Institutions, Risk Perceptions, and Adaptation: Exploring Behavioral Response to Climate Change in Thailand

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Abstract

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Social science investigations about human and social vulnerability, adaptation, risk perception, and migration as a result of climate change is the focus of research in the developing world. Rural residents, especially those who rely on agriculture for a significant share of their household income, are expected to be particularly vulnerable to increases in climate shocks. Most social science research relies on objective measures to explore the relationship between the environment and human behavior. These objective measures give a sense of the severity and direction of changes in the environment, but provide limited information about how rural residents perceive the impacts of climate change on their daily lives. Risk perception research finds that human behavior is often shaped more by perceptions of risk than objectively measured risk. The primary question that motivates the three papers in my dissertation is: How do people living in rural areas perceive the environment as a source of livelihood risk, and what do these perceptions tell us about the human-environment relationship, above and beyond objective data?

My first paper explores the dynamic association between proximate and cumulative subjective and objective environmental measures and the likelihood of a respondent perceiving an environmental cause of a poor economic outcome. The analysis suggests differential associations between proximate and cumulative environmental measures, and environmental risk perceptions. In my second paper, I explore the association between household composition and livelihood assets and the likelihood of a household respondent perceiving the environment as a cause of a bad income year. My results suggest that household size and composition influence environmental risk perceptions, as does occupational diversity of household members, and social learning. Finally, in my third paper, I examine the association between proximate and cumulative subjective and objective environmental measures, and a household's decision to send a migrant as a possible coping strategy. I find that in the near term, household migration decisions are not sensitive to environmental stress, but that the likelihood of sending a migrant is a function of both long term cumulative objective exposure and proximate risk perceptions.

The key finding of my dissertation is that proximate and cumulative subjective and objective measures of the environment better elaborate the human-environment nexus than objective measures alone. Policymakers, crafting policies to initiate and support mitigation and adaptation efforts should consider both the objective and subjective exposure and experience of climatic shocks to create more efficient and targeted results.

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Dedication

To Harrie and Marina Meijer

Introduction

Social science investigations about human and social vulnerability, adaptation, risk perception, and migration as a result of climate change is the focus of research in the developing world (Porter et al. 2014). Rural residents, especially those who rely on agriculture for a significant share of their household income, are expected to be particularly vulnerable to increases in climate shocks. Current models predict increases in climate variability that might include prolonged drought and increases in frequency and duration of flood events. The primary question that motivates the three papers in my dissertation is: How do people living in these areas perceive the environment as a source of livelihood risk, and what do these perceptions tell us about the human-environment relationship, above and beyond objective data?

Researchers typically rely on objective, physical measures of the environment to model the role of the environment on human behavior. While objective measures give a sense for environmental exposure and historical trends, using objective measures to model human behavior is problematic, as environmental exposure is differentially experienced and assessed by individuals. Human behavior and decision-making may be more influenced by subjective perceptions than by objective conditions alone (Volker et al. 2011).

There are a number of factors that shape how people assess a given risk and the behavior that results; exposure to risk, captured by objective measures, is just one factor. Meteorological data on drought, for example, is a narrow measure that does not consider contextual factors, such as the psychological, cultural, social and institutional processes that influence how people experience and understand risk (Kasperson et al. 1988). Perception of risk is also conditioned by whether or not an individual has the ability to mitigate a risk. Thus, whether an individual has access to a diversity of occupational opportunities, or assets to draw upon when a shock hits influences the extent to which she perceives risk (Carney 1998; Scoones 1998). The ability to cope after a shock also shapes perceptions of risk; access to financial borrowing, or the ability to migrate following an environmental risk might reduce one's perception of a shock (Barrett et al. 2001). Given the multiple components that shape human behavior, beyond just objective conditions, my dissertation incorporates subjective perceptions of the environment to improve upon models that examine human behavior in reaction to climatic shocks.

Inclusion of subjective perceptions of the environment, provided by the people who are exposed to climate variability, adds an additional layer to the human-environment relationship. In particular, these subjective perceptions illustrates whether people who are exposed to an objective environmental risk indicate this as a primary source of risk to their livelihood. This is important for a number of reasons. First, if there is a mismatch between objective risk and subjective perceptions, it might be that people do not perceive a risk because they are able to adapt *in situ*, something that relying on objective data alone does not reveal (Barrett et al. 2001). Second, perhaps repeat exposure to climate variability normalizes the event, decreasing the perception of the environment as a risk, even though they remain objectively vulnerable (Casimir 2008; Slovic et al. 1986). On the other hand, outside agencies or researchers, relying on objective environmental data, might assume a risk that, when contextualized within the area of interest, is not considered to be a significant barrier to daily life (Hunter 2005). For policymakers who seek to derive policy recommendations to address vulnerability to climate change, understanding how stakeholders perceive their risks may be the most effective way to influence behavioral change (Volker et al. 2011).

To explore the association between objective and subjective environmental measures and human behavior in a rural developing world setting, I take advantage of the Townsend Thai

Data, a unique annual panel dataset (Townsend et al. 1997). This dataset contains household-level information on income and assets, access to capital endowments, household composition, migration activity, as well as the household respondent's perceived cause of a poor economic outcome in the past year. To this dataset, I add robust objective environmental data that coincides with the time period (1997 to 2006) of the Townsend Thai Data to create the various analysis files for my three dissertation papers.

In my first paper, "Dynamic Processes of Subjective and Objective Environmental Measures", I explore how the likelihood of a household attributing a bad income year to the environment is influenced by proximate and cumulative subjective and objective environmental measures. Prior research finds that experience and exposure to more recent events shapes perceptions (Taylor et al. 1988) but, on the other hand repeat exposure to a hazard might condition subjective perceptions, possibly normalizing the event and reducing the perception of risk (Casimir 2008; Slovic et al. 2006). I take advantage of a unique panel data set with repeat measures of both subjective perceptions and objective conditions to test a number of hypotheses about the dynamic nature of risk perceptions. First, I explore whether temporal proximity to objectively, experienced exposure to environmental stress is highly associated with perceiving environmental causes for poor economic outcomes. I find that respondents who perceive a decline in income, and who live in households located in districts with below average environmental conditions in the previous 12 months, are more likely to attribute their poor economic outcome to an environmental cause. I also find that perceiving an environmental cause of a poor economic outcome in the previous year is positively correlated with the perception that the environment is a cause of a poor economic outcome in the current year. These results are consistent with past research that finds proximate exposure shapes perceptions.

