from theoretical and empirical standpoint.

We include a set of individual-, household-, and community-level characteristics that are generally associated with migration. The individual-level characteristics include age, gender, marital status, level of education and previous migration experience. Household-level controls include number of children under 6 and under 15 in the household, and house, land and livestock ownership status of each household. Community-level variables are binary indicators of whether each community has access to telephones and a post office.

Average age of all individuals in the sample is 35 years old, migrants are younger on average, at 28 years; non-migrants' average age is 37. About 49% of our sample are male, however men are more likely to migrate. 53% of all migrants are male, compared to 48% of non-migrants. 53% of our sample are married, with 46% of migrants married, compared to 55% of non-migrants.

40% of our sample completed high school. Migrants are better educated, 60% of migrants have a high school degree; only 37% of non-migrants do. Migrants are more likely to have previous migration experience. Among non-migrants, most have between 0 and 1 previous migrations, migrants underwent between 2 and 3 previous moves.

Migrants come from households that have fewer children under the age of 6 or 15. On average, 79% of the sample live in a household that owns their house or part thereof. Migrants come from households that are less likely to own their homes, only 61% of migrants come from such households. 77% of sample individuals come from households that own at least a little land, but there is no difference in migrant-sending patterns. Nearly 34% of sample households own livestock, but only 31% of all households send at least one migrant.

Since the present study clusters outcomes on community level, we are limited to choice of community-specific characteristics to those that vary over time. The two controls selected are a binary indicator of whether the community has access to telephones, either landline or mobile, and a binary indicator of whether there is a post

[13] Here, an OLS specification with household level fixed effects explains about 9% of variation in the data, while the same specification clustering at a community level explains 72%.

office, either stationary or mobile, in the community. Both variables are intended to proxy for how connected a community is to the outside world.

Table 2.2 presents detailed summary break down by wave and migrant status. All variables are reported as percents of total, except age, previous migration experience, and number of children under 6 and under 15 in households, which are averages. M and NM designations stand for migrant and non-migrant, respectively. Variables for migrants and non-migrants are summarized as reported at preceding wave. For example, of those who migrated between 1993 and 1997, 52.7% had high school degree as reported in 1993. 48.6% of households that sent migrants between 1993 and 1997 owned their house, compared to 82.8% of households that did not send migrants in 1993–1997. 53.3% of migrants that moved between 1993 and 1997 came from communities with phone access. Only 35.4% of non-migrants in the same period resided in communities that had telephones.

2.4 Model

In order to model migration outcomes, we employ a panel version of the logistic regression, conditional fixed effects logit with standard errors adjusted for random effects clustering on community level. This logistic model is standard in migration literature.[14] Here we exploit the longitudinal design of the IFLS and variation in timing of natural disasters across communities. An important advantage of our research design is that we can compare mobility in areas affected by floods and those that are not affected in a particular year. Additionally we can compare out-migration from a community in years when it was affected by floods and years of calm.

Formally, we specify the following equation:

$$Pr(y_{ihc,t+1} = 1 | D_{ct}, X_{ihct}, X_{hct}, X_{ct}, \alpha_c) = \Lambda\left(\beta D_{ct} + \gamma X_{ihct} + \theta X_{hct} + \mu X_{ct} + \alpha_c\right)$$

where $Pr(y_{it+1} = 1)$ is the conditional probability an individual i from household h moves out of community c in year $t+1$. D_{ct} is a binary indicator taking value of 1 if a source community experienced a flood in year t. Xs are vectors of individual, household, and community characteristics respectively. α_c is the vector of community-specific fixed effects. Outmigration at time $t+1$ is predicted by individual, household and community variables at time t. The model is estimated using Stata *xtlogit* command.[15]

Let $c = 1, ..., C$ denote the community, $i = 1, ...I_c$ denote the observations of the $c's$ community, y_{ci} denote the dependent variable and x_{ci} denote the vector of covariates as defined above. Finally, y_c denotes the outcomes of the $c's$ community

[14] For example, see Massey and Espinosa (1997) among many others.

[15] `http://www.stata.com/manuals13/xtxtlogit.pdf`

as a whole. Let $k_{1c} = \sum_{i=1}^{I_c} y_{ci}$ be the observed number of migrations out of a given community.

The conditional log-likelihood is given by

$$lnL = \sum_{c=1}^{C} \left\{ \sum_{i=1}^{I_c} y_{ci} x_{ci} \beta - log f_c(T_c, k_{1c}) \right\}$$

where $f_c(T_c, k_{1c})$ is the denominator of the conditional probability function.

One drawback of a conditional fixed-effects logit model is that communities without any out-migrants or communities where everyone migrated drop out of the estimation sample. This is not, however, a concern here, as every community has seen at least one out-migration in the sixteen year period considered and no community experienced total migration. Additionally, we selected time-varying community-level controls discussed above to avoid them being differenced out during estimation.

We assume that unobserved error is uncorrelated with the covariates, but can be correlated within a community. Following Angeles et al. (2005) we correct for clustering on the community level in order to account for potential correlation of households in the same community and allow for use of community-level controls.

From a theoretical standpoint, floods can have two distinct effects on out-migration. On one hand, floods can make migration more likely as living conditions in the origin community deteriorate. Stal (2011) presents evidence from Mozambique, showing that fast onset disasters such as floods and tropical cyclones induce migration because of deteriorating living conditions. In particular, he cites the World Health Organization (2007) which in turn states that floods often cause loss of housing, access to medical facilities, sanitation, and safe drinking water. Paul and Routray (2010) lists additional potential flood impacts detrimental to living conditions in affected communities. Those include soil erosion, drinking water pollution, loss of earnings and assets, loss of food security, damage to infrastructure, and upper respiratory and water-borne diseases.

Another study by Poston et al. (2009) shows that people tend to avoid undesirable climates. The authors document that voluntary internal migrants in the U.S. try to avoid weather extremes when making their migration decisions. McLeman and Smit (2006) show that migration can be viewed as an adaptive response, using 1930s Oklahoma as a case study. A number of other studies show similar results. Additionally, households may be using migration as ex ante or ex post disaster mitigation strategy, increasing migration in order to smooth consumption and augment income through remittances. Most recent examples of research in this area include Kleemans (2014) and Gray and Mueller (2012a).

However, a number of studies find migration in the aftermath of natural disasters to be less likely. This could be due to several factors among which most prominent are immediate loss of income, making migration difficult to finance, expectation of future government help and increased employment, and desire to remain in the affected community to help with the recovery effort.

Halliday (2006) looks at migration as an ex-post risk management strategy. Using 2001 earthquake in El Salvador, he shows that out-migration from the affected communities to the U.S. is reduced. He proposes two explanations for this behavior. On one hand, households may be unable to finance migration due to post-disaster liquidity constraints. On the other hand, households may want to keep family members at home to increase availability of labor for recovery effort. Halliday (2006) finds that households reduce migration at any level of wealth, thus stating that worker retention is the primary motivation for reduction in out-migration.

Stal (2011) shows that flood-induced displacement is either periodic or temporary, noting that respondents depend on their origin communities for their livelihood and are reluctant to move away even in presence of natural disasters. He attributes this reluctance to importance of social networks and local farming/fishing knowledge in rural Mozambique. Penning-Roswell et al. (2013) show that severe floods in Bangladesh have only modest effect on out-migration. While people temporarily move away for safety and income recovery, most view migration as last resort, preferring to weather the shocks in place.

In other studies, Paul (2005) and Mueller et al. (2014) find more evidence against the hypothesis that disasters induce migration. The former study uses data from Bangladesh to show that there was no out-migration from affected communities following a 2004 tornado. This finding is attributed to government and non-government help for disaster recovery. The latter study uses floods data from rural Pakistan to show that flooding has at best modest impact on probability of out-migration. Mueller et al. (2014) is particularly interesting in the context of present study. The authors estimate a model that is very similar to ours and find somewhat similar, although insignificant results.[16]

To test this theory, we estimate several specifications of the logistic regression detailed above. In some specifications we control for age, gender, marital status and education, as these have been shown to be strong predictors of migration in non-disaster contexts. Additional individual- and household-level covariates include number of minor children residing in the household, wealth, measured as ownership of a house, farmland/equipment or livestock, and whether a migrant has previous migration experience. Community-level controls include presence of phones and post offices in pre-disaster communities.

Our data do not allow us to identify separately which of the theoretical channels could be primarily responsible for decrease in likelihood of migration following a flood. The IFLS did not collect data about out-of-community rebuilding and recovery financing until the last wave. Even in the last wave of data collection, the information about which agency provided help following a flood and the nature of this help is

[16]The model used by Mueller et al. (2014) is a fixed effects logit with village and time fixed effects.

incomplete.[17] In addition, individual and household incomes are only collected at the years of survey, rendering it impossible to track annual migrations in response to immediate short-lived income shocks. We do, however, provide limited check and a discussion of results in the following section.

2.5 Results

Table 2.3 shows the results of four different specifications of the logit regression using floods as the variable of interest. We build up from controlling only for recent floods to including individual-, household- and community-level controls into the model.[18] Column (5) of Table 2.3 presents results of estimating the same specification as shown in Column (4), but with addition of year dummies to control for time effects. The variable of interest — flood — is negative and significant in all five specifications. Other controls, such as marital status, age, migration experience and property ownership are in line with findings of previous literature.[19] All else equal, older people are less likely to move, education and migration experience have positive effects on probability of migration, members of households that own their homes are more likely to stay put.

We then repeat our estimation for disasters other than floods. The results are presented in Table 2.4. While most other covariates are similar to the flood specification in signs and significance, disasters other than floods are significant at 10% only in the first two specifications (columns (1) and (2) of Table 2.4). They are not significant when controlling for household- and community level characteristics (columns (3) and (4) of Table 2.4) as well as when estimating full specification that includes year dummies (column (5) of Table 2.4).

On the household level, we estimate two specifications for each control of interest. Columns (1) and (2) of Table 2.11 show results for household- and community-level specifications of flood regressions respectively. Floods are still negative and significant, while all other controls are comparable to migration literature in signs and magnitude. Other disasters are positive and significant with household-level controls (column (3) of Table 2.11), but not significant when controlling for community characteristics (column (4) of Table 2.11). All other covariates are comparable to those in columns (1) and (2) and are similar to other literature.

[17] Ideally, we would have access to detailed accounts of the kinds of agencies providing help and the kind/amount/duration of help provided. Information regarding clean up effort, rebuilding and future disaster mitigation would provide us with more precise identification of post-disaster recovery on community level.

[18] Columns (1)–(4) of Table 2.3 respectively.

[19] In particular, see Massey and Espinosa (1997) for expected linkages between migration determinants and migration outcomes.

2.5.1 Robustness Checks

We have estimated various other specifications to check the results. We have used two alternative definitions of flood to account for possible time discrepancy in our definitions of floods in relation to migration. Rather than defining flood-related migration as a move that occurred in a calendar year after the calendar year of a disaster, we have defined contemporaneous flood-related migrations as the ones occurring in the same calendar year as a flood. In addition, we've estimated the effects of floods on migration using a definition of flood-related migration that combines contemporaneous and lagged definitions. Columns (2) and (3) of Table 2.12 show results of these regressions using full specification with individual-, household- and community-level controls. To facilitate comparison, column (1) repeats column (4) of Table 2.3. Results of other specifications are similar and are not shown here to conserve space.

Tables 2.5 and 2.6 present specifications identical to those described above for Tables 2.3 and 2.4, but also include age squared terms. Presence of the age squared terms does not change the main results. Floods are still significant predictors of reduced out-migration from affected communities, while other disasters are not.

Tables 2.7 and 2.8 show several additional specifications to ensure robustness of the results. In order to conserve space and facilitate comparison between the two tables, the only coefficients shown are those that are significant in at least one specification. All specifications described below include a full set of individual-, household- and community-level variables as well as year dummies. These specifications are comparable to specifications in column (5) of Tables 2.3 and 2.4.

We have tried to restrict our sample by age, following VanWey (2005), Groen and Polivka (2008) and Massey et al. (2010) among others. We re-estimated all models using a sample of adults between ages of 15 and 49 only, but results still stand. Coefficient on floods variable is negative and significant at 1%, as can be seen in column (1) of Table 2.7. Other disasters are not significant predictors of out-migration among adults of ages 15–49, as seen in the first column of Table 2.8. We have then estimated the same specification for all adults ages 20 and above. The results are shown in column (2) of Tables 2.7 and 2.8. Coefficient on floods is negative and significant, while other disasters are not significant at 10%.

The last three columns of Tables 2.7 and 2.8 present specifications that include interaction of flood/disaster dummy with gender, age, and previous migration experience.[20] In all cases, coefficients for flood dummies, shown in Table 2.7 are negative and significant; coefficients for other disaster dummies, shown in Table 2.8 are not significant; all interaction terms are not significant.

Table 2.9 shows estimation results separate for men and women. In all cases, we estimate a full specification that includes individual-, household-, and community-level controls as well as year dummies. Floods are negative and significant in predicting out-migration from affected communities for both men and women; other disasters

[20] Columns (3), (4), and (5) of Tables 2.7 and 2.8 respectively.

are not. Age and house ownership are negative and significant in all four cases, previous migration experience is positive and significant. While livestock ownership reduces the probability men migrate following any type of a natural disaster, there is no significant difference for women. Married women are less likely to move following a natural disaster other than flood. While not significant, presence of children in household has opposite sign for men and women. Community characteristics, when significant, are negative across the board.

We perform a limited check of the role of outside recovery financing using the last wave of the IFLS. We re-estimate the specification detailed in Table 2.3, including one additional control: a binary indicator taking a value of one when a community head reports that the community received outside help for recovery following a flood. Results of this estimation are shown in Table 2.10. Provision of outside help has a positive and significant effect on probability of out-migration from affected communities in all specifications. Separately, floods still affect migration probability in a negative way, however, floods are significant predictors of out-migration only in the first two specifications.

The subsample considered here is limited to 17 flood occurrences affecting 2,597 individuals and 81 corresponding out-migrations in years 2001–2007. Such small sample is likely to produce noisy estimates. However, the signs and relative magnitudes of estimates are comparable to those shown in Table 2.3. There is not enough variation in the data to allow for examination of differential effects provision of outside help might have on various sub-populations.

Communities that receive monetary help following a flood are more likely to send out migrants.[21] This result suggests that desire to stay behind and help with recovery effort is partly mitigated by provision of government and non-government post-disaster help. Furthermore, this result is suggestive of predominance of income channel as restricting out-migration from affected communities. In order to further test this theory we would require more details regarding the nature of outside help provided and how different communities are affected by the help following floods. There is currently not enough variation in the data to study this interaction.

2.6 Conclusion

In this paper, we study the effects of recent local floods on probability of leaving an affected community in the following year. Using at 16-year panel provided by the RAND Corporation, we estimate conditional fixed effects maximum likelihood logit, clustering on community level to account for potential within-community correlation.

[21] We calculate corresponding predicted probabilities using specification shown in Column (5) of Table 2.10. Predicted probability of out-migration from a flood-affected community that received outside recovery help is 61%, compared to 15% probability of out-migration from a flood-affected community that did not receive any help following a flood. This 46% difference is significant at 5% confidence level.

We find that unlike any other disaster type, floods have a significant negative effect on probability of out-migration.

This can be explained by several factors. First, while floods diminish the immediate quality of life, they shouldn't have an affect on long-term income and wealth. In this respect, floods are different from droughts that can have persistent and negative effects on income. Floods are also different from sudden-onset disasters such as earthquakes and hurricanes since they are less likely to permanently destroy housing and infrastructure in large areas.

Furthermore, jobs are created when central and local governments step in to mitigate the effects of a flood. Availability of temporary jobs, together with the expectation of return to normal income levels next year convince household and individuals to stay put and recover from flood instead of migrating away, even if temporarily.

Our results have important implications for the policy-makers working on disaster relief programs. Traditionally immediate disaster relief effort is concentrated in temporary resettlement areas, while non-moving residents of disaster communities are left to wait for the recovery programs. However, since floods don't induce migration, in the event of local floods it would be advisable to focus on helping the stayers, not movers.

While we illuminate the immediate affects of floods on out-migration probability, further research is required. The first step would be to explicitly include provincial policies and reconstruction efforts into our estimation. Once we control for government help, it's plausible to think that floods would have smaller effect on migration. This result would be expected, since floods are likely to destroy income in the current period only, with nearly full recovery in the following years.

It would also be interesting to investigate econometric and structural dynamics of migration decisions in presence of floods. Such models would provide researchers and policy makers with flexibility to investigate the effects of proposed flood mitigation strategies and further our understanding of affects of flooding on migration.