Next, I explore whether cumulative exposure to objectively measured environmental stress is highly associated with perceiving an environmental cause of a bad income year. I find that cumulative exposure to above or below-average environmental conditions increases the predicted probability of a household respondent perceiving an environmental cause of a bad income year. However, when I explore the association between cumulative prior subjective perceptions of the environment as a livelihood risk, and the likelihood of perceiving an environmental cause of a bad income year, a different pattern emerges. I find that the more often a respondent in a household has previously attributed a bad income year to an environmental cause, the less likely he is to attribute an additional bad income year to an environmental cause. This finding supports the notion that as familiarity and perception of a given risk increases, the more normal the event might become to a respondent, decreasing a perception of environmental risk. Respondents might still perceive a poor economic outcome in the previous year, but they are less likely to attribute the cause to the environment. The significant contribution of this paper is the longitudinal analysis of a dynamic risk process to uncover how both proximate and cumulative measures of environmental risk shape perceptions of risk.

In my second paper, "Who Perceives What? A Demographic Analysis of Subjective Risk Perception in Rural Thailand", I explore whether a household's access to a portfolio of livelihood assets, occupational diversity, cumulative environment risk perceptions, and household composition are highly associated with the likelihood of a household respondent perceiving the environment as a primary source of poor economic outcomes. I use the Sustainable Livelihoods Framework (Carney 1998; Scoones 1998) as a conceptual mode to select appropriate variables for my analysis. The strength of this framework is the ability to parse out how differential access to capital assets influences both how vulnerable a household might be to exogenous risks, but also how a household's access to these assets might condition perceptions of environmental risk.

While past research enhances understanding of individual and household-level determinants that shape risk perceptions (Barrett 2001; Bunting et al. 2013; Doss et al. 2008; Hunter et al. 2010; Volker et al. 2011), they are limited in a number of key ways. First, the majority of the studies that model determinants of risk perceptions in the developing world are cross-sectional. These cross-sectional data do not allow researchers to account for how accumulated experience with the environment, and changing economic and household compositions shape dynamic risk perceptions. Second, the data analyzed in past research do not include robust measures of household demographic data or income and asset data. Using longitudinal data, my paper addresses a number of the gaps in these previous studies. I find that respondents from larger households have higher odds of indicating a bad income year, regardless of cause, relative to a good income year. However, respondents who live in households with higher numbers of elderly and older (age 25 to 59) women have significantly higher odds of perceiving an environmental cause of a bad income year. I also find that respondents from households where 50% of working aged members are engaged in agriculture as a primary occupation (relative to households with less than 50% of total members engaged in agriculture) have significantly increased odds of reporting lack of rainfall, floods, or pests as cause of an bad income year. On the other hand, the cumulative measure that counts the number of times that a household had previously reported an environmental cause for a bad year decreased the odds of a respondent reporting an additional cause of a bad income year, but increases the odds of reporting a bad income year due to some other cause.

In my third paper, “Environmental Migration: The Role of Proximate and Cumulative Subjective and Objective Environmental Measures on Mobility in Rural Thailand”, I investigate migration as a coping mechanism in response to environmental shocks. I assess whether migration events within a household are highly associated with proximate and cumulative experience and exposure to environmental stress. Past research finds that migration following environmental stress may be a household risk-minimizing strategy employed by household members in the absence of credit and insurance markets (Findley 1994; Stark and Bloom 1985; Stark and Taylor 1989). This household decision to send a migrant may, in turn, be mediated by a household’s access to capital endowments and capital entitlements. One example is the role of social capital that either allows one to remain in the origin, or serves as a draw for migrants in the destination (Adger 2003; Carney 1998; Curran 2002; Eakin and Luers 2006; Gilbert and McLeman 2010; Raleigh et al. 2008; Scoones 1998). Despite some evidence of an association between environmental stress and migration, previous research only considers proximate exposure, and more rarely, proximate subjective perceptions of environmental risk.

The results of my study show that proximately measured deviations from average conditions and attributing a bad income year to the environment, reduce the odds of a household sending a migrant. This might suggest that in the near-term, households are able to adapt locally, or perhaps choose a wait-and-see approach, before deciding to engage in migration in response to the environment. Modelling longer-term, cumulative exposure to the environment also reveals how repeated exposure to a shock influences the decision to migrate, and these results differ depending on the shock. Cumulative exposure to below average environmental conditions reduces odds of migration, but increases the odds of migration when a household’s proximate environmental perceptual measure is also considered, suggesting that household’s decision to migrate is not based solely on objective environmental conditions. Cumulative exposure to above average environmental conditions increases migration, although it is unclear whether this is because of financial gains due to increases in agricultural production following higher levels of rainfall, or due to flooding that makes it difficult to maintain crops. Finally, the odds of a household sending a migrant is influenced by subjective measures of environmental perception, although like the objective measures, follow different patterns depending on proximate and cumulative measures. In the former case, a household's proximate subjective perception that the environment was a risk to their livelihood reduces the odds of a household sending a migrant. However, as the cumulative number of previous times a household reported an environmental shock increases, so do the odds of a household sending a migrant.

These papers suffer from a number of data limitations, which future research can improve on. First, the survey instrument does not measure timing or severity of the drought or flooding events that are reported. This limits the ability to more accurately match subjective measures to objective measures to model seasonal as well as annual trends. Second, the objective data are measured at a scale that is coarser than the subjective data, and a finer scale may reveal additional information about the objective exposure of respondents. Finally, a qualitative survey to complement the quantitative survey might get at individualized definitions of environmental stress that a pre-populated survey does not allow.

Despite the limitations, the key insight of these three dissertation papers is that a fully elaborated understanding of the human-environment nexus requires an analysis of both objective and subjective measures of environmental stress. These preliminary results suggest that humans might, in some cases, respond to environmental stresses based on their perceptions of the environment, in addition to or instead of their actual exposure to objective conditions. This last point is key for policymakers and development agencies concerned with crafting sound solutions to address vulnerable populations in the future. A more nuanced analysis of who is vulnerable to climatic shocks that incorporates subjective as well as objective measures of the environment will allow for more targeted and effective policy solutions.

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Paper One: Dynamic Processes of Subjective and Objective Environmental Measures

<u>Abstract</u>

Social scientists concerned with human response to environmental stress tend to rely on objective measures of the environment when modelling socio-environmental impacts. While objective measures give a sense for both severity and direction of changes in environmental indicators, such as rainfall, these measures alone give little indication of how people experience these stresses. Drawing on the social vulnerability and risk perception literatures, I argue that the inclusion of subjective perception or causal attribution measures in studies of environmental impacts on livelihoods can deepen our understanding of how people experience environmental stress, including how adaptation might alter subjective reports of exposure. In this paper, I draw on a unique longitudinal dataset to ask several key questions. First, how do self-reports of the environment as a primary source of income risk covary with objective environmental measures? Second, how does a household's previous attribution of the environment as a risk influence future attributions? I model past environmental attributions as cumulative measures and lagged effects to understand how past attributions of the environment as an income risk by a household can predict future responses. Understanding trends in these longitudinal perceptual measures modelled together with objective measures, can better inform policymakers concerned with human response to environmental stresses, such as climate change.

Introduction

Global warming induced climate, weather, and agro-ecological change is predicted to manifest itself as either more frequent severe and catastrophic events, such as flooding, or as slower-onset changes like drought and drier conditions (Porter et al. 2014). The people most at risk for disruptions to their livelihoods are those who rely on agricultural and fisheries production for a substantial percentage of their household income, and who lack sufficient access to various forms of capital that might help them employ strategies to protect shocks to their welfare (Adger et al. 2003). A growing area of scholarship drawing on a variety of disciplines, considers the impact of climate change and environmental perturbations on human behavior. These studies that model the impact of environmental conditions on behavior generally use historical physical data, such as rainfall (Volker et al. 2011), temperature, drought indices, or other objective measures of plant health and vigor to predict how households might experience environmental shocks. Yet, despite similar exposure to objective conditions, people experience and perceive these conditions differently. These differential perceptions, which are a function of individual characteristics and history, might influence human behavior more than objective measures (Barrett et al. 2001).

Incorporating prior experience with climate variability, as well as understanding past reactions to climate stress, may influence how people experience new shocks and may be a good predictor of how people will respond to shocks in the future. Subjective perceptions may provide considerable information on their own, even when they differ from objective measures; households might respond proactively if they anticipate a shock that they have experienced in the past, rather than wait to see if conditions improve (Sanchez Pena & Fuchs 2013). An individual or household response might be influenced more by perceptions of environmental conditions, rather than by objective measures of the environment, resulting in responses that seem out of character given objective conditions (Taylor et al. 1988). Studies that incorporate both subjective measures of the environment and objective environmental data might reveal resilience or adaptive capacity previously overlooked (Barrett et al. 2001). Conversely, a reduction in risk perception of environmental stress over time might be explained by a person's familiarity with environmental stress. The more often an event occurs, the more chances a person has to understand or personalize the risk, which might in turn decrease his or her perception of the environment as a risk to livelihoods, even when the objective risk remains (Slovic et al. 1986).

In response to these disparities in observed human behavior new line of inquiry has emerged that questions the sole reliance on objective environmental data to predict human behavior. This work argues that a more nuanced understanding of the human impacts of climate variability must include the local perceptions of how environmental stresses, such as droughts or floods, impact the socio-cultural and economic well-being of the very people assumed to be at risk (Meze-Hauzken 2004; Doss, et al. 2008; Barrett et al. 2001; Hunter 2012). Despite an increased interest in the issue of incorporating both subjective and objective environmental measures in research that considers the impacts of stresses on human behavior, few studies to date incorporate longitudinal social and environmental data into their analyses. Doing so will allow researchers to understand the dynamic processes that underlie environmental concern and how it might vary by repeat exposure and proximity to an environmental stress; past perceptions of environmental stress might also influence how household members perceive current environmental.

This paper describes a longitudinal analysis that assesses whether lagged and cumulative measures of objective exposure and causal attribution of environmental stress are highly associated with a household reporting a bad income year due to the environment. I find that inclusion of both objective and perceptual measures reveals differential patterns of predicted probabilities of household attributions than an analysis that only considers objective environmental exposure. The key contribution of this paper is to provide empirical support for studying dynamic causal attributions, along with dynamic objective environmental exposure, to better understand how each of these measures conditions future environmental risk perceptions.

To model these dynamics, I take advantage of a unique dataset from rural Thailand. A number of regions within Thailand already suffer from episodes of drought and flooding, and these areas are expected to experience more of the same in the future. The Townsend Thai Data (Townsend et al. 1997) a longitudinal survey, collects annual measures of a household's perceived cause of a bad income year, including environmental causes. My paper uses these longitudinal perceptual measures as a complement to longitudinal physical environmental data in order to explore the co-variation of temporal and spatial patterns of variable climate measures. I test a number of ways to measure a household's past attribution of environmental causes of a poor income year to understand how these shape future attributions of environmental risk. These results suggest a number of possible future studies that can capitalize on the dynamic nature of subjective measures to gain additional insight into the complex relationship between objective environmental conditions and the subjective or cognitive processes that might explain human response in the face of a changing climate.

I first review the literature that examines environmental risk perception, mostly in the developing world, and situate my work in that ongoing scientific inquiry. Next, I review the emerging literature that includes both subjective and objective measures and discuss ways in which my research contributes to and extends this dialogue. I then describe my environmental and social data, and how the use of these data adds complexity to the discussion of objective versus subjective analyses of environmental risk. Finally, I present multivariate analyses that models the influence of both proximate and cumulative objective and subjective measures on the likelihood of a household attributing a bad income year to the environment. I end with discussion of my results and suggest future research.