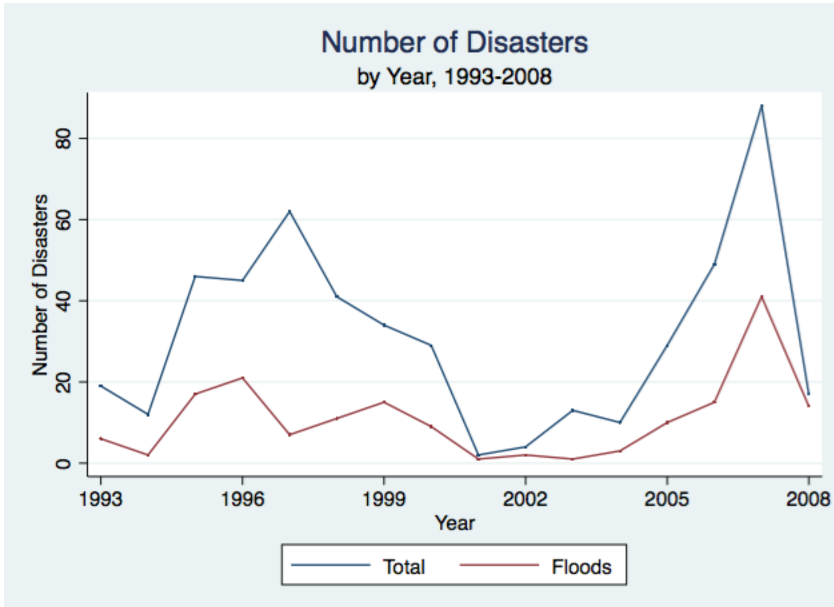


Figure 2.1: Number of Disasters per Year

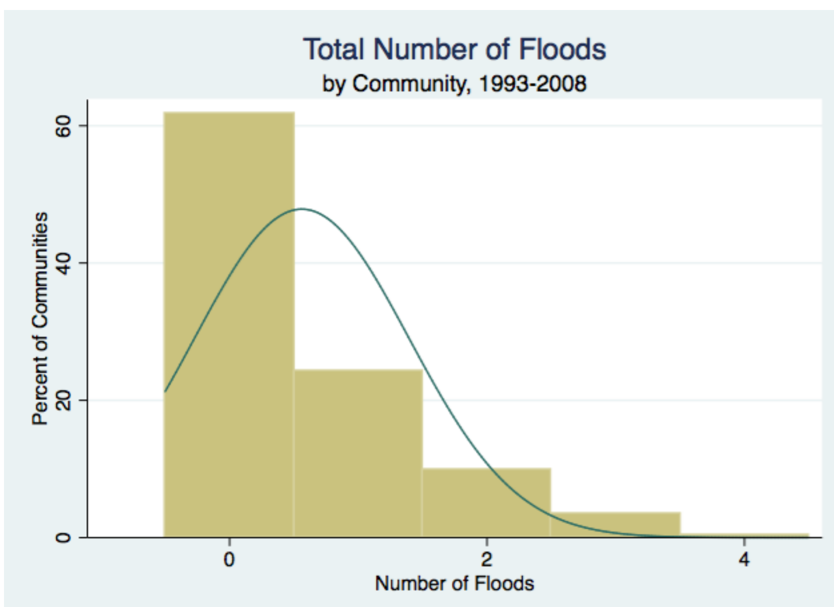


Figure 2.2: Number of Floods per Community

Table 2.1: Top-8 Natural Disasters in Indonesia, 1993–2007

Disaster Type	Number of Incidents	Number of Deaths	Number of Injured	Number of Homeless	Total Number Affected	Total Damages in 000 $U.S.
Flood	62	2,985	1,795	25,235	4,690,805	2,268,276
Earthquake	45	174,367	152,613	1,397,288	5,331,126	8,830,676
Landslide	27	1,088	393	34,855	332,329	115,004
Epidemic	18	3,009	0	0	139,023	0
Volcano	16	102	139	0	134,031	0
Wildfire	8	243	470	0	3,034,470	9,315,800
Drought	2	672	0	0	1,080,000	89,000
Storm	2	4	0	0	3,715	0

Source: “EM-DAT: The OFDA/CRED International Disaster Database
www.em-dat.net - Universit Catholique de Louvain - Brussels - Belgium”

Table 2.2: Summary Statistics by Migrant Status

	1997		2000		2007	
	M	NM	M	NM	M	NM
Flood	3.88	0.54	2.38	3.75	2.03	3.55
Individual controls						
Age	28.3	37.0	27.2	37.0	26.3	36.9
Male	53.1	47.5	53.4	47.8	53.0	47.6
Married	59.6	68.7	45.3	52.2	40.9	50.2
Previous migration	1.63	0.43	1.80	0.53	1.45	0.63
High School	52.7	27.0	54.9	32.3	62.0	36.9
Household controls						
Kids under 6 in HH	0.37	0.36	0.07	0.08	0.07	0.09
Kids under 15 in HH	0.70	0.81	0.16	0.22	0.21	0.24
Own house	48.6	82.8	65.1	83.0	60.5	82.4
Own land	74.2	79.9	75.6	78.9	78.4	78.4
Own livestock	30.8	36.4	32.0	34.3	31.6	34.1
Community controls						
Phone	53.3	35.4	49.6	35.9	58.7	48.9
Post	48.2	29.9	48.0	35.4	47.4	38.0
Nobs	1,620	20,050	2,985	22,652	5,269	24,677

Rates, except average age, average number of previous migrations, average number of children under 6 and under 15, and total number of observations; all at preceding wave.

Table 2.3: Floods

	(1)	(2)	(3)	(4)	(5)
Flood	-0.39***	-0.37***	-0.45***	-0.47**	-0.39*
	(0.101)	(0.101)	(0.189)	(0.236)	(0.238)
Individual controls					
Age		-0.03***	-0.04***	-0.02***	-0.02***
		(0.001)	(0.002)	(0.003)	(0.003)
Male		0.08***	0.07	0.08	0.08
		(0.026)	(0.047)	(0.059)	(0.059)
Married		0.02	-0.20***	-0.20***	-0.22***
		(0.026)	(0.051)	(0.067)	(0.067)
Previous migration		0.27***	0.34***	0.36***	0.36***
		(0.006)	(0.012)	(0.014)	(0.014)
High School		0.18***	0.21***	0.24***	0.27***
		(0.032)	(0.059)	(0.074)	(0.074)
Household controls					
Kids under 6 in HH			-0.01	0.04	0.02
			(0.070)	(0.082)	(0.084)
Kids under 15 in HH			0.02	-0.02	-0.03
			(0.034)	(0.044)	(0.045)
Own house			-0.33***	-0.50***	-0.48***
			(0.061)	(0.077)	(0.078)
Own land			-0.08	-0.10	-0.11
			(0.066)	(0.080)	(0.081)
Own livestock			-0.01	-0.11	-0.12
			(0.057)	(0.070)	(0.070)
Community controls					
Phone				-0.18	-0.09
				(0.113)	(0.123)
Post				-0.19	-0.20
				(0.138)	(0.143)
Nobs	305,914	305,401	128,074	116,761	116,761
LR chi2	16.41	2732.00	1406.98	861.52	902.97
Prob > chi2	0.000	0.000	0.000	0.000	0.000
Predicted probabilities†					
No flood	0.50	0.31	0.19	0.21	0.18
Flood	0.40	0.24	0.13	0.15	0.13
Difference	-0.10***	-0.07***	-0.06***	-0.06**	-0.05*
	(0.024)	(0.017)	(0.020)	(0.028)	(0.026)

† At means of other covariates

Table 2.4: Disasters other than Floods

	(1)	(2)	(3)	(4)	(5)
Disaster	-0.12*	-0.11*	0.01	-0.13	-0.12
	(0.065)	(0.065)	(0.100)	(0.124)	(0.129)
Individual controls					
Age		-0.03***	-0.04***	-0.02***	-0.02***
		(0.001)	(0.002)	(0.003)	(0.003)
Male		0.08***	0.07	0.08	0.08
		(0.026)	(0.047)	(0.059)	(0.059)
Married		0.02	-0.20***	-0.20***	-0.22***
		(0.026)	(0.051)	(0.067)	(0.067)
Previous migration		0.27***	0.34***	0.36***	0.37***
		(0.005)	(0.012)	(0.014)	(0.014)
High School		0.18***	0.21***	0.24***	0.27***
		(0.032)	(0.059)	(0.074)	(0.074)
Household controls					
Kids under 6 in HH			0.02	0.04	0.02
			(0.070)	(0.082)	(0.084)
Kids under 15 in HH			0.02	-0.02	-0.03
			(0.034)	(0.044)	(0.045)
Own house			-0.34***	-0.48***	-0.49***
			(0.061)	(0.077)	(0.078)
Own land			0.08	-0.10	-0.11
			(0.066)	(0.081)	(0.081)
Own livestock			-0.01	-0.11	-0.11
			(0.057)	(0.070)	(0.070)
Community controls					
Phone				-0.16	-0.09
				(0.113)	(0.123)
Post				-0.18	-0.19
				(0.137)	(0.143)
Nobs	305,914	305,401	128,074	116,761	116,761
LR chi2	3.73	2720.27	1400.47	858.23	900.90
Prob > chi2	0.053	0.000	0.000	0.000	0.000
Predicted probabilities†					
No flood	0.50	0.31	0.18	0.21	0.18
Flood	0.47	0.29	0.18	0.19	0.17
Difference	-0.03*	-0.02*	0.00	-0.02	-0.01
	(0.016)	(0.012)	(0.014)	(0.018)	(0.017)

† At means of other covariates

Table 2.5: Floods

	(1)	(2)	(3)	(4)	(5)
Flood	-0.39***	-0.37***	-0.45**	-0.47**	-0.39*
	(0.101)	(0.101)	(0.190)	(0.236)	(0.238)
Individual controls					
Age		-0.01**	-0.04***	-0.01	-0.01
		(0.006)	(0.010)	(0.012)	(0.012)
Age squared		-0.001***	0.001	-0.001	-0.001
		(0.000)	(0.001)	(0.001)	(0.001)
Male		0.08***	0.07	0.08	0.08
		(0.026)	(0.047)	(0.058)	(0.059)
Married		-0.01	-0.19***	-0.23***	-0.25***
		(0.027)	(0.053)	(0.071)	(0.071)
Previous migration		0.26***	0.34***	0.36***	0.36***
		(0.006)	(0.012)	(0.015)	(0.015)
High School		0.19***	0.21***	0.25***	0.27***
		(0.032)	(0.059)	(0.074)	(0.074)
Household controls					
Kids under 6 in HH			0.02	0.03	0.01
			(0.070)	(0.082)	(0.084)
Kids under 15 in HH			0.02	-0.02	-0.03
			(0.034)	(0.044)	(0.045)
Own house			-0.34***	-0.48***	-0.48***
			(0.061)	(0.077)	(0.078)
Own land			-0.08	-0.10	-0.11
			(0.066)	(0.081)	(0.081)
Own livestock			-0.01	-0.11	-0.11
			(0.057)	(0.070)	(0.070)
Community controls					
Phone				-0.18	-0.10
				(0.113)	(0.123)
Post				-0.19	-0.20
				(0.138)	(0.143)
Nobs	305,914	305,401	128,074	116,761	116,761
LR chi2	16.41	2743.67	1407.30	863.22	905.07
Prob > chi2	0.000	0.000	0.000	0.000	0.000
Predicted probabilities†					
No flood	0.50	0.37	0.18	0.25	0.22
Flood	0.40	0.29	0.12	0.18	0.17
Difference	-0.10***	-0.08***	-0.06***	-0.07**	-0.05*
	(0.024)	(0.020)	(0.020)	(0.033)	(0.031)

† At means of other covariates

Table 2.6: Disasters other than Floods

	(1)	(2)	(3)	(4)	(5)
Disaster	-0.12*	-0.11*	0.01	-0.13	-0.12
	(0.065)	(0.065)	(0.100)	(0.124)	(0.129)
Individual controls					
Age		-0.01**	-0.04***	-0.01	-0.01
		(0.006)	(0.010)	(0.012)	(0.012)
Age squared		-0.001***	-0.001	-0.001	-0.001
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Male		0.08***	0.07	0.08	0.08
		(0.026)	(0.047)	(0.058)	(0.059)
Married		-0.01	-0.19***	-0.24***	-0.25***
		(0.027)	(0.053)	(0.071)	(0.071)
Previous migration		0.26***	0.34***	0.36***	0.36***
		(0.006)	(0.012)	(0.015)	(0.015)
High School		0.19***	0.21***	0.25***	0.27***
		(0.032)	(0.059)	(0.074)	(0.074)
Household controls					
Kids under 6 in HH			0.02	0.03	0.01
			(0.070)	(0.082)	(0.084)
Kids under 15 in HH			0.02	-0.02	-0.03
			(0.034)	(0.044)	(0.045)
Own house			-0.34***	-0.48***	-0.48***
			(0.061)	(0.077)	(0.078)
Own land			-0.08	-0.10	-0.11
			(0.066)	(0.081)	(0.081)
Own livestock			-0.01	-0.17	-0.11
			(0.057)	(0.070)	(0.070)
Community controls					
Phone				-0.17	-0.09
				(0.113)	(0.123)
Post				-0.18	-0.19
				(0.138)	(0.143)
Nobs	305,914	305,401	128,074	116,761	116,761
LR chi2	3.73	2731.95	1401.00	859.91	902.97
Prob > chi2	0.053	0.000	0.000	0.000	0.000
Predicted probabilities†					
No flood	0.50	0.37	0.17	0.25	0.22
Flood	0.47	0.35	0.17	0.23	0.20
Difference	-0.03*	-0.02*	0.00	-0.02	-0.02
	(0.016)	(0.014)	(0.013)	(0.020)	(0.019)

† At means of other covariates

Table 2.7: Robustness checks: Floods

	(1)	(2)	(3)	(4)	(5)
Flood	-0.43***	-0.44***	-0.35**	-0.81**	-0.55***
	(0.153)	(0.144)	(0.180)	(0.374)	(0.168)
Individual controls					
Age	-0.01***	-0.02***	-0.02***	-0.02***	-0.02***
	(0.003)	(0.001)	(0.002)	(0.002)	(0.002)
Male	-0.001	0.02	-0.003	0.08	-0.01
	(0.041)	(0.039)	(0.038)	(0.038)	(0.038)
Married	-0.01	-0.11**	-0.001	-0.002	-0.002
	(0.050)	(0.044)	(0.043)	(0.043)	(0.043)
Previous migration	0.30***	0.26***	0.29***	0.29***	0.27***
	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)
High School	0.24***	0.26***	0.22***	0.22***	0.33***
	(0.050)	(0.047)	(0.046)	(0.046)	(0.046)
Household controls					
Own house	-0.66***	-0.61***	-0.66***	-0.66***	-0.66***
	(0.047)	(0.045)	(0.044)	(0.044)	(0.044)
Community controls					
Post	-0.44***	-0.35***	-0.39***	-0.39***	-0.39***
	(0.083)	(0.082)	(0.078)	(0.078)	(0.078)
Interaction variables					
Gender w Flood			-0.26		
			(0.273)		
Age w Flood				0.01	
				(0.01)	
Experience w Flood					0.05
					(0.056)
Nobs	163,854	196,952	116,761	116,761	116,761
LR chi2	1192.48	1386.08	1474.67	1474.75	1474.59
Prob > chi2	0.000	0.000	0.000	0.000	0.000
Predicted probabilities†					
No flood	0.30	0.21	0.26	0.26	0.26
Flood	0.22	0.15	0.19	0.19	0.18
Difference	-0.08***	-0.06***	-0.07***	-0.07***	-0.08***
	(0.025)	(0.017)	(0.020)	(0.021)	(0.021)

† At means of other covariates

Table 2.8: Robustness checks: Other Disasters

	(1)	(2)	(3)	(4)	(5)
Disaster	-0.14	-0.12	-0.24	0.16	-0.17
	(0.135)	(0.127)	(0.177)	(0.329)	(0.151)
Individual controls					
Age	-0.03***	-0.03***	-0.02***	-0.02***	-0.02***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Male	0.08	0.13**	0.07	0.08	0.08
	(0.064)	(0.060)	(0.060)	(0.058)	(0.058)
Married	-0.18**	-0.34***	-0.21***	-0.20***	-0.20***
	(0.076)	(0.068)	(0.067)	(0.067)	(0.067)
Previous migration	0.38***	0.33***	0.36***	0.36***	0.36***
	(0.016)	(0.015)	(0.014)	(0.014)	(0.015)
High School	0.188**	0.28***	0.25***	0.24***	0.25***
	(0.078)	(0.076)	(0.074)	(0.074)	(0.074)
Household controls					
Own house	-0.51***	-0.44***	-0.48***	-0.48***	-0.48***
	(0.082)	(0.080)	(0.078)	(0.077)	(0.077)
Community controls					
Post	-0.18	-0.12	-0.18	-0.18	-0.18
	(0.148)	(0.144)	(0.138)	(0.138)	(0.138)
Interaction variables					
Gender w Flood			0.22		
			(0.237)		
Age w Flood				-0.01	
				(0.009)	
Experience w Flood					0.02
					(0.049)
Nobs	81,414	104,683	116,761	116,761	116,761
LR chi2	648.89	164.60	859.06	859.16	858.46
Prob > chi2	0.000	0.000	0.000	0.000	0.000
Predicted probabilities†					
No flood	0.25	0.14	0.21	0.21	0.21
Flood	0.23	0.13	0.19	0.19	0.19
Difference	-0.02	-0.01	-0.02	-0.02	-0.02
	(0.022)	(0.013)	(0.018)	(0.018)	(0.019)