Literature Review

Most research on rural households' ability to adapt to climate change focuses on identifying those at risk by considering how social, economic, and institutional elements influence both vulnerability and adaptive capacity within a community (Kelly and Adger 2000). Adaptive capacity, defined as change or modification within a system or behavior, in order to respond to external stresses (Brooks 2003), might also be conditioned, in part, on the extent to which people are able to anticipate a given risk (Blaikie et al. 2004). Actuarial or statistical measures of environmental risk, are fairly narrow measures that do not consider contextual factors, including psychological, cultural, and social process that influence how people experience and understand risk (Kasperson et al. 1988). A number of recent studies have stressed the importance of incorporating farmer's risk perception in studies of adaptation, arguing that adaptive response to climate change might be more influenced by these perceptions than climatic patterns themselves (Adger et al. 2009; Mertz et al. 2009; Volker 2011).

Incorporating subjective risk assessments alongside objective, physical measures adds richness to the discussion of adaptation, as it might help predict how people within a given context respond to future risk. The use of subjective data as a complement to objective data is not new in the social sciences. Subjective poverty and health status studies provide robust indicators of underlying objective measures, while also providing new insights into underlying causes of income disparity and variable health outcomes (B. Hunter et al. 2013; Crossley & Kennedy 2002). Mental models research bridges lay and expert knowledge of a given phenomenon to reveal agreement and gaps in knowledge than can be used to inform effective risk communication, or inform policy by drawing on underlying mechanisms people use to make sense of the world (Bostrom et al. 1994; Jones et al. 2011; Morgan et al. 2002; Reynolds et al. 2010). Mental models are cognitive representations of the world that individuals draw on to explain events and can shape perceptions, and may provide different information than objective data alone.

Yet to date, most studies concerned with the impact of environmental risk on livelihoods rely on objective data to model these interactions. From a policy perspective, it is crucial that policymakers understand both the technical, objective risk that a society faces, and how embedded social structures might help create and perpetuate vulnerability, but also the cultural values and past experience that help shape understanding of that risk (Leiserowitz 2006; Kasperson et al. 1988; Meze-Hauzken 2004; Slegers 2008; Simelton et al. 2011; Slovic 1987; Taylor et al. 1988; Volker et al. 2011).

A limited empirical literature focused on climate change in the developing world has explored how subjective and objective covary. These studies reveal a number of ways subjective measures can enrich our understanding of the factors that influence adaptation. First, lay people possess personalized concerns that are not always considered in technical risk assessments that are often a by-product of personal history and context; individuals experiencing identical exposure to a hazard, might report distinctly different subjective perceptions (Barrett et al. 2001; Slovic 1987). Meze-Hauzken discovered during fieldwork in Northern Ethiopia that farmers possess an idealized rainfall amount that determines whether or not a year is “good or bad”.

Thus, their perception of a year might not square with the scientific community's idea of a healthy year. (Meze-Hauzken 2004). Climate has statistical and cultural foundations that are continually updated as cultural norms and livelihoods change, and measures of objective data are updated. Community members whose livelihoods are tied to the environment construct their ideas about "normal" through an assessment of past experience that may or may not be influenced by how objective data is framed and reported (Hulme et al. 2008).

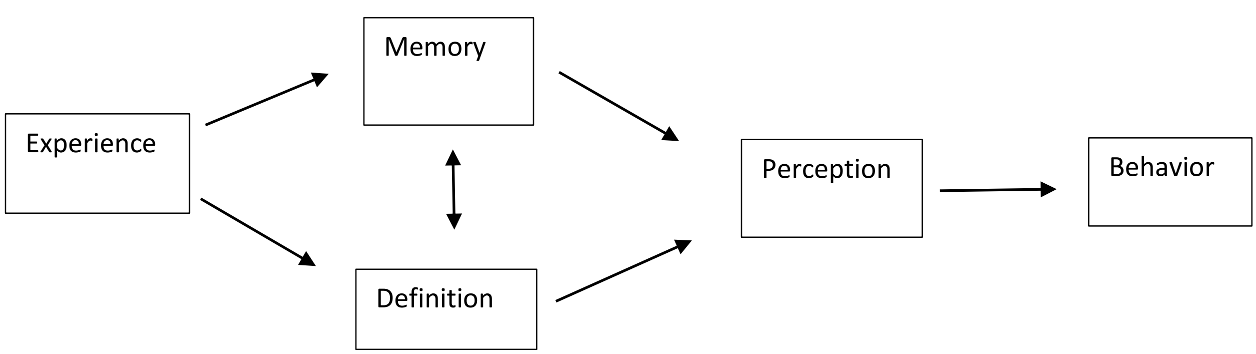
Second, repeat exposure to or familiarity with a hazard might attenuate subjective perceptions, possibly normalizing the event in the eyes of local community members, while objective data might indicate the persistence of a hazard (Casimir 2008; Slovic et al. 1986). In flood-prone Bangladesh, not all flooding is perceived as a hazard by local residents, only abnormal flooding, characterized as abnormal in onset, severity or length (Paul 1984). In some cases, repeat exposure to an environmental stress instigates adaptive capacity. Residents interviewed during field work in Burkina Faso were asked to recount incidents of past droughts, and these subjective recollections matched with historical data. However, when asked to discuss how these droughts have impacted daily life, residents indicate that they had grown accustomed to drought and were able to employ adaptive strategies to maintain their livelihoods during drought episodes (West et al. 2008).

Next, while objective measures can tell us about environmental exposure, subjective measures provide an additional level of complexity that more fully elaborates our understanding of human behavior. Incorporating subjective perceptions along with physical data can reveal how the environment interacts with local conditions and social systems, as well as the local concerns that arise. This in turn reveals problems that might arise on a local scale that can't be addressed by models that rely on environmental data measured at coarser levels (Byg and Salick 2009). A recent study among rural households in Australia compares self-reports of drought with meteorological measures of drought (rainfall deficits) and researchers find the subjective measures are correlated and consistent with the objective data. Regressing both subjective and objective measures of drought on financial well-being among these households, the results from self-reports show a stronger relationship between perceptions of drought and financial well-being. These results suggest that the subjective responses might better capture local impacts and understanding of drought, and the use of this measure is more meaningful to understanding local response than the objective rainfall measures alone (B. Hunter et al. 2013). On the other hand, studies in Guinea reveal a disconnect between objective data about historical deforestation and the people who rely on the forest for their livelihoods; physical evidence of forest expansion contradicts strongly held local subjective notions of forest contraction over time. Reliance on these subjective perceptions over objective data have resulted in public policy initiatives that limit local use of forest land, and unnecessarily threatened local livelihoods by discouraging use of forest land (Fairhead and Leach 1996).

Finally, more recent exposure to an extreme (or at least different from "normal") climate event might shape subjective perceptions, which in turn plays a more significant role in determining behavior than longer-term climate trends (Bryan et al. 2013; Taylor et al. 1988). Cognitive psychologists refer to this as the availability heuristic, where people make judgments based on how easily they can recall a similar event in the past (Tverksy and Kahneman 1973). Farmers in Kenya perceived long-term fluctuations in temperature and precipitation, although data from nearby weather stations do not support these trends. However, at the time of the survey, there had been more recent severe droughts and higher temperatures, which together might shape how they form perceptions about climate (Bryan et al. 2013). A survey of farmers located within the Ogallala Aquifer Region in the United States show differential recollection of past droughts, despite scientific evidence of repeated drought during the period in question. Extreme events are recalled, as well as more recent events, while more distant drought is generally forgotten (Taylor et al. 1988). The results of these surveys indicate that more proximate experience with drought influences perception, future expectation of drought, and also adaptation strategies, regardless of longer-term climatic trends.

In both the Kenyan and the Ogallala cases, researchers argue that understanding subjective perception of the more recent past is key to understanding how people respond in the future, as this perception may carry more weight than statistical measures indicating changes in the environment. From their research, Taylor et al. (1988) produced a conceptual map that can be used to understand how experience shapes perceptions, and possible adaptive behavior, illustrated in Figure 1 below.

Figure 1 Factors Shaping Perceptions of Drought (Taylor et al. 1988)



According to this conceptual map, recent experience with the objective environment (in this case drought) shapes memory and how environmental stress is defined, which in turn influences expectation or perception and ultimately, behavior. On the other hand attribution theory, pioneered by a number of researchers (Heider 1958; Kelley 1973; Kelley & Michella

1980) examines how people make causal inferences about behaviors or events that have occurred. Kelley (1973) argues that causal inferences drawn by a person about past events is a strong predictor of future behavior.

Taken together, perceptions might be shaped both by more recent experience with an environmental stress, but also by how people have perceived the environment as a risk in the past. This latter point reveals some limitations in the current literature that examines the relationship between objective and subjective data on environmental stress. First, most studies reviewed here do not consider the dynamic process of risk perception. In particular, how might perceptions of risk be updated in response to changes in objective environmental conditions, cumulative exposure to various objective environmental conditions, or past risk perceptions? A dynamic analysis of risk perceptions can reveal how the accuracy of risk perceptions to environmental conditions track over time, but also whether there is some level of psychological adaptation to repeat exposure to an objective environmental risk, or a partial adjustment that might indicate initial perception of risk that declines after some time (Loewenstein and Mather 1990).

Second, the objective data examined in these studies are often longitudinal in nature, however the subjective data are typically collected via focus groups that ask the respondents to recall rainfall patterns over a long time-horizon (in some cases as far back as 30 to 50 years) (Meze-Hauzken 2004; West et al. 2008). Collecting these data in one time period does not allow for a more nuanced analysis between the longitudinal objective data and how people perceived the environmental events at the time they occurred, and does not allow for a more nuanced study of how past reports of environmental concern shape current perceptions. In this paper, I take advantage of a unique dataset that collects annual perceptions of the environment as a risk to household income as well as a dataset with longitudinal measures of vegetative health, to investigate how recent experience and attributions (proximate objective and subjective environmental measures) and past experience and attributions (cumulative objective and subjective environmental measures) together influence environmental perceptions. I explore whether a household member's likelihood of attributing a bad income year to the environment is highly associated with recently experiencing an environmental stress, as discussed in the case of Kenya and the Ogallala Aquifer. I also explore whether there is an association between how often a household respondent has either attributed a bad income year to the environment in the past, or experienced environmental stress, and the likelihood that a household member attributes the environment as a cause of a bad income year in year t. However, this may be mediated by adaptation or partial adjustment, as climatic exposure and perception lead to familiarity with more frequent climate variability, decreasing the likelihood that a household member perceives the environment to be the main cause of a bad income year.

Thailand and Climate Change

Thailand is a suitable area to explore the relationship between exposure to environmental stress and perceptions of those stresses as a risk to livelihoods. First, there is empirical evidence that suggests that rural Thai households are both aware of climate risks, and they are willing to share their perceptions of how these risks impact their livelihoods. Volker et al. (2011), conducted a cross-sectional survey of risk perceptions in rural households in Thailand and Vietnam. In this study, members of 4400 rural households in NE Thailand and Central Vietnam were asked to recall experience with climatic, biological, socio-demographic and economic shocks between 2002 and 2008, and to assess the severity of these shocks in terms of impacts to their livelihood. Flooding and drought were the two most common climatic shocks mentioned by household respondents in the survey.

Second, rice, a mainstay of agricultural production in rural Thailand, is sensitive to both quantity and timing of rainfall. A large number of farmers in Thailand rely on rain fed irrigation to water their paddies (Marks 2011). Recent weather trends indicate that the climate is already changing; in the past 50 years, the number of rainy days has decreased, and the mean annual temperate between 1981 and 2007 has risen by one degree Celsius (Dore 2005; Marks 2011). Felkner et al. (2009) estimate the impact of climate change on rice production, using three possible emissions scenarios: neutral to high; neutral to low; and low to high. They also include information about farm inputs, soil quality and household socioeconomic conditions as well as current environmental data. Their analysis indicates that, depending on the level of emissions, a slight increase in rice production may occur due to increases in rainfall at the right stage in the growth cycle, which assumes that farmers are able to respond to climate change if changes aren‘t too great. Their overall conclusion is that at higher emissions levels, with greater changes to rice production, farmers will be unable to mitigate the effects on production yields. At more moderate levels of change, farmers may be able to make adjustments in inputs in order to preserve rice yields, but they conclude that poorer farmers (those with access to fewer resources) will not be able to respond, even at lower levels of climatic impact. Prolonged drought due to climate change may further compound production of rice and the livelihoods of households in the region. Due to the sensitivity of rice to drought, a delay in the start of the rainy season may cause a drop in yields. Hayano et al. (2008) report that when the rainy season began 20 days later than normal, rice production decreased by 20 percent (Hayano, et al. 2008).