† At means of other covariates

Table 2.9: Robustness checks: Split by gender

	Men		Women	
	Flood	Other	Flood	Other
Flood/Disaster	-0.60***	-0.12	-0.36**	-0.13
	(0.219)	(0.170)	(0.185)	(0.183)
Individual controls				
Age	-0.01***	-0.02***	-0.02***	-0.03***
	(0.003)	(0.004)	(0.002)	(0.004)
Married	0.08	-0.11	-0.07	-0.34***
	(0.069)	(0.104)	(0.058)	(0.093)
Previous migration	0.27***	0.34***	0.33***	0.43***
	(0.012)	(0.020)	(0.014)	(0.024)
High School	0.30***	0.25**	0.20***	0.23**
	(0.068)	(0.105)	(0.067)	(0.113)
Household controls				
Kids under 6 in HH	-0.05	-0.07	0.03	0.09
	(0.082)	(0.128)	(0.073)	(0.109)
Kids under 15 in HH	-0.01	-0.04	0.01	0.01
	(0.043)	(0.065)	(0.040)	(0.062)
Own house	-0.58***	-0.36***	-0.71***	-0.52***
	(0.065)	(0.113)	(0.061)	(0.111)
Own land	-0.15	-0.15	-0.01	-0.01
	(0.116)	(0.116)	(0.118)	(0.118)
Own livestock	-0.30***	-0.303***	0.06	0.06
	(0.102)	(0.102)	(0.101)	(0.101)
Community controls				
Phone	-0.01	0.05	-0.27**	-0.48***
	(0.114)	(0.154)	(0.116)	(0.172)
Post	-0.41***	-0.42**	-0.32***	0.10
	(0.117)	(0.202)	(0.107)	(0.192)
Nobs	46,371	46,371	48,370	48,370
LR chi2	654.32	397.81	810.51	465.68
Prob > chi2	0.000	0.000	0.000	0.000
Predicted probabilities†				
No flood	0.31	0.23	0.23	0.19
Flood	0.21	0.21	0.18	0.18
Difference	-0.10***	-0.02	-0.05**	-0.01
	(0.034)	(0.026)	(0.025)	(0.024)

† At means of other covariates

Table 2.10: Help Paying for Flood Recovery

	(1)	(2)	(3)	(4)	(5)
Flood	-0.42***	-0.38***	-0.29	-0.33	-0.18
	(0.156)	(0.157)	(0.261)	(0.270)	(0.269)
Individual controls					
Age		-0.04***	-0.04***	-0.04***	-0.04***
		(0.002)	(0.003)	(0.004)	(0.004)
Male		0.08**	0.11	0.12*	0.12*
		(0.037)	(0.068)	(0.070)	(0.071)
Married		-0.22***	-0.45***	-0.46***	-0.40***
		(0.039)	(0.074)	(0.078)	(0.079)
Previous migration		0.29***	0.34***	0.34***	0.35***
		(0.010)	(0.017)	(0.017)	(0.018)
High School		0.17***	0.22***	0.27***	0.26***
		(0.047)	(0.084)	(0.087)	(0.087)
Household controls					
Kids under 6 in HH			-0.04	0.01	-0.04
			(0.110)	(0.111)	(0.111)
Kids under 15 in HH			-0.01	-0.01	-0.05
			(0.051)	(0.052)	(0.052)
Own house			-0.27***	-0.29***	-0.33***
			(0.087)	(0.090)	(0.090)
Own land			-0.02	-0.03	-0.02
			(0.097)	(0.099)	(0.100)
Own livestock			-0.34***	-0.32***	-0.32***
			(0.086)	(0.088)	(0.089)
Community controls					
Phone				-0.52***	-0.56***
				(0.125)	(0.130)
Post				-0.16	-0.18*
				(0.104)	(0.105)
Outside help	2.02***	1.86***	3.05***	3.06***	2.67**
	(0.524)	(0.516)	(1.029)	(1.033)	(1.06)
Nobs	161,528	161,353	65,625	64,138	64,138
LR chi2	16.63	1412.07	757.68	758.29	825.31
Prob > chi2	0.000	0.000	0.000	0.000	0.000
Predicted probabilities†					
No flood	0.50	0.27	0.16	0.13	0.15
Flood	0.40	0.21	0.13	0.10	0.13
Difference	-0.10***	-0.06***	-0.03	-0.03	-0.02
	(0.037)	(0.024)	(0.018)	(0.022)	(0.026)

† At means of other covariates

Table 2.11: Household Level

	Flood		Other	
	(1)	(2)	(3)	(4)
Disaster	-0.35*	-0.42*	0.20**	0.09
	(0.187)	(0.226)	(0.098)	(0.12)
Household controls				
Kids under 6 in HH	1.04***	1.03***	1.04***	1.03***
	(0.082)	(0.095)	(0.082)	(0.095)
Kids under 15 in HH	-0.19**	-0.16*	-0.19**	-0.16*
	(0.078)	(0.088)	(0.078)	(0.088)
Males in HH	-0.34***	-0.34***	-0.34***	-0.34***
	(0.062)	(0.076)	(0.062)	(0.076)
HS graduates in HH	0.17***	0.17**	0.17***	0.17**
	(0.060)	(0.071)	(0.059)	(0.071)
Experience	2.30***	2.05***	2.30***	2.05***
	(0.080)	(0.083)	(0.081)	(0.083)
Own house	-0.38***	-0.54***	-0.38***	-0.54***
	(0.065)	(0.079)	(0.065)	(0.079)
Own land	0.05	-0.06	-0.05	-0.06
	(0.071)	(0.082)	(0.071)	(0.082)
Own livestock	-0.14**	-0.13*	-0.14**	-0.13*
	(0.057)	(0.066)	(0.057)	(0.066)
Community controls				
Phone		-0.09		-0.08
		(0.110)		(0.110)
Post		-0.13		-0.12
		(0.137)		(0.137)
Nobs	82,829	74,614	82,829	74,614
LR chi2	1618.37	1099.09	1618.56	1095.73
Prob > chi2	0.000	0.000	0.000	0.000
Prediction†	-0.06*	-0.08*	0.04**	0.02
	(0.034)	(0.042)	(0.018)	(0.022)

† Differences at means of other covariates

Table 2.12: Alternative Flood Definitions

	Lagged	Contemp	Both
Flood	-0.47**	-0.73***	-0.88***
	(0.236)	(0.251)	(0.193)
Individual controls			
Age	-0.02***	-0.03***	-0.03***
	(0.003)	(0.003)	(0.003)
Male	0.08	0.08	0.07
	(0.059)	(0.057)	(0.058)
Married	-0.20***	-0.15**	-0.15**
	(0.067)	(0.066)	(0.066)
Previous migration	0.36***	0.35***	0.35***
	(0.014)	(0.014)	(0.014)
High School	0.24***	0.23***	0.24***
	(0.074)	(0.072)	(0.072)
Household controls			
Kids under 6 in HH	0.04	-0.06	-0.06
	(0.082)	(0.085)	(0.085)
Kids under 15 in HH	-0.02	-0.07	-0.07
	(0.044)	(0.046)	(0.046)
Own house	-0.50***	-0.49***	-0.49***
	(0.077)	(0.076)	(0.076)
Own land	-0.10	-0.12	-0.11
	(0.080)	(0.079)	(0.079)
Own livestock	-0.11	-0.20***	-0.20**
	(0.070)	(0.069)	(0.069)
Community controls			
Phone	-0.18	-0.29***	-0.30***
	(0.113)	(0.011)	(0.113)
Post	-0.19	-0.31**	-0.32**
	(0.138)	(0.139)	(0.140)
Nobs	116,761	115,219	115,219
LR chi2	861.52	880.12	895.34
Prob > chi2	0.000	0.000	0.000
Prediction†	-0.06**	-0.08***	-0.09***
	(0.028)	(0.022)	(0.017)

† Differences at means of other covariates

Chapter 3

THE EFFECTS OF INTERNAL MIGRATION ON HEALTH OF ADULTS IN INDONESIA

3.1 Introduction

The United Nations estimates that in 2010 over 200 million people were living outside of their country of birth. Nearly four times as many people — 740 million — were internal migrants, relocating to other regions of their home country (UNDP, 2009). Migration has important implications for human development. Mohapatra et al. (2010) identify a number of social and economic challenges facing developing and developed countries as they try to integrate an ever increasing number of migrants. Abbas and Varma (2014) add to the discussion by addressing individual challenges, namely restricted access of recent migrants to housing, financial services and social programs.

One important aspect of migrant well-being is migrants' health. Good health is vital for the ability to successfully adjust to new surroundings and become a productive member of the society in a destination community. Therefore, if migrants have specialized health needs compared to natives at destination locations, understanding health consequences of migration is important to migrants, health professionals, and policy makers alike.

There is a long established, but relatively sparse literature on the effect of migration on health. This literature primarily addresses questions of post-migration adaptation and the role of remittances in health outcomes of family members that remain in the origin communities. Only a handful of studies look at the effects of relocation on physical health of migrants. To a large extent this lack of scholarly research has to do with data limitations (Massey (2010), Schenker et al. (2014)). Studies focusing on physical health usually look at a limited number of very specific measures of health and find that there are ambiguous effects of migration on health.

Depending on health measures used, migration can have positive, negative or no effect at all.[1]

In addition, health selectivity of migrants — addressed in the healthy migrant literature — often masks potentially large negative effects of migration-correlated stressors, such as loss of familiar network, harsh working conditions, and environmental pressure on migrants' physical health.[2]

Health status, however, is a complex conceptual construct. Its measurements are inherently multidimensional with broad classifications being along physical and mental health dimensions as well as biological measurement, physical impairment, and self-perceived status dimensions. Even within each of those dimensions, there are numerous measurements of health status, some substitutes, others complements for each other. Therefore, it is not surprising that the empirical evidence on the effects of migration on health is mixed.

Previous studies suggest several reasons why migration might lead to deterioration of migrants' health. First, lack of familiarity with health systems in destination locations may result in limited access to health care services even in absence of legal restrictions (Norredam, 2011). Second, health care professionals are often unaware of specific health needs of migrants, thus delaying proper diagnosis and treatment of migrant-specific ailments (Hansen and Donohoe, 2003). Lastly, stress associated with acculturation and adaptation to destination lifestyle often leads to uptake in unhealthy behaviors such as smoking and unhealthy diet (Renzaho and Burns (2006); Bosdriesz et al. (2013)). On the other hand, increased income and wealth may have positive effect on migrants' health (LaLonde and Topel (1997); McKenzie et al. (2006)).[3]

In this paper, I quantify the effect of migration on physical health. I account for potential selectivity of health in migration using a potential outcomes framework of Athey and Imbens (2006) to disentangle health-selectivity of migrants from causal effects of migration. I use data on six measurements of physical and general health that are potentially modifiable over short periods of time (e.g., less than five years). These variables are all included in the "Global Reference List of Core Health Indicators" published by the World Health Organization (2015), a universal list of indicators "prioritized by the global community to provide concise information on the health situation and trends, including responses at national and global levels".[4] These six measures have well defined clinical cutoffs and are widely used in epidemiological and health economics studies.

I construct a latent class model of the joint probabilities of the six health mea-

[1]See Kasl and Berkman (1983), McKay et al. (2003), Lassetter and Callister (2008), and Veary et al. (2011) for a comprehensive literature review.

[2]Pre-migration health selectivity is well documented in literature on "healthy migrant hypothesis". For more recent examples, see Rubalcava et al. (2008) and Lu (2010).

[3]Also see Goldman et al. (2014) for extended discussion.

[4]`http://apps.who.int/iris/bitstream/10665/173589/1/WHO_HIS_HSI_2015.3_eng.pdf?ua=1`

sures in which individuals are assumed to belong to one of a small number of (latent) health-types or classes. Thus, my model acknowledges the commonalities of the measurements while allowing for potential substitutability. Each latent class is associated with a probability and these class probabilities sum to one over the latent classes. The class probabilities are modeled as being individual-specific; i.e., they are functions of individual characteristics. This latent class model is closely related to the Grade of Membership (GoM) model of Manton and Woodbury (1982).

While the GoM method is similar to other data reduction models, such as Factor Analysis, Principle Components Analysis, and Multiple Indicator, Multiple Cause, this method is non-parametric; it does not rely on underlying distributional assumptions regarding individuals' health when assigning individuals into health classes. Furthermore, GoM method takes into account individual heterogeneity when assigning respondents into discrete groups. This methodology allows for partial membership along different health dimensions, constructing a proximity measure between an respondent and a pure health type. Since only few people can be classified as perfectly healthy or completely unhealthy, GoM methodology offers additional advantages over other data reduction models (Portrait et al., 1999).

I estimate this model using data from the Indonesian Family Life Survey (IFLS), an ongoing longitudinal survey of households and individuals in Indonesia, representative of 83% of population of the country.[5] Since its inception in 1993, this survey has been used in several hundred peer-reviewed papers.[6] IFLS is unique in the way it treats migrants. It is designed to locate migrants following a move, thus greatly reducing migration related sample attrition and allowing me to study health of migrants as well as non-migrants. Most other surveys do not track down migrants, thus limiting researchers' ability to investigate the effects of migration on health.

The vector of covariates in the class probability equation includes indicators for whether the individual migrated in the recent past, indicators for whether the individual was affected by a flood in the recent past and interactions of migration and flood indicators. The coefficients on migration indicators account for possible self-selection into migration based on pre-migration health status. The indicators for floods account for possible health effects of exposure to floods. The interaction variables compare migrants who were pushed to migrate because of a recent flood to individuals who migrated from communities not affected by floods, and those who did not migrate at all. Thus, the coefficients on the interaction terms have a difference-in-difference interpretation (Athey and Imbens, 2006).

Confidence in the causal interpretation of the interaction of migration status and exposure to floods is based on two features of floods, combined with my focus on physical aspects of human health. First, conditional on geographic characteristics, the timing of floods is essentially random. Second, while research indicates that there

[5] Indonesia is home to over 23 million migrants, 90% of them internal migrants (Lu, 2008), which makes these data well suited for the problem at hand.

[6] `http://www.rand.org/labor/FLS/IFLS.html`

are some effects of flood on physical health of survivors, namely increase in diarrheal disease, mosquito-borne diseases, and upper respiratory infections, these effects are short lived (Ahern et al. (2005); Morgan et al. (2005)).[7] Therefore, we can assume that floods don't have long lasting impact on individuals' physical health. On the other hand, recent floods in origin communities do have an effect on subsequent migration probability (Kuhn, 2005).

I find evidence that migration negatively affects health, and this effect becomes pronounced two or more years following a move. Migrating two or more years ago as a consequence of a flood increases the probability of being in poor health by 12 percentage points, an increase of nearly 20%, comparable to a loss of an average of five years of life. Migration a year ago has a small and statistically insignificant effect on the probability of being in poor health.

The remainder of the paper is structured as follows. Section 3.2 presents an overview of the data and summary statistics. Methodology is described in section 3.3. Section 3.4 presents results and section 3.5 concludes.

3.2 Data

In this study, I use the Indonesian Family Life Survey (IFLS), a periodic panel survey administered by RAND. There are currently four waves available, spanning years 1993–2007. The sample spreads across 13 of 32 provinces in Indonesia, but represents about 83% of population. The 1993 wave has over 33,000 people living in 7,224 households in 312 sample communities. The sample grows to over 50,000 people in 13,536 households by 2007.[8] Recontact rate in each wave of the the survey is over 90%.

The unique feature of the IFLS is that it provides retrospective annual migration histories for all respondents age 12 and older. Additionally, it follows migrants even after they move out of sample communities. This reduces attrition due to out-migration and allows me to investigate the effects of recent floods even in communities that are not in the IFLS sample. Average migration rate of all respondents age 15 and older in the IFLS is 6.25%, which is nearly identical to the rate found by Gray (2009) using different data sources.

I build a person-year panel, spanning all sixteen years of the survey. There are over 26,000 migration instances during the survey years, 1.2% of which are out of a community that has experienced a flood in the previous calendar year. I restrict my

[7]EM-DAT: The OFDA/CRED International Disaster Database reports 62 major flood events in Indonesia during the period of 1993–2007. 4,690,805 individuals are estimated to have been affected by floods, with 2,985 dying as a result of a flood (0.064% of those affected). www.em-dat.net — Universit Catholique de Louvain — Brussels — Belgium.

[8]Sample grows because survey respondents marry partners that were initially out of sample. In addition, those sample respondents who were under the age of 12 during sampling enter the following wave if old enough.

sample to adults of ages 15 to 65. Furthermore, once I take into account information on between sample year migrations and their relationship to flood events, I focus on the years of the last three waves of the survey for which I have exact measurements of health variables. This results in an unbalanced panel of over seventy thousand person-year observations.

Health of respondents is measured only at survey years. Children of sample household and individuals that entered the sample between the waves do not have previous health measures. For this reason, and to avoid sample attrition, I use only one health measurement per respondent. The study design described below allows me to look at a "cross-section" of health outcomes and draw inferences regarding between-wave health changes using potential outcomes framework of Athey and Imbens (2006).

3.2.1 Measurement of health variables

I construct six dichotomous measures of health based on body mass index, systolic and diastolic blood pressure, hemoglobin count, health status as reported by the interviewer, and self-reported health status. I select cutoffs to distinguish normal health from poor health based on commonly used clinical values. Specifically, I classify individuals as overweight if their BMI is 25 kg/m^2 or above.[9] Almost 20% of total sample are individuals who are overweight or obese, as defined by BMI of at least 30 kg/m^2. Hypertension is defined as per American Medical Association, with abnormal values of systolic blood pressure of at least 130, diastolic blood pressure of at least 90. Nearly half of the individuals in the sample have hypertension. Lung capacity depends on an individual's gender, age and height, and functional deficiency is defined as having a lung capacity that is below 80% of group-specific normal function (Roberts and Mapel, 2012). 20% of sampled individuals have low lung capacity. Normal hemoglobin levels are gender specific. National Heart, Lung, and Blood Institute states that normal cutoffs are at least 12 g/dl for women and at least 13.5 g/dl for men. Nearly 30% of sampled individuals have low hemoglobin. Two additional measures are based on self-reported health status and on interviewers' observations about the respondents. 12% of respondents say the are unhealthy, while interviewers report nearly 30% of respondents being less healthy than the comparison group. Summary statistics of these variables by survey year are shown in Table 3.1. In addition, Figure 3.1 shows rates of these poor health indicators by migrant status and exposure to floods.

[9]Only a small proportion of the sample is underweight; those individuals are included in the normal weight group.

3.2.2 Other controls

Additional controls include socio-economic measures for individuals and households generally associated with migration, as well as controls for original community location and other characteristics. On average, migrants are younger and better educated than non-migrants. Migrants are more often male and not married, coming from households that are less likely to own a house. While there is virtually no difference between proportion of migrants and non-migrants in urban and shore locations, floods are somewhat more likely to hit urban areas and areas located on shores. Flood and non-flood communities are very similar along other dimensions. Tables 3.2 and 3.3 show these and other mean characteristics by migrant and flood status, and by survey year respectively.

3.2.3 Measurement of migration and exposure to floods

I define two indicators of migration status – whether the person migrated in the year before the survey, and whether the person migrated two or more years before the survey. I also define two indicators of exposure to floods – whether the person was exposed to a flood two years prior to the survey, and whether a flood occurred three or more years prior to the survey. The indicator for migration a year prior is interacted with exposure to a flood two years ago. The indicators for migration two or more years prior is interacted with exposure to a flood three or more years prior.

Figure 3.2 shows relationship between flood occurrences and flood-related migrations. Blue bars in both panels correspond to number of communities that experienced floods at any given year. In most years, 3–5% of sample communities experience a flood. The orange line in the left panel shows percent of all migrants that left a community that experienced a flood in the year prior to migration. For example, about 3% of all migrants in 1996 left a community that had a flood in 1995. The orange line in the right panel shows similar statistics, but for migrants leaving a community that experienced a flood two or more years prior to migration. There is a clear correlation between number of communities experiencing floods and percent of migrants leaving flood-affected communities a year later. This correlation is much weaker two or more years following a flood.[10]

3.3 Methods

3.3.1 Treatment effects in nonlinear potential outcomes models

Consider a design in which there is a binary migration indicator M (with $M = 1$ denoting the treatment group), a binary flood indicator F (with $F = 1$ denoting

[10] Correlation values are 0.67 for the left panel, 0.15 for the right panel.

exposure to a flood) and X denoting a set of control covariates. Then, using the potential outcomes framework, Athey and Imbens (2006) show that under assumptions of flood exogeneity and potential migrant self-selectivity the treatment effect in a potential outcomes model can be written as

$$\tau = E[\pi^1|F=1, M=1, X] - E[\pi^0|F=1, M=1, X],$$

where π^1 and π^0 denote the potential outcomes with and without treatment respectively.[11] Envision π as a latent measure of the likelihood of poor health, determined by a latent class model described below. In a nonlinear model parameterized with a linear index of covariates and parameters such that

$$E[\pi|F, M, X] = \boldsymbol{f}\left(\beta_1 F + \beta_2 M + \beta_3 FM + X\boldsymbol{\theta}\right),$$

Puhani (2012) shows that when $FM = 0$,

$$E[\pi^0|F=1, M=1, X] = \boldsymbol{f}\left(\beta_1 + \beta_2 + X\boldsymbol{\theta}\right)$$

and

$$E[\pi^1|F=1, M=1, X] = \boldsymbol{f}\left(\beta_1 + \beta_2 + \beta_3 FM + X\boldsymbol{\theta}\right),$$

when $FM = 1$, so that the sign of τ is the same as the sign of β_3. Therefore, one can assess whether a treatment effect exists (and is statistically significant) by examining the coefficient on the interaction term in the regression specification, similar to treatment effect interpretation in difference-in-difference (DiD) models. In this framework, the treatment effect is given by

$$\tau = \boldsymbol{f}\left(\beta_1 F + \beta_2 M + \beta_3 FM + X\boldsymbol{\theta}\right) - \boldsymbol{f}\left(\beta_1 + \beta_2 + X\boldsymbol{\theta}\right).$$

3.3.2 A Latent Class Model

We begin with a set of observed outcomes that describe an underlying health concept. Each particular outcome is not sufficient to fully describe the underlying concept. However, taken together these variables can better summarize all available information about an individual's unobserved health. The method adopted here is closely related to the Grade of Membership (GoM) model of Manton and Woodbury (1982) and is a nonparametric characterization of the latent construct. It allows for partial participation of an individual in each of the outcomes, recognizing that individuals can have different health conditions.

[11] Consider a population in which individuals can be described as migrant and non-migrant types that could be affected by a flood. Then, look at health of migrants, compared to non-migrants, in absence of treatment, the floods. Assuming that the same would hold for those in treatment group had they not been affected by a flood, estimate the counterfactual outcome distribution for treated and compare the estimated counterfactual distribution to the actual distribution to tease out the effect of migration on subsequent health using floods to reduce concerns about migrant selectivity.

Following Portrait et al. (1999), consider a set of K binary indicators, $\{y_{i1}, y_{i2}, ..., y_{iK}\}$, that are the observed measurements of a common latent construct. Each of these measurements only partially characterizes the latent construct; in fact, all the the measurements, taken together, need not fully characterize the construct. $y_{ik} = 1$ if a respondent i has a condition k and $y_{ik} = 0$ otherwise. An individual that exhibits only symptoms of a single condition would be a "pure type", using the language of the GoM model. We can measure the extent of proximity of each respondent to the pure types using weights that are constrained to fall between 0 and 1 and sum to 1 over all profiles; the respondents' health conditions are then represented by a convex combination of the pure type profiles. Associated with each of these binary indicators is a probability that an individual i exhibits symptoms of a health condition k, $p_{ik} = Pr(y_{ik} = 1)$ and the joint probability associated with a higher value of the latent construct is given by $\prod\limits_{k=1}^{K} p_{ik}$.

A very general latent class model can be specified as follows. Suppose that there are C classes (types) of individuals, with associated measurement probabilities given by p_{cik} for $c = 1, 2, ..., C$ and π_{ci} is the probability that an individual i belongs to class c with $\sum\limits_{c=1}^{C} \pi_{ci} = 1$.

Assume that the measurement probabilities are constant across individuals in a given class, i.e., $p_{cik} = p_{ck}$ and let

$$\pi_{ci} = \Lambda_M \left(\beta_{0c} + \beta_{1c}F_i + \beta_{2c}M_i + \beta_{3c}F_iM_i + X_i\boldsymbol{\theta}_c\right)$$

where Λ_M denotes the multinomial logit function. Let $c = 1$ be the baseline (omitted) category without loss of generality. Although this model is not completely general, it is considerably more parsimonious than the grade of membership model and gives us the ability to understand the determinants of the distribution of class probabilities within the context of the model.[12]

The contribution of an individual i to the likelihood function is

$$L_i = \sum_{c=1}^{C} \pi_{ci} \prod_{k=1}^{K} p_{ck}$$

and the overall log likelihood is

$$lnL = \sum_{i=1}^{N} \ln \left(\sum_{c=1}^{C} \pi_{ci} \prod_{k=1}^{K} p_{ck} \right)$$

I estimate this model using maximum likelihood. Standard errors are adjusted for clustering at the household level.

[12]The estimated mixing probabilities in the grade of membership model can be used as the dependent variable in an auxiliary regression analysis to understand its determinants but this approach has all of the inherent issues in multi-step modeling procedures.

3.3.3 Specification of Model and Treatment Effects

To be more specific, I specify the class probability function as

$$\pi_{ci} = \Lambda_M \left(\beta_{0c} + \beta_{1c}F_i^{t-2} + \beta_{2c}F_i^{t-3} + \beta_{3c}M_i^{t-1} + \beta_{4c}M_i^{t-2} \right. \\ \left. + \beta_{5c}F_i^{t-2}M_i^{t-1} + \beta_{6c}F_i^{t-3}M_i^{t-2} + X_i\boldsymbol{\theta}_c\right)$$

where $M_i^{t-1} = 1$ denotes that migration occurred last year, $M_i^{t-2} = 1$ denotes migration occurred two or more years ago (but after the previous wave of data collection), $F_i^{t-2} = 1$ denotes that the individual was exposed to a flood two years ago, $F_i^{t-3} = 1$ denotes that the individual was exposed to a flood three or more years ago. In my empirical analysis, I find that the distribution of health status can be adequately described with two latent classes, so Λ_M specializes to a logit function Λ. The treatment effects, measured as changes in the probability of being in class 2 are given by

$$\tau_1 = \Lambda\left(\beta_{02} + \beta_{12} + \beta_{32} + \beta_{52} + X_i\boldsymbol{\theta}_2\right) - \Lambda\left(\beta_{02} + \beta_{12} + \beta_{32} + X_i\boldsymbol{\theta}_2\right)$$

and

$$\tau_2 = \Lambda\left(\beta_{02} + \beta_{22} + \beta_{42} + \beta_{62} + X_i\boldsymbol{\theta}_2\right) - \Lambda\left(\beta_{02} + \beta_{22} + \beta_{42} + X_i\boldsymbol{\theta}_2\right)$$

3.3.4 Mundlak fixed effects

In most nonlinear models, as in my latent class model, it is not possible to "sweep out" unobserved group-level characteristics using the usual fixed effects time differencing technique, a within transformation, as one would in the linear model and some nonlinear models. Mundlak (1978) and Chamberlain (1984) note that, in the linear regression model, the fixed-effects (within) estimator produces the same coefficients as an OLS estimator in which the set of regressors includes group-level means of all the individual-level covariates in the regression specification. Taking this idea, they suggest that including group-level means as covariates in nonlinear models could ameliorate confounding caused by group-level characteristics. Therefore, in order to control for group-level fixed effects, in addition to estimating a latent class model that includes no group-level controls, I estimate versions of the model with two sets of group-level covariates – first with household-level means and the second with region-level (Kabupaten) means.

3.3.5 Alternative specifications

In order to compare my results to those in the previous literature, I estimate several alternative model specifications. First, I estimate a set of six potential outcomes logit specifications, one for each of the six binary health measures used in the latent class model. I then allow for correlation of various health measures for an individual, estimating a multivariate probit model with the same health measures. Last, but not least, I estimate a control function specification in order to control for migration selectivity. Details of each specification are described in the following section together with discussion of the specification results.

3.4 Results

Table 3.6 presents coefficients from the two class grade of membership model under a naive assumption that individuals do not self-select into migration based on their health. Since I assume no selection, I do not include flood terms and flood-migration interaction terms that are present in my main specification in order to ameliorate the selectivity problem. Standard errors are clustered on household level. The first column presents results of a specification that includes a full set of individual, household and community characteristics only. Second and third columns show results of specifications that include household- and region (Kabupaten)-level Mundlak terms respectively.

All individual-, household- and community-level controls shown in Table 3.6 have expected signs and significance. Older individuals are more likely to be in poor health as are residents of large and urban communities. Wealthier and more educated householders are more likely to be healthier. However, migration on its own is not a significant predictor of subsequent health. The estimated posterior probability of being in class 2 is slightly above 0.4, regardless of specification. The joint probability of being in poor health given membership in class 2 is almost 45 times that of the joint probability of being in poor health given membership in class 1. In addition, Figure 3 shows that each of the individual measures of poor health are more likely to be observed among individuals a posteriori assigned to class 2. Therefore, I label class 2 as "poor health".

Table 3.7 presents coefficients and summary statistics from the latent class model. The first specification includes a full set of individual characteristics. The second and third specifications include household- and region (Kabupaten)-level Mundlak terms. As before, standard errors are clustered on household level. The estimated posterior probability of being in class 2 is approximately 0.4, regardless of specification. The joint probability of being in poor health given membership in class 2 is about 45 times that of the joint probability of being in poor health given membership in class 1. The coefficients on the interaction terms in Table 3.7 show that migration last year has no effect on health, and that individuals who migrated two or more years ago are significantly more likely to be in poor health as a result of the migration.

The top panel of Figure 4 shows the predicted probabilities for three groups, those who did not migrate because of a flood, those who migrated a year ago because of a flood and those who migrated two or more years ago because of a flood. The bottom panel shows the associated marginal effects of migration because of a flood. Migrating two or more years ago as a consequence of a flood increases the probability of being in poor health by 12 percentage points. Migration a year ago has a small and statistically insignificant effect on the probability on being in poor health.

I find no evidence of the healthy migrant effect. The coefficients on migration are, across the board, statistically insignificant and small. This finding is consistent with Rubalcava et al. (2008), who find limited evidence for health selection among Mexican migrants to the United States. There is, however, a substantial effect of recent floods on health. Individuals exposed to recent floods are more likely to be in poor health.

Turning to other covariates in the model, men, individuals with higher education and those who own a house are less likely to be in poor health. In contrast older people are more likely to be in poor health. Individuals who live in large towns and cities (Desa) and urban areas are more likely to be in poor health. These findings are consistent with results from literature on adult health.

3.4.1 Robustness checks

Table 3.8 presents results of several robustness checks. All four specifications include region (Kabupaten)-level Mundlak terms and standard errors are clustered on household level. Column 1 presents specification that includes age-squared term. The results are as predicted by theory. Age-squared term is significant and the sign is opposite of that of the age term. Individual who migrated two or more years ago following a flood are more likely to be unhealthy. Floods last year positively affect the probability of being in poor health. Floods two or more years ago are significant at 10%. Males and wealthier individuals are less likely to be unhealthy, while older people and residents of large communities have lower probability of being in good health.

Column 2 of Table 3.8 shows results of specification that includes only adults between ages 20 and 65. All coefficients are similar in sign and significance to those presented in column 1. Column 3 of Table 3.8 presents results of estimation for adults ages 20 to 60 to check whether the results are driven by presence of elderly individuals in the sample. Results are across the board similar to those discussed before. Estimation of specification for females only is presented in column 4 of Table 3.8. Women who migrated two or more years ago as a result of a flood, those who are older and are residents of larger communities are more likely to be unhealthy.

Specification shown in Table 3.9 includes interaction terms of age with migration-flood interactions to control for possible differential effect of flood-induced migration on individuals of different ages. Migration following a flood does not affect the probability of being in poor health, however individuals who migrated two or more years ago following a flood are more likely to be in poor health. Floods a year ago have a positive and significant effect on probability of being in poor health. Males and younger respondents are more likely to be healthier, as are more educated and wealthier individuals. The interaction term is only significant for flood-induced migration that happened a year ago. Interaction two or more years after a flood-induced migration is not significant.

3.4.2 Alternative specifications

Logit specification

Consider a standard binary logistic specification

$$pr(y_{it}^k = 1|\cdot) = \Lambda \big(\beta_0^k + \beta_1^k F_i^{t-2} + \beta_2^k F_i^{t-3} + \beta_3^k M_i^{t-1} + \beta_4^k M_i^{t-2} + \beta_5^k F_i^{t-2} M_i^{t-1} + \beta_6^k F_i^{t-3} M_i^{t-2} + X_i \boldsymbol{\theta}^k \big)$$

where $k = 1, ..., 6$ stands for each of the six measures of poor health status and the probability that the observed outcome $y_{it}^k = 1$ is conditional on the RHS.