Description of Data: Townsend Thai Data

The Townsend Thai Data, one of the longest running panel data sets in the developing world, provides rich data on household composition, income, assets, as well as questions about household exposure to a number of exogenous shocks, including the environment. The survey began as a cross-sectional data in 1997 to measure and investigate how informal institutions such as family and social networks mediate exogenous shocks that might otherwise compromise livelihood outcomes. Following the devaluation of the Baht and the subsequent Asian Financial Crisis, Townsend and his colleagues saw a unique opportunity to examine, over time, how an exogenous shock affects households and how members of these households draw on formal and informal institutions to recover. Townsend and his colleagues proposed an annual resurvey that follows a percentage of the households from the original 1997 survey. Households in the study are located in four provinces; two provinces in the poorer Northeast region and two provinces in the better off Central region. 64 villages were randomly chosen, as well as 15 households in each of the villages, totaling 960 villages per year.[1]

Description of Objective Environmental Data: NDVI

To these rich social data I add an objective environmental data file that coincides with the time period of the social data. Traditional measures of drought and flooding that rely on rainfall amounts, including gridded precipitation data sets, can be inaccurate if rainfall gauges are not evenly distributed in the area of interest (Thenkabail et al. 2004). One way to address potential inaccuracies in rainfall data is to use a vegetation index product, derived from satellite images, and available over a long time-scale. NDVI is a measure of plant biomass and general health,

[1] For more detailed information about the design of the dataset, please see: http://cier.uchicago.edu/data/data-overview.shtml

obtained from satellite remote sensing imagery (Tucker et al. 1985), and is being used more frequently as a way to assess the impact of climate environmental change on plant health versus rainfall alone (Pettorelli et al. 2005).

For my analysis, I use the Global Inventory Modelling and Mapping Studies (GIMMS) normalized difference vegetation (NDVI) dataset, which provides 24-years (1982 to 2006) of global bi-monthly (24 measures each year) vegetation changes, obtained via images produced by National Oceanic and Atmospheric Administration-Advanced Very High Resolution Radiometer (NOAA-AVHRR) satellites and instruments, measured in 8km x 8km pixels. While the spatial resolution is coarser than the resolution of more recent NDVI products, the strength of these data lies in the rich temporal resolution, which combines well with longitudinal social data. NDVI is a ratio of light reflectivity in the red and near-infrared bands of the electromagnetic spectrum, and give an indication of how much of the photosynthetically active bands of light are being absorbed by vegetation on the ground (Tucker 1979): NDVI= (NIR-RED) / (NIR+RED).

Actively growing healthy vegetation tends to reflect less red light, and more near-infrared light, so that a higher NDVI value can be interpreted to mean healthier plan. NDVI can be used to assess drought or flooding by examining the NDVI anomaly, defined as the difference in a monthly or annual measure as compared to a longer-term average for the same time period (Anyamba et al. 2005).

Description of Analysis File

I draw on two questions from the Risk Response Survey Module to generate my dependent variable. The question asked of all households is: Comparing this past year (e.g. June 2002 – May 2003) to the year before that (June 2001 – May 2002), which was the worst year for household income? Households that indicate the past year to be the worst for income are prompted to supply the reason that they believe explains why their income was lower in the past year. The survey question is identical each year, the only change is the years that the questions reference (year t-1 compared to year t-2). For this analysis, I assign a household-year a code of "1" when a households attributes a bad income year to the environment if they indicated "flood", "not enough water", or "pests destroy my crops" as their main reason to explain that their income was lower in the previous year. Household-years where a household respondent indicated that the previous year was better than two years ago, or that their level of income is coded "0". Similarly, responses indicating a non-environmental cause of a bad income year are coded "0".

I collapse the responses of good year and bad year due to non-environmental causes in this paper, because for this analysis, I am specifically interested in the influence of proximate and cumulative subjective and objective measures on the odds of a house perceiving an environmental cause of a bad income year. In another, related paper, I expand my dependent variable to include all three categories, and include additional independent variables about the household to explore the association of these additional factors and a household respondent's perceived income year (Meijer-Irons 2015).

I then create a number of measures from this dependent variable, to test whether a household's past attributions might predict how a household attributes the present year. I generate a cumulative measure that counts up the number of times, through t-1, that a household indicated experiencing a bad income year due to the environment. I also generate a one-year lagged measure, to capture the influence of how a household responded to the income question before the current year.

In this paper, I define objective environmental measures to be physical measures of environmental indicators that can be quantified, such as rainfall totals, annual temperatures, or in the case of the environmental measure employed in this research, Normalized Difference Vegetation Index (NDVI) values. A 'risky' year is one when that year's physical measure is significantly different from a longer-term trend of that measure, for example, when rainfall or NDVI is above or below average.

For my objective variables, I first generate an annual NDVI measure for each amphoe (district) where the households are located, aggregating from the bi-monthly values in the GIMMS dataset. I initially generated standardized z-scores based on all available years in the GIMMS data set. However when I used these variables in logistic models to predict how these longer-term objective measures are associated with a household respondent's attribution of a bad income year due to the environment, the predictors were all insignificant. Next, I restrict my objective data to the time period of the survey data to more closely match the objective conditions that survey respondents are likely to consider when they define drought or flooding. To do so, I calculate a period (1997 to 2006) average for each district and then create standardized z-scores to reflect how many standard deviations above or below the annual district-NDVI value is from the period-average. This new variable, which I call my standardized NDVI (or sdvi) variables takes the following form: sdvi = (Annual NDVI – Period Average NDVI) / Period Standard Deviation. Table 1 below highlights coding decisions that generated the three factor variable.