Table 3.4 presents key coefficients from a set of descriptive potential outcomes logit regressions of each of the six measures of poor health status. All specifications include a full set of individual characteristics. In addition, the second and third specifications include household- and region (Kabupaten)-level Mundlak terms. In all cases, standard errors are clustered on household level. The results show that there are small, sometimes positive and sometimes negative, and statistically insignificant treatment effects of migration last year. The coefficients on migration 2 or more years ago interacted with flood exposure are always positive and relatively large, but not statistically significant in most cases. Migration 2 or more years ago (interacted with flood exposure) makes hypertension significantly more likely. The consistent positive signs on the treatment coefficients on migration 2 or more years ago are suggestive, however, that migration may lead to poor health.

Multivariate probit specification

While logit specification described above treats each observed outcome y_{it}^k as independent from the rest of the outcomes y_{it}^{-k}, the information contained in each of the outcomes pertains to the same individual. Thus, to allow for correlation across outcomes, I specify a multivariate probit model

$$\begin{aligned} y_{i1} &= Z_i' \alpha_1 + \epsilon_{i1} \\ &\vdots \\ y_{i6} &= Z_i' \alpha_6 + \epsilon_{i6} \end{aligned}$$

where Z_i stand for floods, migrations, migration-flood interaction terms and all other observed individual-, household- and community-level characteristics from equations associated with outcomes 1 through 6 and $\alpha_1, ..., \alpha_6$ are the coefficients associated with these variables.

Overall log-likelihood is

$$lnL = \sum_{i=1}^{N} ln\Phi_6[Z_i'\alpha_1, ..., Z_i'\alpha_6|\Sigma]$$

where Φ_6 is distributed multivariate normal and Σ is the variance-covariance matrix.

Table 5 presents key coefficients from a set of multivariate probit regressions. As before, all specifications include a full set of individual characteristics. In addition, the second and third specifications include household- and region (Kabupaten)-level Mundlak terms and standard errors are clustered on household level. Results are similar to those from a set of logit regressions presented in Table 3.4 and described above. Note that in addition to hypertension, now migration 2 or more years ago (interacted with flood exposure) makes overweight and obesity significantly more likely. The signs on the treatment coefficients on migration 2 or more years ago are still positive, again suggesting that migration may lead to poor health.

Control function specification

Following Garrido et al. (2012) consider an alternative specification of the problem where probability of out-migration for individual i at time $t-k$, M_{t-k}, can be written as

$$Pr(M = 1|Z, I) = g(Z'\alpha + \delta I)$$

where Z includes observed individual-, household-, and community-level covariates, and I are the unobserved characteristics. This equation corresponds to the first stage of a two stage control function problem. Also included in Z is a binary indicator for flood. This is an instrument that is postulated to affect out-migration, but not directly the outcome of interest in the second stage, health (H).

In the second stage, write the expected value of health outcome H for an individual i as

$$E(H|X, M, I) = f(X'\beta + \gamma M + \lambda I) \tag{3.1}$$

where X includes observed individual-, household-, and community-level covariates, and I and M are as described above. Assume that $g(Z'\alpha+\delta I)$ and $f(X'\beta+\gamma M+\lambda I)$, the implied distributions of the error terms in two equations, are logistic.

Due to timing of floods and corresponding migrations, in the first stage I estimate two logistic regressions

$$\begin{aligned} M_i^{t-1} &= \Lambda\left(\alpha_0^1 + \alpha_1^1 F_i^{t-1} + \alpha_2^1 F_i^{t-2} + X_i^{t-k}\theta^1\right) \\ M_i^{t-2} &= \Lambda\left(\alpha_0^2 + \alpha_1^2 F_i^{t-1} + \alpha_2^2 F_i^{t-2} + X_i^{t-k}\theta^2\right) \end{aligned}$$

In the second stage, I estimate GoM latent class probability model in which probability an individual i belongs to a latent health class c is

$$\pi_{ci} = \Lambda\left(\beta_{0c} + \beta_{1c}M_i^{t-1} + \beta_{2c}M_i^{t-2} + \beta_{3c}R_i^1 + \beta_{4c}R_i^2 + X_i\boldsymbol{\theta}_c\right)$$

where M^{t-1} indicates whether an individual i migrated in period $t-1$, M^{t-2} indicates whether an individual i migrated in period $t-2$, and R_i^1 and R_i^2 are residuals from the first stage estimation of M^{t-1} and M^{t-2} respectively.[13]

Results of this estimation are presented in Tables 3.10 and 3.11. The two columns of Table 3.10 show results of logit regressions of M_{t-1} and M_{t-2} respectively on full set of covariates. In both equations, recent floods exhibit negative effect on probability of out-migration; signs and predictive power of other covariates are in line with previous literature findings.

Table 3.11 shows results of the second stage estimation.[14] While not significant, estimates corresponding to the effect of migration two or more years ago on health are large and similar in magnitude to estimates obtained using the DiD method, varying between 15.6% and 25.4% depending on which group level controls are included in the estimation. Migration two or more years ago increases the probability that the individual belongs to poor health class by an average of 22%. All other estimates are similar in magnitude and significance to those shown in Table 3.7 and discussed above.

Lack of significance in this estimation is possibly due to nonlinearity of the second stage regression and issues of timing of migration relative to flood measures and health measures. For this reason, the DiD method is preferred, since results of the two estimations are comparable in direction in magnitude.

3.4.3 Discussion

One possible channel that explains such deterioration of health is change in socio-economic surroundings of migrants. Khan and Kraemer (2014) state that migrants are more likely to smoke, which in turn can cause decreased lung capacity and other diseases generally associated with smoking. Change in diet is another channel that can adversely influence health. Renzaho and Burns (2006) show that migrants from sub-Saharan Africa to Australia increase consumption of takeaway food, e.g. Pizza Hut and McDonalds, and this increase in high-fat high-calorie consumption is generally associated with increase in body weight. Finally, impaired access to health care and lack of awareness of specialized health needs of migrants among health professionals lead to late diagnosis and inappropriate treatment of migrant-specific ailments (Hansen and Donohoe, 2003). More generally, literature on international migration show that health and health behavior of immigrants deteriorate with duration of stay abroad (Abraido-Lanza et al. (2005); Lara et al. (2005)). Applied to domestic migrants, this would further explain cumulative negative effect of migration on health.

In order to shed some light on reasons why health of migrants deteriorates even though fewer people move following floods, I compare health of migrants and non-migrants by flood status, gender, age and other socio-economic characteristics. Figure

[13] The two floods variables are jointly significant at 1% in both first stage specifications.

[14] Marginal effects at means of other covariates.

3.1 presents a break-down of rates of low health by migrant status and flood status. In addition, I run a series of t-tests to evaluate whether migrants and non-migrants, disaggregated by flood exposure status, have similar health outcomes.[15] The results are presented in Table 3.12.

Column (1) of Table 3.12 presents results of the t-tests for equality of means of health indicators by migrant status. Looking at post-exposure health, migrants who moved following floods are no different from those who stayed in affected communities along all six health dimensions. However, those who were not exposed to floods differ in health outcomes by migrant status. Migrants are less likely to have high BMI, hypertension, low peak expiratory flow rate, and low hemoglobin.

I further disaggregate my sample to look at health outcomes of migrants and non-migrants by flood status and gender. The results of t-tests for the equality of means for male and female migrants and non-migrants potentially exposed to floods are presented in Column (2) of Table 3.12. Health outcomes of migrants that have been exposed to floods do not vary by gender. However, there is gender difference among migrants that have not been exposed to floods. Men are less likely to be unhealthy along all dimensions except hypertension.

Column (3) of Table 3.12 shows results of t-tests for mean age difference of migrants that were exposed to floods and those that were not. While there is still no difference in health outcomes for the individuals that were exposed to floods, among the respondents that were not exposed, younger migrants are less likely to have high BMI and hypertension. One important observation is that among migrants that were not exposed to floods, younger individuals are less likely to report low self-rated health status. This could be interpreted as further evidence to support health selectivity in migration, underlining the importance of correcting for such selectivity.

Finally, I run one last series of t-tests, looking at migrant-sending summaries by household wealth, proxied here by ownership of a house. Individuals leaving wealthier households in presence of floods are no different in health outcomes from individuals leaving households that do not own their houses. However, in absence of floods, individuals leaving wealthier households are less likely to be overweight, but more likely to have low hemoglobin or appear to be less healthy to interviewers. One interpretation is that households that have higher wealth could afford to send out more migrants, even the ones that are on average less healthy. When households lose part of their wealth to floods, they can no longer send out migrants, thus rendering no difference in migrant-sending behavior among all households.

Overall, evidence presented above indicates that households and communities tend to send out fewer migrants following floods, in particular retaining younger, healthier men from wealthier households. The "labor-retention" hypothesis is one theory that would fit all these facts. Households and communities that typically send out migrants individuals prefer to keep them at home to help with recovery efforts in the aftermath of floods, thus increasing labor demand for the exact individuals that would be most

[15] I allow for variances to differ by group.

likely to move out in absence of floods.

3.5 Conclusions

This paper utilizes the GoM method to summarize health as an index that is subsequently used to study the effects of migration on health. This method is designed by Manton and Woodbury (1982) for the purpose of categorizing complex multidimensional health concept, simultaneously identifying underlying dimensions of health and the degree to which individuals fit each of these dimensions. Using this method together with the IFLS data, I identify two broad health classes – good and poor health – and examine the effects of migration on probability of an individual belonging to poor health class.

I depart from existing literature on migration and health by simultaneously addressing the issue of migrants' selectivity on health and treating health as multidimensional, as opposed to looking into each health measure separately. I use data on six available measures of various aspects of health to characterize the underlying health concept. In doing so, I am able to show that migration affects health in an adverse way and that the negative effects of migration on health accumulate over time. While migrants are no less likely to be in poor health than non-migrants a year after a migration, two or more years later migrants are significantly more likely to be in worse health.

Migration is projected to increase in the coming decades in response, in part, to climate change (Drabo and Mbaye, 2011) and civil unrest, as is already evident in Europe and the Middle East. This will put increased pressure on health systems of destination locations, while subjecting an increasing number of people to migration-related health risks. Health care professionals need be made aware of migrant-specific maladies and appropriate testing and treatment procedures. Thus, the emphasis should be placed on further understanding of the causes of migrants' health deterioration in order to reduce the health burden of migration.

Table 3.1: Rates of Low Health by Year

	1997	2000	2007
Overweight	16	17	24
Hypertension	59	44	41
Low Peak Expiratory Flow Rate	24	18	22
Low Hemoglobin	34	33	22
Low Interviewer-Rated Health	28	27	31
Low Respondent-Rated Health	11	12	13

% of total in each year

Table 3.2: Mean Characteristics by Migrant and Flood Status

	Migrant	Never migrant	Flood	Never flood
migrated last year	0.210	0.000	0.025	0.043
migrated 2+ years ago	0.557	0.000	0.059	0.115
flood last year	0.026	0.043	0.215	0.000
flood 2+ years ago	0.052	0.078	0.396	0.000
male	0.493	0.456	0.438	0.468
age in years	32.489	36.424	37.348	35.308
no schooling	0.022	0.095	0.083	0.081
high school or higher education	0.558	0.368	0.375	0.410
married	0.488	0.514	0.554	0.499
owns a house	0.635	0.836	0.816	0.794
year is 2000	0.343	0.339	0.362	0.335
year is 2007	0.508	0.404	0.358	0.438
log(population in Desa)	8.687	8.620	8.687	8.621
proportion of households in Desa with phone	0.015	0.012	0.015	0.012
log(distance to post office)	1.789	1.794	1.743	1.804
Desa is urban	0.476	0.447	0.544	0.432
Desa is on the shore	0.140	0.152	0.213	0.136
N	10,770	46,529	10,566	46,733

Table 3.3: Means Characteristics by Survey Year

	1997	2000	2007
migrated last year	0.030	0.046	0.039
migrated 2+ years ago	0.042	0.119	0.128
flood last year	0.048	0.041	0.034
flood 2+ years ago	0.077	0.103	0.046
male	0.444	0.464	0.472
age in years	36.906	35.526	35.127
no school	0.128	0.088	0.049
high school or higher education	0.314	0.383	0.471
married	0.577	0.531	0.454
own a house	0.822	0.805	0.779
log(population in Desa)	8.555	8.682	8.637
proportion of households in Desa with phone	0.006	0.011	0.018
log(distance to post office)	1.156	2.587	1.512
Desa is urban	0.442	0.492	0.427
Desa is on the shore	0.131	0.142	0.167
N	13,581	19,468	24,250

Table 3.4: Logit Regressions of Low Health Measures

	overweight	hypertension	low PEFR	low hemoglobin	low intrvr rating	low respdnt rating
			No group-level controls			
migrated with flood last year	0.098	-0.140	0.170	-0.004	-0.019	-0.062
	(0.318)	(0.262)	(0.315)	(0.288)	(0.311)	(0.404)
migrated with flood 2+ years ago	0.239	0.480***	0.249	0.226	0.105	0.022
	(0.172)	(0.140)	(0.196)	(0.138)	(0.159)	(0.202)
			Includes household-level controls			
migrated with flood last year	-0.106	-0.132	0.202	0.055	-0.108	0.066
	(0.317)	(0.272)	(0.299)	(0.303)	(0.314)	(0.443)
migrated with flood 2+ years ago	0.234	0.456***	0.196	0.191	0.002	0.073
	(0.154)	(0.138)	(0.187)	(0.152)	(0.175)	(0.215)
			Includes Kabupaten-level controls			
migrated with flood last year	0.179	-0.169	0.036	-0.083	-0.215	0.025
	(0.323)	(0.263)	(0.330)	(0.296)	(0.315)	(0.411)
migrated with flood 2+ years ago	0.247	0.435***	0.231	0.237*	0.136	0.136
	(0.169)	(0.140)	(0.203)	(0.139)	(0.169)	(0.199)

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 3.5: Multivariate Probit Regressions of Low Health Measures

	overweight	hypertension	low PEFR	low hemoglobin	low intrvr rating	low respdnt rating
			No group-level controls			
migrated with flood last year	0.024	-0.148	0.131	0.031	0.034	-0.082
	(0.175)	(0.162)	(0.178)	(0.162)	(0.172)	(0.215)
migrated with flood 2+ years ago	0.168*	0.201**	0.075	0.054	-0.019	0.003
	(0.088)	(0.081)	(0.082)	(0.081)	(0.172)	(0.102)
			Includes household-level controls			
migrated with flood last year	-0.080	-0.067	0.146	0.053	-0.026	-0.019
	(0.178)	(0.168)	(0.169)	(0.172)	(0.175)	(0.230)
migrated with flood 2+ years ago	0.118	0.096	0.022	0.035	-0.011	-0.040
	(0.085)	(0.079)	(0.084)	(0.092)	(0.091)	(0.105)
			Includes Kabupaten-level controls			
migrated with flood last year	0.061	-0.155	0.070	-0.083	-0.061	-0.012
	(0.178)	(0.165)	(0.183)	(0.296)	(0.184)	(0.216)
migrated with flood 2+ years ago	0.016*	0.170**	0.043	0.060	0.091	-0.036
	(0.090)	(0.081)	(0.084)	(0.081)	(0.095)	(0.103)

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 3.6: Two-class GoM with Endogeneity

	(1)	(2)	(3)
migrated last year	-0.093	-0.107	-0.087
	(0.160)	(0.161)	(0.157)
migrated 2+ years ago	-0.041	-0.001	-0.066
	(0.095)	(0.097)	(0.097)
male	-0.960***	-0.905***	-0.933***
	(0.112)	(0.112)	(0.112)
age in years	0.166***	0.160***	0.164***
	(0.006)	(0.007)	(0.006)
no schooling	-0.085	0.213	0.054
	(0.163)	(0.174)	(0.161)
high school or higher education	-0.181**	-0.444***	-0.163**
	(0.085)	(0.101)	(0.083)
married	0.077	0.120*	0.108*
	(0.063)	(0.065)	(0.064)
owns a house	-0.240***	-0.227***	-0.132*
	(0.073)	(0.072)	(0.075)
year is 2000	-0.094	-0.079	-0.177**
	(0.079)	(0.078)	(0.086)
year is 2007	0.950***	1.012***	0.877***
	(0.079)	(0.081)	(0.086)
log(population in Desa)	0.134***	0.129**	0.185***
	(0.052)	(0.051)	(0.067)
proportion of households in Desa with phone	0.360	0.086	-0.558
	(1.476)	(1.451)	(1.964)
log(distance to post office)	-0.010	-0.012	0.025
	(0.030)	(0.030)	(0.037)
Desa is urban	0.289***	0.255***	-0.008
	(0.094)	(0.092)	(0.135)
Desa is on the shore	0.074	0.084	-0.007
	(0.102)	(0.101)	(0.167)