Table 1: Standardized NDVI Variable

SDVI Value	Corresponding z-score
0 – Average NDVI	0
1 – Below Average NDVI	-1/-2
2 – Above Average NDVI	1 / 2

In addition to the standardized NDVI measure for year t, I created additional objective measures that are similar to my attribution variables. First, I created one- and two- year lagged measures that capture the environmental condition that the household was exposed to in those time periods. In addition to these lagged variables, I created three cumulative variables, meant to capture a household's accumulated exposure to average, below average, and above average environmental conditions. Table 2 provides summary statistics for the dependent and independent variables used in this analysis.

Table 2: Descriptive Statistics of Dependent and Independent Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Household Attributes Bad Income Year Due to Environment					
No	9576	0.80	0.40	0	1
Yes	9576	0.20	0.40	0	1
Cumulative # of Times Reporting an Environmental Cause of Bad Year up to time t	9576	0.92	1.21	0	7
One Year Lagged Environmental Response					
No	8408	0.80	0.40	0	1
Yes	8408	0.20	0.40	0	1
Standardized NDVI Year t					
Average	9576	0.49	0.50	0	1
Drier than Average	9576	0.27	0.44	0	1
Wetter than Average	9576	0.24	0.43	0	1
Standardized NDVI for year t-1					
Average	9576	0.41	0.49	0	1
Drier than Average	9576	0.25	0.43	0	1
Wetter than Average	9576	0.34	0.47	0	1
Standardized NDVI for year t-2					
Average	9576	0.45	0.47	0	1
Drier than Average	9576	0.18	0.38	0	1
Wetter than Average	9576	0.37	0.48	0	1
Cumulative # of Years with Average NDVI to t-1	9576	2.45	1.86	0	7
Cumulative # of Years with Below Average NDVI to t-1	9576	1.25	1.12	0	5
Cumulative # of Years with Above Average NDVI to t-1	9576	2.82	1.04	0	6

Methods

Test for Multicollinearity

Before I run my multivariate models, I first test for multicollinearity among my independent variables. The presence of multicollinearity results in standard errors that are inflated, making it more difficult to obtain precise, and statistically significant, estimates. I use the collin function in Stata, a user-written command to test for multicollinearity of the independent variables in a model. This command reports the variance inflation factor of each variable, the values are presented in Table 3 below. The VIF values for my variables are well within the range of acceptable (general rule of thumb is a VIF value below 10), and I can keep each of these variables in my final models (O'Brien, 2007).

Table 3: Results of Diagnostic Test for Multicollinearity

Variable	**SQRT VIF**	**R-VIF**	**Tolerance**	**Squared**
Cumulative # of Times Reporting an Environmental Cause of Bad Year up to time t	1.58	1.26	0.6341	0.3659
One Year Lagged Environmental Response	1.32	1.15	0.7593	0.2407
Standardized NDVI for year t	1.15	1.07	0.8724	0.1276
Standardized NDVI for year t-1	1.36	1.17	0.7338	0.2662
Standardized NDVI for year t-2	1.44	1.2	0.6921	0.3079
Cumulative # of Years with Average NDVI to t-1	2.14	1.46	0.4681	0.5319
Cumulative # of Years with Below Average NDVI to t-1	1.17	1.08	0.8579	0.1421
Cumulative # of Years with Above Average NDVI to t-1	1.4	1.18	0.715	0.285
Mean	VIF	1.44		

Objective Measures

Next, I run a series of additive logit models for my objective measures, controlling for village and year effects (excluded from table below), to determine which objective measures to include in my full model. The first column in Table 4 presents results of Model 1, which assess the relationship between a household reporting a bad income year due to the environment based on objective environmental conditions in the district that the household lives in. To Model 1, I then add a one-year lag of standardized NDVI, which I call Model 2 and the results are reported in column 2 of Table 4 below. In Model 3, I add a two-year lag of standardized NDVI, and report the model results in column 3 in Table 4. Finally, I include measures of cumulative exposure of average, below average, and above average environmental conditions in the full Model 4. I consider both AIC and BIC values and select Model 4, the full additive model, as the best model to analyze my attribution measures.

Table 4: Additive Models of Objective Measures with Model Fit Statistics

HH Reports Bad Income Year Due to Environment	**Objective Measure Current Year**	**Objective Measure Lagged One Year**	**Objective Measure Lagged Two Years**	**Cumulative Objective Measures**
NDVI (average year as referent)				
Below Average NDVI	1.258**	1.236*	1.260**	1.496***
Above Average NDVI	0.648***	0.652***	0.634***	0.791**
NDVI Lagged One Year				
Below Average NDVI		0.579***	0.540***	0.476***
Above Average NDVI		0.696***	0.688***	0.439***
NDVI Lagged Two Years				
Below Average NDVI			0.648***	0.572***
Above Average NDVI			0.850*	0.559**
Cumulative # of Years with Below Average NDVI to t-1				1.339***
Cumulative # of Years with Above Average NDVI to t-1				1.977***
Number of Household Years	9576	9576	9576	9576
Model Fit Statistics				
AIC	8721.90	8689.14	8671.23	8590.82
BIC	9266.59	9248.87	9244.59	9178.52

Attribution Measures

My last step in my modeling approach is to build on the structure of my objective model by adding causal attribution measures. In Model 1, I add the cumulative attribution variable, which counts up the number of times, through t-1, that a household reported an environmental cause of a bad income year. I then add the one-year lag variable that measures whether a household reported a bad income year due to the environment in year t-1 to Model 2. The model results are summarized in Table 5 below. Again, I consult the AIC and BIC values for model fit. In this case, the AIC values indicate that Model 2, containing both a cumulative and a one-year lag of attribution, is the best fit.