Continued on next page

Table 3.6: Two-class GoM with Endogeneity

	(1)	(2)	(3)
Mean posterior pr.: class 1	0.597	0.597	0.597
Mean posterior pr.: class 2	0.403	0.403	0.403
Pr. poor health $\times 1000$: class 1	0.022	0.022	0.021
Pr. poor health $\times 1000$: class 2	0.960	0.952	0.961
Group level controls	None	Household	Kabupaten

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 3.7: Two-class GoM Estimates

	(1)	(2)	(3)
migrated with flood last year	0.127	-0.229	0.144
	(0.841)	(0.800)	(0.878)
migrated with flood 2+ years ago	1.106**	1.088**	1.040**
	(0.470)	(0.429)	(0.460)
migrated last year	-0.078	-0.087	-0.093
	(0.160)	(0.164)	(0.158)
migrated 2+ years ago	-0.082	-0.045	-0.104
	(0.097)	(0.098)	(0.098)
flood last year	0.520***	0.335**	0.495***
	(0.142)	(0.165)	(0.148)
flood 2+ years ago	0.255**	0.077	0.189
	(0.124)	(0.128)	(0.126)
male	-0.957***	-0.905***	-0.927***
	(0.112)	(0.113)	(0.113)
age in years	0.165***	0.159***	0.164***
	(0.006)	(0.007)	(0.006)
no schooling	-0.088	0.201	0.044
	(0.164)	(0.174)	(0.161)
high school or higher education	-0.185**	-0.463***	-0.168**
	(0.086)	(0.100)	(0.083)
married	0.072	0.114*	0.105
	(0.063)	(0.065)	(0.064)
owns a house	-0.251***	-0.235***	-0.139*
	(0.073)	(0.072)	(0.075)
year is 2000	-0.103	-0.081	-0.177**
	(0.078)	(0.077)	(0.086)
year is 2007	0.967***	1.031***	0.887***
	(0.079)	(0.081)	(0.086)

Continued on next page

	(1)	(2)	(3)
log(population in Desa)	0.136***	0.133***	0.181***
	(0.052)	(0.051)	(0.068)
proportion of households in Desa with phone	0.432	-0.098	-0.335
	(1.465)	(1.447)	(1.982)
log(distance to post office)	-0.012	-0.011	0.015
	(0.030)	(0.030)	(0.037)
Desa is urban	0.258***	0.218**	-0.007
	(0.094)	(0.093)	(0.135)
Desa is on the shore	0.040	0.029	-0.003
	(0.101)	(0.101)	(0.166)
Mean posterior pr.: class 1	0.597	0.597	0.597
Mean posterior pr.: class 2	0.403	0.403	0.403
Pr. poor health $\times 1000$: class 1	0.022	0.021	0.021
Pr. poor health $\times 1000$: class 2	0.962	0.953	0.963
Group level controls	None	Household	Kabupaten

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 3.8: Two-class GoM Robustness Checks

	(1)	(2)	(3)	(4)
migrated with flood last year	0.281	0.094	0.262	0.065
	(0.906)	(1.247)	(1.007)	(1.199)
migrated with flood 2+ years ago	1.019**	0.990*	0.904*	1.104**
	(0.508)	(0.559)	(0.525)	(0.531)
migrated last year	-0.107	-0.097	-0.114	0.020
	(0.163)	(0.209)	(0.183)	(0.171)
migrated 2+ years ago	-0.105	-0.180	-0.084	-0.275**
	(0.099)	(0.123)	(0.108)	(0.116)
flood last year	0.495***	0.541***	0.468***	0.376**
	(0.144)	(0.165)	(0.152)	(0.028)
flood 2+ years ago	0.213	0.168	0.242	0.140
	(0.123)	(0.140)	(0.130)	(0.139)
male	-0.958***	-0.926***	-1.034***	
	(0.102)	(0.132)	(0.125)	
age in years	0.338***	0.364***	0.452***	0.230***
	(0.021)	(0.029)	(0.032)	(0.028)
age squared in years	-0.002***	-0.02***	-0.004***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
no schooling	-0.015	0.128	-0.113	-0.159
	(0.136)	(0.150)	(0.149)	(0.137)
high school or higher education	-0.065	-0.214**	0.053	-0.694***
	(0.087)	(0.103)	(0.111)	(0.093)
married	0.033	-0.051	0.034	0.027
	(0.061)	(0.069)	(0.066)	(0.072)
owns a house	-0.131*	-0.153*	-0.124	-0.062
	(0.077)	(0.088)	(0.084)	(0.088)

Continued on next page

Table 3.8: Two-class GoM Robustness Checks

	(1)	(2)	(3)	(4)
year is 2000	-0.126	-0.161*	-0.019	-0.119
	(0.080)	(0.093)	(0.087)	(0.093)
year is 2007	0.931***	0.859***	1.079***	0.811***
	(0.081)	(0.095)	(0.090)	(0.093)
log(population in Desa)	0.170***	0.219***	0.167**	0.175**
	(0.066)	(0.082)	(0.073)	(0.074)
proportion of households in Desa with phone	-0.040	0.921	-0.608	-1.597
	(2.060)	(2.422)	(2.245)	(2.181)
log(distance to post office)	0.009	0.025	-0.006	-0.001
	(0.036)	(0.042)	(0.039)	(0.042)
Desa is urban	-0.013	-0.155	-0.035	-0.088
	(0.134)	(0.157)	(0.146)	(0.148)
Desa is on the shore	-0.012	0.063	-0.018	0.146
	(0.167)	(0.192)	(0.180)	(0.194)
Mean posterior pr.: class 1	0.618	0.634	0.637	0.606
Mean posterior pr.: class 2	0.382	0.366	0.363	0.394
Pr. poor health ×1000: class 1	0.023	0.039	0.034	0.040
Pr. poor health ×1000: class 2	1.014	1.234	0.917	1.385

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 3.9: Two-class GoM with Interactions

migrated with flood last year	-23.074
	(15.022)
migrated with flood 2+ years ago	2.237*
	(1.247)
migrated last year	-0.091
	(0.158)
migrated 2+ years ago	-0.114
	(0.099)
flood last year	0.497***
	(0.148)
flood 2+ years ago	0.195
	(0.127)
male	-0.930***
	(0.113)
age in years	0.164***
	(0.006)
age squared in years	-0.002***
	(0.000)
age in years w mf1	0.817*
	(0.459)
age in years w mf2	-0.036
	(0.033)
no schooling	0.044
	(0.161)
high school or higher education	-0.169**
	(0.084)
married	0.106*
	(0.064)
owns a house	-0.142*
	(0.075)

Continued on next page

Table 3.9: Two-class GoM with Interactions

year is 2000	-0.179**
	(0.087)
year is 2007	0.893***
	(0.087)
log(population in Desa)	0.174***
	(0.068)
proportion of households in Desa with phone	-0.460
	(2.005)
log(distance to post office)	0.017
	(0.037)
Desa is urban	0.010
	(0.136)
Desa is on the shore	-0.035
	(0.166)
Mean posterior pr.: class 1	0.597
Mean posterior pr.: class 2	0.403
Pr. poor health $\times$1000: class 1	0.021
Pr. poor health $\times$1000: class 2	0.963

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 3.10: First-Stage Logit Regressions

	Predicting M_{t-1}	Predicting M_{t-2}
flood_{t-1}	-0.27**	-0.64***
	(0.116)	(0.089)
flood_{t-2}	-0.35***	-0.34***
	(0.090)	(0.059)
male	0.14***	0.12***
	(0.038)	(0.026)
age in years	-0.03***	-0.01***
	(0.002)	(0.001)
no schooling	-1.06***	-0.90***
	(0.170)	(0.092)
high school or higher education	0.47***	0.47***
	(0.041)	(0.028)
married	0.01	0.11***
	(0.041)	(0.028)
owns a house	-0.66***	-0.85***
	(0.040)	(0.028)
year is 2000	0.25***	0.98***
	(0.053)	(0.042)
year is 2007	-0.08	0.99***
	(0.051)	(0.039)
log(population in Desa)	0.03	0.04**
	(0.025)	(0.017)
proportion of households in Desa with phone	-0.67	-0.69
	(0.944)	(0.058)
log(distance to post office)	-0.03*	0.02
	(0.016)	(0.011)
Desa is urban	-0.18***	-0.13***
	(0.053)	(0.035)
Desa is on the shore	-0.03	-0.09**
	(0.058)	(0.040)

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 3.11: Second Stage Two-class GoM

	(1)	(2)	(3)
migrated last year	0.012	-0.023	-0.005
	(0.264)	(0.272)	(0.261)
migrated 2+ years ago	0.242	0.156	0.254
	(0.175)	(0.172)	(0.176)
CF_1 residual	-0.025	-0.020	-0.021
	(0.053)	(0.053)	(0.053)
CF_2 residual	0.072	0.056	0.066
	(0.0.057)	(0.055)	(0.057)
male	-0.958***	-0.902***	-0.927***
	(0.112)	(0.112)	(0.112)
age in years	0.166***	0.159***	0.164***
	(0.006)	(0.007)	(0.006)
no schooling	-0.096	0.203	0.089
	(0.164)	(0.174)	(0.161)
high school or higher education	-0.174**	-0.443***	-0.169**
	(0.086)	(0.101)	(0.085)
married	0.079	0.121**	0.107*
	(0.063)	(0.065)	(0.064)
owns a house	-0.256***	-0.226***	-0.217***
	(0.074)	(0.074)	(0.074)
year is 2000	-0.084	-0.070	-0.079
	(0.079)	(0.078)	(0.078)
year is 2007	0.961***	1.021***	0.946***
	(0.079)	(0.082)	(0.079)

Continued on next page

Table 3.11: Second Stage Two-class GoM

	(1)	(2)	(3)
log(population in Desa)	0.135***	0.130**	0.53***
	(0.052)	(0.051)	(0.051)
proportion of households in Desa with phone	0.312	0.057	-0.022
	(1.477)	(1.449)	(1.488)
log(distance to post office)	-0.010	-0.011	-0.018
	(0.030)	(0.030)	(0.030)
Desa is urban	0.286***	0.247***	0.259***
	(0.094)	(0.092)	(0.096)
Desa is on the shore	0.072	0.078	0.166
	(0.102)	(0.101)	(0.107)
Mean posterior pr.: class 1	0.597	0.597	0.597
Mean posterior pr.: class 2	0.403	0.403	0.403
Pr. poor health $\times 1000$: class 1	0.022	0.022	0.022
Pr. poor health $\times 1000$: class 2	0.959	0.951	0.958
Group level controls	None	Household	Kabupaten

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 3.12: Differences in Health by Status/Flood

	Migrant†	Male‡	Age♭	Own house♮
Overweight				
Flood	0.069	0.082	0.002	0.052
	(0.043)	(0.082)	(0.004)	(0.095)
No Flood	0.020**	0.072***	0.007***	0.044***
	(0.008)	(0.016)	(0.001)	(0.017)
Hypertension				
Flood	0.026	-0.159	0.009	-0.029
	(0.056)	(0.111)	(0.005)	(0.119)
No Flood	0.102***	-0.136***	0.012***	0.010
	(0.010)	(0.019)	(0.001)	(0.019)
Low Peak Expiratory Flow Rate				
Flood	0.023	0.009	-0.006	-0.001
	(0.049)	(0.098)	(0.004)	(0.105)
No Flood	0.032***	0.050***	0.001	-0.005
	(0.008)	(0.016)	(0.001)	(0.016)
Low Hemoglobin				
Flood	0.012	0.179*	0.004	0.061
	(0.052)	(0.098)	(0.005)	(0.113)
No Flood	0.054***	0.152***	0.001	-0.037**
	(0.009)	(0.018)	(0.001)	(0.018)
Low Interviewer-Rated Health				
Flood	0.013	0.105	0.005	-0.096
	(0.051)	(0.099)	(0.005)	(0.103)
No Flood	0.048***	0.045**	0.001	-0.063***
	(0.009)	(0.018)	(0.001)	(0.018)
Low Respondent-Rated Health				
Flood	-0.051	-0.006	-0.005	0.055
	(0.046)	(0.093)	(0.004)	(0.102)
No Flood	-0.002	0.012	0.003***	0.014
	(0.007)	(0.014)	(0.001)	(0.014)

* p< 0.1; ** p< 0.05; *** p< 0.01

† Differences in means between non-migrants (0) and migrants (1)

‡ Differences in means between female (0) and male (1), migrants only

♭ Differences in mean age, migrants only

♮ Differences in house ownership status, migrants only

Figure 3.1: Rates of Low Health by Migrant and Flood Status

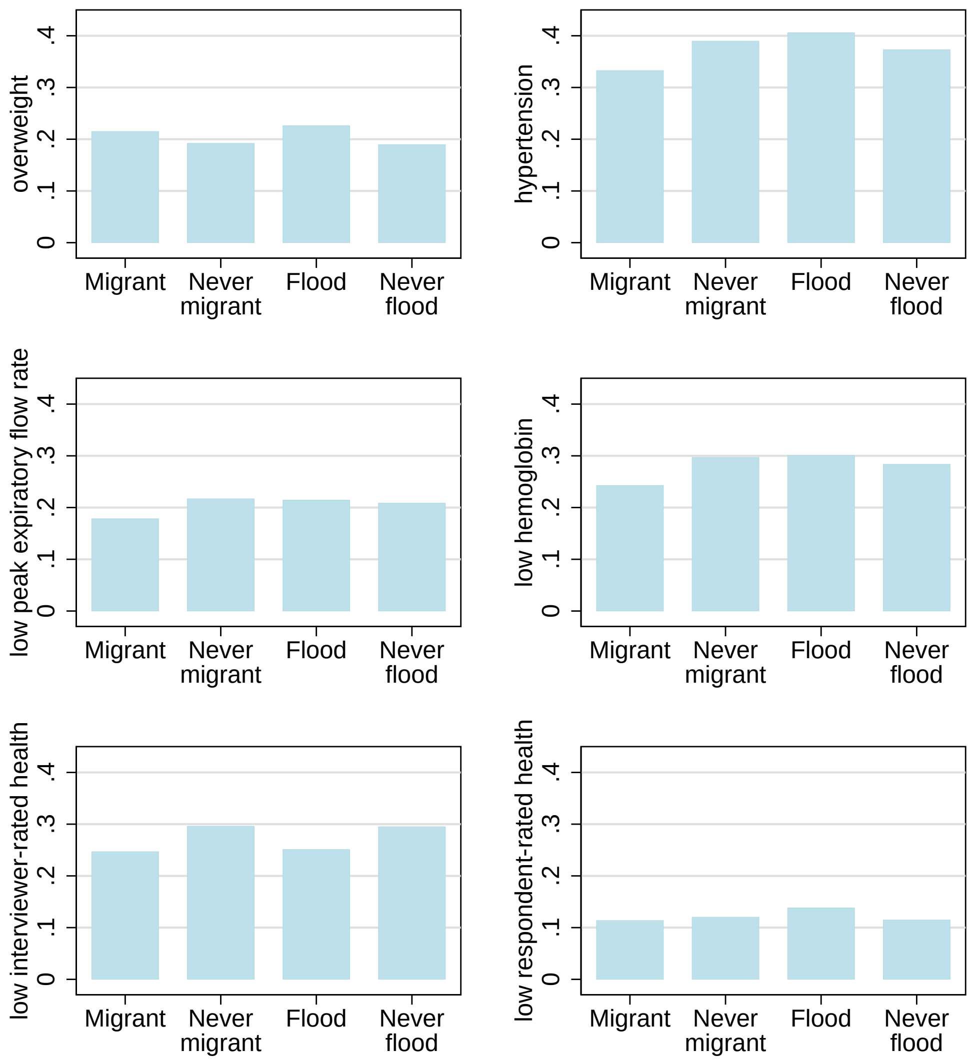


Figure 3.2: Flood-related Migrations as Percent of Total Migrations

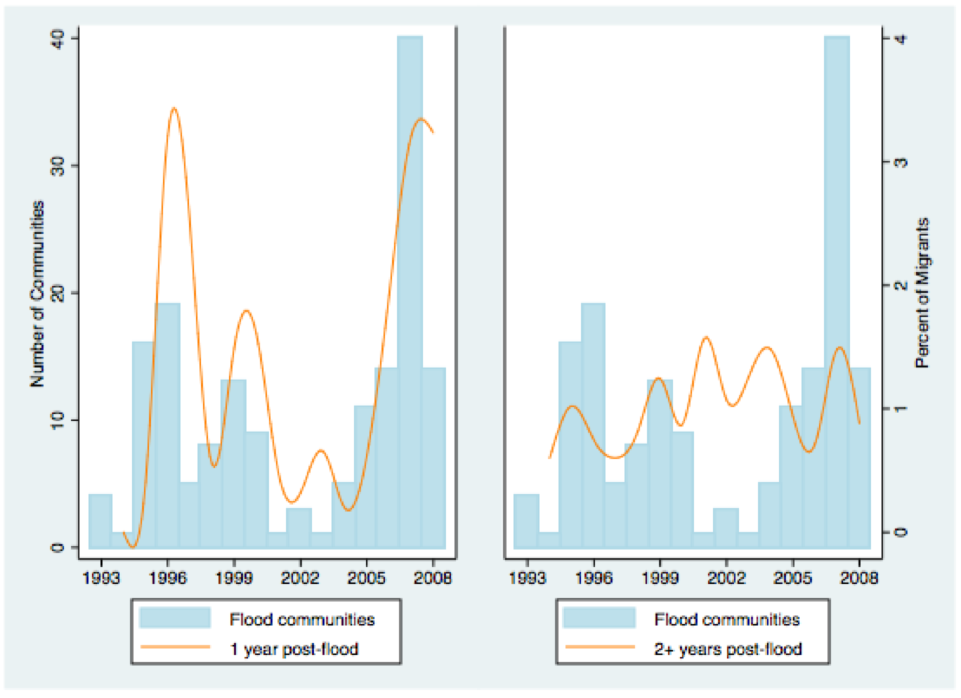


Figure 3.3: Probabilities of Health Conditions by Latent Class

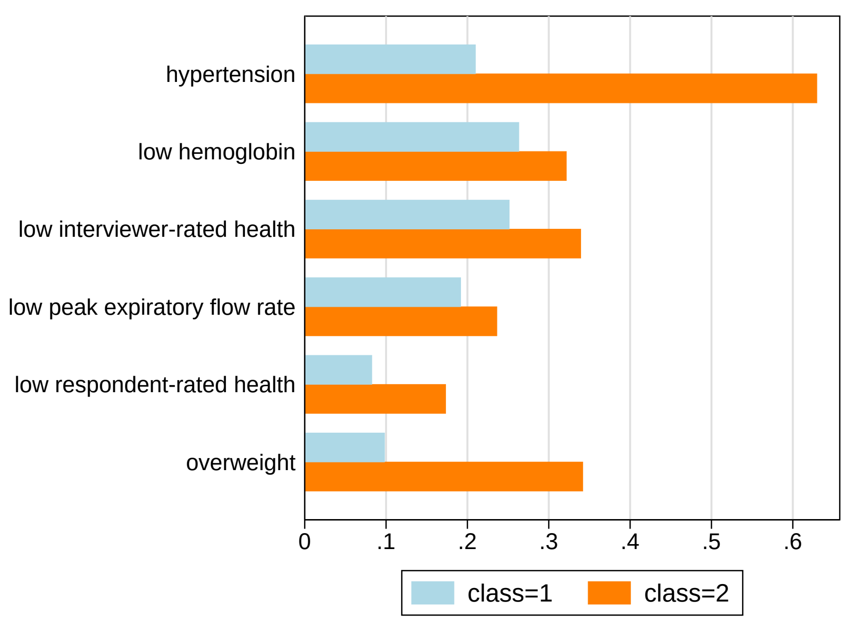
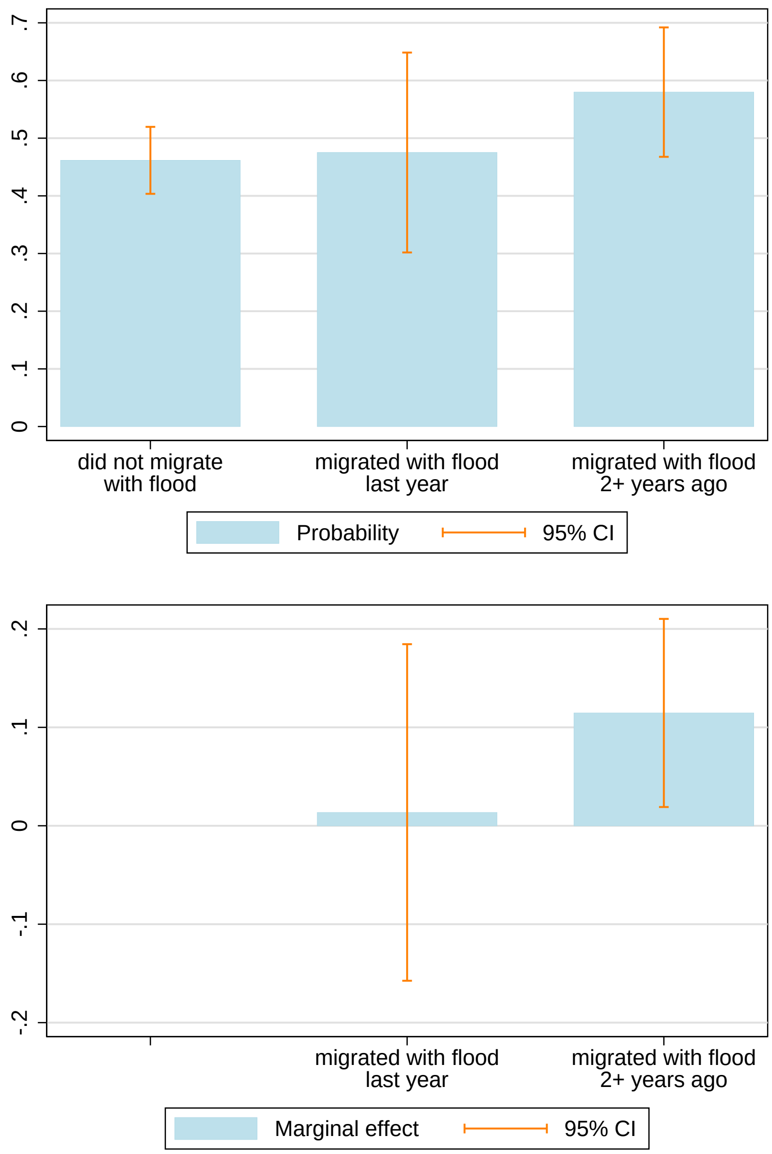


Figure 3.4: Effects of Migration on Probability of Class Membership



Chapter 4

CONCLUSION

In this dissertation, I first investigate the effects of floods on probability of out-migration from affected communities. I then turn to examine health of migrants subsequent to migration, using floods to reduce concerns regarding potential migration selectivity. I find that floods have a negative and significant effect on out-migration probability, and that individuals who undergo migration following a flood are more likely to be in "poor" health two or more years after migration.

The first result, described in Chapter 2, is not unique to literature. For example, Gray and Mueller (2012b) and Mueller et al. (2014) show that sometimes floods are associated with reduced migration. There are several possible explanations for such response. Floods destroy immediate income, making it difficult for households to send out migrants. On the other hand, the effects of floods are often temporary, with the long-term income and wealth being affected to a lesser degree or not affected at all. Furthermore, recovery efforts are usually associated with creation of temporary employment. The combination of reduced immediate income, job creation, and expectation of returning to normal income levels in the future could provide incentives for individuals and households to remain in the affected areas.

I provide a discussion on potential role of disaster recovery financing in out-migration. I find preliminary evidence that communities that receive outside help following a flood are more likely to send out migrants than the communities that did not receive help. In other words, the negative effects of floods on out-migration probability are partly mitigated by provision of government and non-government help. This result suggests that in absence of such help, individuals who would otherwise become migrants are more likely to stay in their origin communities and help with recovery effort following floods.

In Chapter 3, I use results obtained in Chapter 2 to examine the effects of migration on subsequent health. I use the fact that floods change out-migration probabilities to reduce concerns regarding potential migrant self-selectivity, in particular based on health. Then, treating health as a multidimensional concept, I am able to ascertain that health of migrants deteriorates and that this effect becomes pronounced over time.

While previous literature is inconclusive on whether migrants' health deteriorates or improves following a migration, researchers that find health to be declining offer various explanations for why this may be the case. Socio-economic, behavioral, and dietary changes in lives of people who recently moved are often blamed for the deterioration of health (Khan and Kraemer (2014), Renzaho and Burns (2006)). More systemically, literature show that migrants have lower rates of health services utilization, while health care providers often lack awareness of specialized health needs of migrants (Hansen and Donohoe, 2003).

My findings are consistent with the previous literature, and also consistent with "labor-retention" hypothesis – a theory positing that instead of moving away in the aftermath of natural disasters, individuals stay in their home communities to help with the recovery efforts since the affected communities increase labor demand for the young and healthy.

My results highlight the need for future research in the effects of floods on migration and subsequent health of migrants in developing countries. In particular, there is a great need to incorporate characteristics of destination communities directly into the models. Such "push" and "pull" models will prove to be useful in understanding flood-induced migration dynamics and health outcomes resulting from such moves.

Bibliography

Rameez Abbas and Divya Varma. Internal Labor Migration in India Raises Integration Challenges for Migrants. Feature, Migration Policy Institute, March 2014. URL `http://www.migrationpolicy.org/article/internal-labor-migration-india-raises-integration-challenges-migrants`. [Online; posted 3-March-2014].

A. F. Abraido-Lanza, M. T. Chao, and K. R. Florez. Do Healthy Behaviors Decline with Greater Acculturation? Implications for the Latino Mortality Paradox. *Social Science & Medicine*, 61:1243–1255, 2005.

Ana F. Abraido-Lanza, Bruce P. Dohrenwend, Daisy S. Ng-Mak, and J. Blake Turner. The Latino Mortality Paradox: A Test of the "Salmon Bias" and Healthy Migrant Hypotheses. *American Journal of Public Health*, 89(10):1543–1548, 1999.

Mike Ahern, R. Sari Kovats, Paul Wilkinson, Roger Few, and Franziska Matthies. Global Health Impacts of Floods: Epidemiological Evidence. *Epidemiological Reviews*, 27:36–46, 2005.

Gustavo Angeles, David K. Guilkey, and Thomas A. Mroz. The Impact of Community-Level Variables on Individual-Level Outcomes: Theoretical Results and Applications. *Social Methods & Research*, 34(1):76–121, 2005.

Joaquin Arango. Theories of International Migration. In Daniele Joly, editor, *Global Movement and Settlement*. Ashgate, Burlington, VT, 2004.

Mohamed Arouri, Cuong Nguyen, and Adel ben Youssef. Natural Disasters, Household Welfare, and Resilience: Evidence from Rural Vietnam. *World Development*, 70:59–77, 2015.

Susan Athey and Guido W. Imbens. Identification and Inference in Nonlinear Difference-in-Difference Models. *Econometrica*, 74(2):431–497, 2006.

Reena Badiani and Abla Safir. Coping with Aggregate Shocks: Temporary Migration and Other Labor Responses to Climatic Shocks in Rural India. Technical report, 2008.

Edward B. Barbier. Cash Crops, Food Crops, and Sustainability: The Cace of Indonesia. *World Development*, 17(6):879–895, 1989.

Crostopher B Barrett and Michael R Carter. The Economics of Poverty Traps and Persistent Poverty: Policy and Empirical Implications. 2012.

Salvador Barrios, Luisito Bertinelli, and Eric Strobl. Climatic Change and Rural–Urban Migration: The Case of sub-Saharan Africa. *Journal of Urban Economics*, 60:357–371, 2006.

Martin Bell and Elin Charles-Edwards. Cross-National Comparisons of Internal Migration: An Update on Global Patterns and Trends. Technical Paper 2013/1, United Nations, Department of Economic and Social Affairs, Population Division, 2013.

Martin Bell and Salut Muhidin. Cross-National Comparisons of Internal Migration. Research Paper 2009/30, United Nations Development Programme, Human Development Reports, 2009.

Richard Black, W Neil Adger, Nigel W Arnell, Stefan Dercon, Andrew Geddes, and David S G Thomas. The Effect of Environmental Change on Human Migration. *Global Environmental Change*, 21S:S3–S11, 2011a.

Richard Black, W Neil Adger, Nigel W Arnell, Stefan Dercon, Andrew Geddes, and David S G Thomas. Migration and Global Environmental Change. *Global Environmental Change*, 21S:S1–S2, 2011b.

Richard Black, Dominic Kniveton, and Kerstin Schmidt-Verkerk. Migration and Climate Change: Toward an Integrated Assessment of Sensitivity. *Environment and Planning A*, 43:431–450, 2011c.

Richard Black, Nigel W Arnell, W Neil Adger, David Thomas, and Andrew Geddes. Migration, Immobility and Displacement Outcomes Following Extreme Events. *Environmental Science and Policy*, 27S:S32–S43, 2013.

Pratikshya Bohra-Mishra, Michael Oppenheimer, and Solomon M. Hsiang. Nonlinear Permanent Migration Response to Climatic Variations but Minimal Response to Disasters. *Proceedings of the National Academy of Sciences*, 111(27):9780–9785, 2014.

Jizzo R. Bosdriesz, Nienke Lichthart, Margot I. Witvliet, Wim B. Busschers, Karien Stronks, and Anton E. Kunst. Smoking Prevalence among Migrants in the US Compared to the US-Born and the Population in Countries of Origin. *PLOS One*, 8(3), 2013.

Paul J. Boyle, Keith Halfacree, and Vaughan Robinson. *Exploring Contemporary Migration*. Longman, Harlow, UK, 1998.

Edward R Carr. Placing the environment in migration: Environment, economy, and power in ghana's central region. *Environment and Planning A*, 37(5):925–946, 2005.

S. Castles and M. J. Miller. *The Age of Migration: International Population Movements in the Modern World*. Macmillan, Basingstoke, 1993.

Gary Chamberlain. Chapter 22: Panel Data. In Zvi Griliches and Michael Intriligator, editors, *Handbook of Econometrics*, pages 1247–1318. Elsevier Science, 1984.

Sara R. Curran and Estela Rivero-Fuentes. Engendering Migrant Networks: The Cace of Mexican Migration. *Demography*, 40(2):289–307, 2003.

Susan L. Cutter. Vulnerability to Environmental Hazards. *Progress in Human Geography*, 20(4):529–539, 1996.

Partha Deb and Pravin K. Trivedi. Demand for Medical Care by the Elderly: A finite Mixture Approach. *Journal of Applied Econometrics*, 12(3):313–336, 1997.

Carlo del Ninno, Paul A Dorosh, Lisa C Smith, and Dilip K Roy. The 1998 Floods in Bangladesh: Disaster Impacts, Household Coping Strategies, and Response. Technical Report 122, International Food Policy Research Institute, 2014.

A. P. Dempster, N. M. Laird, and D. B. Rubin. Maximum Likelihood from Incomplete Data via the EM Algorithm. *Journal of the Royal Statistical Society. Series B (Methodological)*, 39(1):1–38, 1977.

Andrew Dillon, Valerie Mueller, and Sheu Salau. Migratory Responses to Agricultural Risk in Northern Nigeria. Technical Report 01007, International Food Policy Research Institute, 2010.

Alassane Drabo and Linguere Mously Mbaye. Climate Change, Natural Disasters, and Migration: An Empirical Analysis in Developing Countries. Technical Report 5927, IZA, 2011.

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

Alice Fothergill, Enrique G.M. Maestas, and JoAnne DeRouen Darlington. Race, Ethnicity and Disasters in the United States: A Review of the Literature. *Disasters*, 23(2):156–173, 1999.

Elizabeth Fussell, Katherine J Curtis, and Jack DeWaard. Recovery Migration to the City of New Orleans after Hurricane Katrina: A Migration Systems Approach. *Population and Environment*, 35:305–322, 2014a.

Elizabeth Fussell, Lori M Hunter, and Clark L Gray. Measuring the Environmental Dimensions of Human Migration: The Demographer's Toolkit. *Global Environmental Change*, 28(1):182–191, 2014b.

Melissa M. Garrido, Partha Deb, Jr. James F. Burgess, and JOan D. Penrod. Choosing Models for Health Care Cost Analyses: Issues of Nonlinearity and Endogeneity. *Health Services Research*, 47(6):2377–2397, 2012.

Ramesh Ghimire, Susana Ferreira, and Jeffrey H. Dorfman. Flood-Induced Displacement and Civil Conflict. *World Development*, 66:614–628, 2015.

Noreen Goldman, Anne R. Pebley, Mathew J. Creighton, Graciela M. Teruel, Luis N. Rubalcava, and Chang Chung. The Consequences of Migration to the United States for Short-Term Changes in the Health of Mexican Immigrants. *Demography*, 51: 1159–1173, 2014.

Clark Gray and Richard Bilsborrow. Environmental Influences on Human Migration in Rural Ecuador. *Demography*, 50:1217–1241, 2013.

Clark Gray and Valerie Mueller. Drought and Population Mobility in Rural Ethiopia. *World Development*, 40(1):134–145, 2012a.

Clark Gray, Elizabeth Frankenberg, Thomas Gillespie, Cecep Sumantri, and Duncan Thomas. Studying Displacement After a Disaster Using Large-Scale Survey Methods: Sumatra After the 2004 Tsunami. *Annals of the Association of American Geographers*, 104(3):594–612, 2014.

Clark L Gray. Environment, Land, and Rural Out-migration in the Southern Ecuadorian Andes. *World Development*, 37(2):457–468, 2009.

Clark L Gray. Gender, Natural Capital, and Migration in the Southern Ecuadorian Andes. *Environment and Planning A*, 42:678–696, 2010.

Clark L Gray and Valerie Mueller. Natural Disasters and Population Mobility in Bangladesh. *Proceedings of the National Academy of Sciences of the United States of America*, 109(16):6000–6005, 2012b.

Jeffrey Groen and Anne E. Polivka. Hurricane Katrina Evacuees: Who They Are, Where They Are, and How They Are Faring. *Monthly Labor Review*, 131(3):32–51, 2008.

Timothy Halliday. Migration, Risk, and Liquidity Constraints in El Salvador. *Economic Development and Cultural Change*, 25(5):893–925, 2006.

Eric Hansen and Martin Donohoe. Health Issues of Migrant and Seasonal Farmworkers. *Journal of Health Care for the Poor and Underserved*, 14(2):153–164, 2003.

John R. Harris and Michael P. Todaro. Unempoyment and Development: A Two-Sector Analysis. *The American Economic Review*, 60(1):126–142, 1970.

Sabine Henry, Bruno Schoumaker, and Cris Beauchemin. The Impact of Rainfall on the First Out-Migration: A Multi-level Event-History Analysis in Burkina Faso. *Population and Environment*, 25(5):423–460, 2004.

Nicole Hildebrandt, David J. McKenzie, Gerardo Esquivel, and Ernesto Schargrodsky. The Effects of Migration on Child Health in Mexico. *Economia*, 6(1):257–289, 2005.

Graeme Hugo. Environmental Concerns and International Migration. *International Migration Review*, 30(1):105–131, 1996.

Lori M Hunter, Sheena Murray, and Fernando Riosmena. Rainfall Patterns and U.S. Migration from Rural Mexico. *International Migration Review*, 47(4):874–909, 2013.

Lori M Hunter, Raphael Nawrotzki, Stefan Leyk, Galen J Maclaurin, Wayne Twine, Mark Collinson, and Barend Erasmus. Rural Outmigration, Natural Capital, and Livelihoods in South Africa. *Population, Space and Place*, 20:402–420, 2014.

Lori M Hunter, Jessie K Luna, and Rachel M Norton. Environmental Dimensions of Migration. *Annual Review of Sociology*, 41:377–397, 2015.

Stanislav V. Kasl and Lisa Berkman. Health Consequences of the Experience of Migration. *Annual Reviews of Public Health*, 4:69–90, 1983.

Harounan Kazianga and Christopher Udry. Consumption Smoothing? Livestock, Insurance and Drought in Rural Burkina Faso. *Journal of Development Economics*, 79:413–446, 2006.

Md. Mubarak Hossain Khan and Alexander Kraemer. Are Rural-Urban Migrants Living in Urban Slums More Vulnerable in Terms of Housing, Health Knowledge, Smoking, Mental Health and General Health? *International Journal of Social Welfare*, 23:373–383, 2014.

Marieke Kleemans. Migration Choice under Risk and Liquidity Constraints. 2014.

M. M. Kritz, L. L. Lim, and H. Zlotnik. *International Migration Systems: A Global Approach*. Clarendon Press, Oxford, 1992.

Randal S. Kuhn. The Determinants of Family and Individual Migration: A Case-Study of Rural Bangladesh. Working Paper, 2005.

Frank Laczko and Christine Aghazarm. Migration, Environment and Climate Change: Assessing the Evidence. *International Organization for Migration*, 2009.

Robert J. LaLonde and Robert H. Topel. Economic Impact of International Migration and the Economic Performance of Migrants. In Mark R. Rosenzweig and Oded Stark, editors, *Handbook of Population and Family Economics*, pages 799–850. Elsevier Science, 1997.

M. Lara, C. Gamboa, M. I. Kahramanian, L. Morales, and D. Bautista. Acculturation and Latino Health in the United States: A Review of the Literature and its Sociopolitical Context. *Annual Review of Public Health*, 26:367–397, 2005.

Jane H. Lassetter and Lynn C. Callister. The Impact of Migration on the Health of Voluntary Migrants in Western Societies. *Journal of Transcultural Nursing*, 20(1): 93–104, 2009.

D. P. Lindstrom and N. Lauster. Local Economic Opportunity and the Competing Risks of Internal and U.S. Migration in Zacatecas, Mexico. *International Migration Review*, 35(4):1232–1256, 2001.

Yao Lu. Test of the 'Healthy Migrant Hypothesis': A Longitudinal Analysis of Health Selectivity of Internal Migration in Indonesia. *Social Sscience and Medicine*, 67: 1331–1339, 2008.

Yao Lu. Rural-Urban Migration and Health: Evidence from Longitudinal Data in Indonesia. *Social Sscience and Medicine*, 70:412–419, 2010.

Kenneth G. Manton and Max A. Woodbury. A New Procedure for Analysis of Medical Classification. *Methods of Information in Medicine*, 21(4):210–220, 1982.

Kenneth G. Manton, Eric Stallard, and Max A. Woodbury. Applications of the Grade of Membership Technique to Event History Analysis: Etensions to Multivariate Unobserved Heterogeneity. *Mathematical Modelling*, 7:1375–1391, 1986.

Kenneth G. Manton, Max A. Woodbury, James C. Vertrees, and Eric Stallard. Use of Medicare Services Before and After Introduction of the Prospective Payment System. *Health Services Research*, 28(3):269–292, 1993.

Luca Marchiori, Jean-Francois Maystadt, and Ingmar Schumacher. The Impact of Weather Anomalies on Migration in sub-Saharan Africa. *Journal of Environmental Economics and Management*, 63:355–374, 2012.

Maximillan Martin, Motasim Billah, Tasneem Siddiqui, chowdhury Abrar, Richard Black, and Dominic Kniveton. Climate-Related Migration in Rural Bangladesh: A Behavioural Model. *Population and Environment*, 36:85–110, 2014.

D. Massey, J. Arango, G. Hugo, A. Kouaouci, A. Pellegrino, and J. E. Taylor. Theories of International Migration: A Review. *Population and Development Review*, 19: 431–466, 1993.

D. S. Massey and F. G. España. The Social Process of International Migration. *Science*, 237(4816):733–738, 1987.

Douglas S Massey. Immigration Statistics for the 21st Century. *Annals of the American Academy of Political and Social Science*, 631(1):124–140, 2010.

Douglas S. Massey and Kristin E. Espinosa. What's Driving Mexico–U.S. Migration? A Theoretical, Empirical, and Policy Analysis. *American Journal of Sociology*, 102 (4):939–999, 1997.

Douglas S. Massey, William G. Axinn, and Dirgha J. Ghimire. Environmental Change and Out-Migration: Evidence from Nepal. *Population and Environment*, 32(2): 109–136, 2010.

Jean-Francois Maystadt, Valerie Mueller, and Ashwini Sebastian. Environmental Migration and Labor Markets in Nepal. Technical Report 01364, International Food Policy Research Institute, 2014.

Laura McKay, Sally Macintyre, and Anne Ellaway. Migration and Health: A Review of the International Literature. 2003.

David McKenzie, John Gibson, and Steven Stillman. How Important is Selection? Experimental vs. Non-Experimental Measures of the Income Gains from Migration. 2006.

Geoffrey McLachlan and David Peel. *Finite mixture models*. John Wiley & Sons, 2004.

R A McLeman and B Smit. Migration as an Adaptation to Climate Change. *Climatic Change*, 76:31–53, 2006.

Robert A. McLeman and Lori M. Hunter. Migration in the context of vulnerability and adaptation to climate change: insights from analogues. *Wiley Interdisciplinary Reviews: Climate Change*, 1(3):450–461, 2010.

F Mialhe, Y Gunnell, and C Mering. The Impact of Shrimp Farming on Land Use, Employment, and Migration in Tumbes, Northern Peru. *Ocean and Coastal Management*, 73:1–12, 2013.

J. Mincer. Family Migration Decisions. *Journal of Political Economy*, 86(5):749–773, 1978.

Sanket Mohapatra, Dilip Ratha, and Elina Scheja. Impact of Migration on Economic and Social Development: A Review of Evidence and Emerging Issues. Technical report, Migration and Remittances Unit, World Bank, 2010.

Mark R. Montgomery and Paul C. Hewett. Urban Poverty and Health in Developing Countries: Household and Neighborhood Effects. *Demography*, 42(3):397–425, 2005.

O. Morgan, M. Ahern, and S. Cairncross. Revisiting the Tsunami: Health Consequences of Flooding. *PLoS Med*, 2(6), 2005.

V Mueller, C Gray, and K Kosec. Heat Stress Increases Long-term Human Migration in Rural Pakistan. *Nature Climate Change*, 4:182–185, 2014.

Wahyu Mulyana, Ivo Setiono, Amy Kracker Selzer, Sainan Zhang, David Dodman, and Daniel Schensul. Urbanization, Demographics, and Adaptation to Climate Change in Semarang, Indonesia. *Human Settlements Group*, 2013. URL `http://www.iied.org/pubs/display.php?o=10632IIED`.

Yair Mundlak. On the Pooling of Time Series and Cross Section Data. *Econometrica*, 46(1):69–85, 1978.

Norman Myers. Environmental Refugees: A Growing Phenomenon of the 21st Century. *Philosophical Transactions of The Royal Society B*, 357(1420):609–613, 2002.

Raphael J Nawrotzki, Lori M Hunter, and Thomas W Dickinson. Rural Livelihoods and Access to Natural Capital: Differences between Migrants and Non-migrants in Madagascar. *Demographic Research*, 26:661–700, 2012.

Raphael J Nawrotzki, Fernando Riosmena, Lori M Hunter, and Daniel M Runfola. Amplification or Suppression: Social Networks and the Climate Change–Migration Association in Rural Mexico. *Global Environmental Change*, 35:463–474, 2015.

Marie Norredam. Migrant's Access to Healthcare. *Danish Medical Bulletin*, 58(10): B4339, 2011.

Bimal Kanti Paul. Evidence Against Disaster-Induced Migration: The 2004 Tornado in North-Central Bangladesh. *Disasters*, 29(4):370–385, 2005.

Shitangsu Kumar Paul and Jayant K. Routray. Flood proneness and coping strategies: The experiences of two villages in bangladesh. *Disasters*, 34(2):489–508, 2010.

Edmund C Penning-Roswell, Parvin Sultana, and Paul M Thompson. The 'Last Resort'? Population Movement in Response to Climate-Related Hazards in Bangladesh. *Environmental Science and Policy*, 27S:S44–S59, 2013.

Yusnita Permana, Johan Woltjer, and Roos Akbar. An Assessment of Local Government Capacity in Managing Floods: A Cace Srudy of Municipality of Cirebon, West Java, Indonesia. *Jurnal Perencanaan Wilayah dan Kota*, 1(2):257–265, 2013.

A. Portes. Immigration Theory for a New Century: Some Problems and Opportunities. *International Migration Review*, 31:799–825, 1997.

France Portrait, Maarten Lindeboom, and Dorly Deeg. Health and Mortality of the Elderly: The Grade of Membership Method, Classification and Determination. *Health Economics*, 8:441–457, 1999.

Dudley L Poston, Li Zhang, David J Gotcher, and Yuan Gu. The Effects of Climate on Migration: United States, 1995–2000. *Social Science Research*, 38:743–753, 2009.

Patrick A. Puhani. The Treatment Effect, the Cross Difference, and the Interaction Term in Nonlinear "Difference-in-Differences" Models. *Economic Letters*, 115:85–87, 2012.

Agnes Quisumbing. Food Aid and Child Nutrition in Rural Ethiopia. *World Development*, 31(7):1309–1324, 2003.

Andre M.N. Renzaho and Cate Burns. Post-Migration Food Habits of Sub-Saharan African Migrants in Victoria: A Cross-Sectional Study. *Nutrition & Dietetics*, 63: 91–102, 2006.

Melissa H. Roberts and Douglas W. Mapel. Limited Lung Function: Impact of Reduced Peak Expiratory Flow on Health Status, Health-Care Utilization, and Expected Survival in Older Adults. *American Journal of Epidemiology*, 176(2): 127–134, 2012.

Mark R. Rosenzweig and Oded Stark. Consumption Smoothing, Migration, and Marriage: Eevidence from Rural India. *The Journal of Political Economy*, 97(4): 905–926, 1989.

Luis N. Rubalcava, Graciela M. Teruel, Duncan Thomas, and Noreen Goldman. The Healthy Migrant Effect: New Findings From the Mexican Family Life Survey. *American Journal of Public Health*, 98(1):78–84, 2008.

Sergio O. Saldaña-Zorrilla and Krister Sandberg. Spacial Econometric Model of Natural Disaster Impact on Human Migration in Vulnerable Regions of Mexico. *Disasters*, 33(4):591–607, 2009.

Narayan Sastry and Jesse Gregory. Dislocation and Return of New Orleans Residents Following Hurricane Katrina. Marrakech, 2009. International Union for the Scientific Study of Population.

Marc B Schenker, Xòchitl Castañeda, and Alfonso Rodriguez-Lainz. *Migration and Health: A Research Methods Handbook*. University of California Press, Oakland, California, 2014.

Emmanuel Skoufias and Katja Vinha. The Impacts of Climate Variability on Household Welfare in Rural Mexico. *Population and Environment*, 34:370–399, 2013.

Marc Stal. Flooding and relocation: The zambezi river valley in mozambique. *International Migration*, 49:e125–e145, 2011.

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

Jonathan D. Stringfield. Higher Ground: An Eexploratory Analysis of Characteristics Affecting Rreturning Populations After Hurricane Katrina. *Population and Environment*, 31:43–63, 2010.

J. E. Taylor and A. Lopez-Feldman. Does Migration Make Rural Households More Productive? Evidence from Mexico. *Journal of Development Studies*, 46(1):68–90, 2010.

Michael P. Todaro and Lydia Maruszko. Illegal Migration and US Immigration Reform: A Conceptual Framework. *Population and Development Review*, 13(1):101–114, 1987.

United Nations, Depatment of Economic and Social Affairs, Population Division. International Migration Report 2009: A Global Assessment. Report, United Nations, 2009.

United Nations Development Program, UNDP. Human Development Report 2009 — Overcoming Barriers: Human Mobility and Development. Report, United Nations, 2009.

J. van Lottum and D. Marks. The Determinants of Internal Migration in a Developing Country: Quantitative Evidence for Indonesia, 1930–2000. *Applied Economics*, 44: 4485–4494, 2012.

L. K. VanWey, A. O. D'Antona, and E. S. Brondizio. Household Demographic Change and Land Use/Land Cover Change in the Brazilian Amazon. *Population and Environment*, 28(3):163–185, 2007.

Leah K. VanWey. Land Ownership as a Determinant of International and Internal Migration in Mexico and Internal Migration in Thailand. *International Migration Review*, 39(1):141–172, 2005.

J. Vearey and B. Wheeler. Migration and Health in SADC: A Review of the Literature, 2010.

Peter von Rooij. Labour and Social Trends in Indonesia 2011: Promoting Job-Rich Growth in Provinces, 2012.

Robert Walker, Stephen Perz, Marcellus Caldas, and Luiz Guilherme Teixeira Silva. Land use and land cover change in forest frontiers: The role of household life cycles. *International Regional Science Review*, 25(2):169–199, 2002.

Koko Warner. Environmental Change and Migration: Methodological Considerations from Ground-Breaking Global Survey. *Population and Environment*, 33:3–27, 2001.

Ben Wisner, Piers Blaikie, Terry Cannon, and Ian Davis. *At Risk: Natural Hazards, People's Vulnerability and Disasters*. Routledge, 2004.

W. Wood. Ecomigration: Linkages between Environmental Change and Migration. In A. Zolberg and P. Benda, editors, *Global Migrants, Global Refugees: Problems and Solutions*, pages 42–61. Berghahn Books, New York, 2001.

World Health Organization. Global Reference List of Core Health Indicators: Working Version 5. Report, World Health Organization, Geneva, Switzerland, 2015.

World Health Organization. Flooding and Communicable Diseases Fact Sheet. `http://www.who.int/hac/techguidance/ems/flood_cds/en/`, 2016. Accessed: 2016-05-01.

Dean Yang. Risk, Migration and Rural Financial Markets: Evidence from Earthquakes in El Salvador. *Social Research*, 73(3):955–992, 2008.

Yaohui Zhao. Labor Migration and Earnings Differences: The Case of Rural China. *Economic Development and Cultural Change*, 47(4):767–782, 1999.

A. Zolberg. The Next Waves: Migration Theory for a Changing World. *International Migration Review*, 23:403–430, 1989.