Table 5: Additive Models of Objective and Attribution Measures with Model Fit Statistics

HH Reports Bad Income Year Due to Environment	**Cumulative Attribution**	**Cumulative and Proximate Attribution**
Cumulative # of Times Reporting an Environmental Cause of Bad Year up to time t	1.710***	1.571***
Cumulative # of Times Reporting an Environmental Cause of Bad Year up to time t, Squared	0.917***	0.932***
One Year Lagged Environmental Response		1.325***
NDVI (average year as referent)		
Below Average NDVI	1.415***	1.457***
Above Average NDVI	0.624*	0.646***
NDVI Lagged One Year		
Below Average NDVI	0.493***	0.482***
Above Average NDVI	0.448***	0.461***
NDVI Lagged Two Years		
Below Average NDVI	0.659***	0.674***
Above Average NDVI	0.520**	0.540***
Cumulative # of Years with Below Average NDVI to t-1	1.30**	1.30**
Cumulative # of Years with Above Average NDVI to t-1	1.957***	1.91*
Model Fit Statistics		
AIC	7599.08	7549.69
BIC	8143.15	8140.79

Finally, I include a series of interaction effects in my full model, to test whether a household's response differs, given the environmental condition that the household is exposed to in the year they are surveyed.

Table 6: Interaction of Attribution Measures and Objective Environmental Conditions in Year t

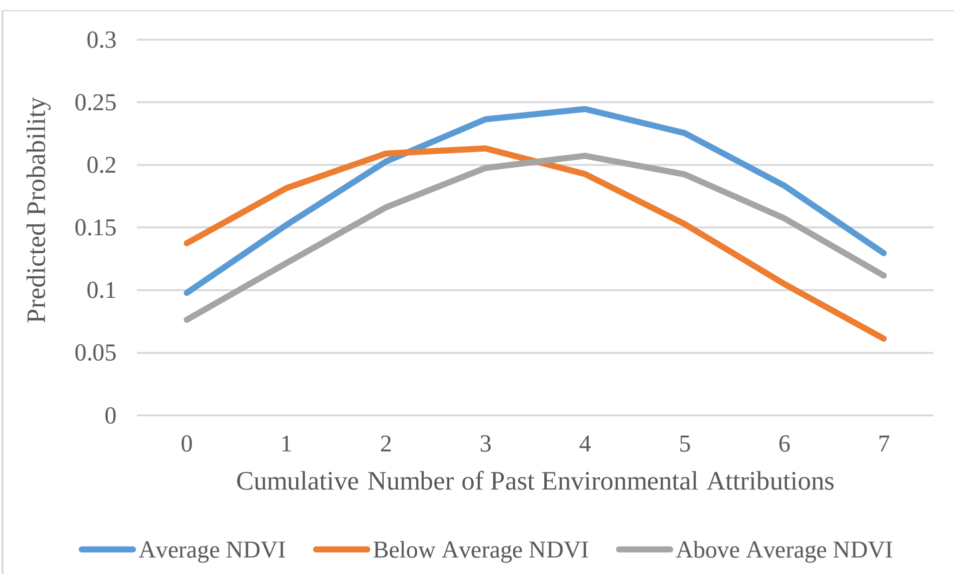
Interactions		
Below Average NDVI * Cumulative # of Times Reporting an Environmental Cause of Bad Year up to time t	0.842**	
Above Average NDVI * Cumulative # of Times Reporting an Environmental Cause of Bad Year up to time t	1.015	
Below Average NDVI * One Year Environmental Attribution Response Lagged		0.784
Above Average NDVI * One Year Environmental Attribution Response Lagged		0.968

Results

As Table 5 above shows, the lagged and cumulative measures have a significant and differential effect on a household reporting a bad income year due to the environment. Net of other factors, the cumulative measure of past environmental attribution increases the log odds of a household reporting a bad income year due to the environment by 57%. However, the squared term suggests an inverse relationship, with declining likelihood of reporting an environmental cause of a bad income year as the number of past reports of an environmental cause of a bad income year increases. This inverse relationship suggests that a household respondent's perceptions of the environment as a risk to income declines, perhaps as familiarity with environmental stresses increases; or that earlier experience with a hazard might decrease a household's likelihood to attribute a bad year to the environment even if the hazard remains

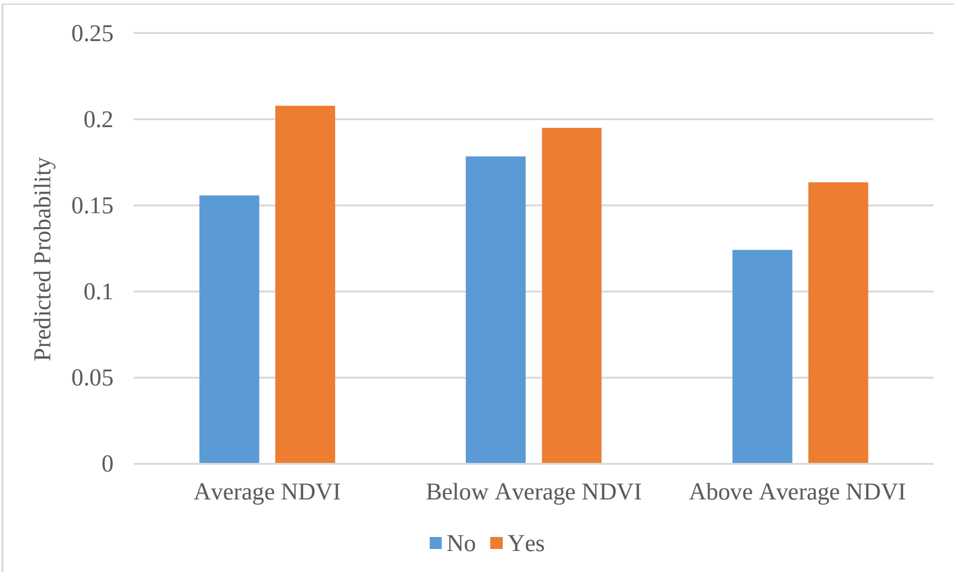
(Casimir 2008; Loewenstein and Mather 1990). Figure 2 shows this possible adaptation process graphically, presenting the probability of a household respondent attributing a bad income year to the environment, conditional on the environmental condition that household members are exposed to immediately prior to the administration of the survey, and the cumulative number of times a household respondent attributed a bad income year due to the environment. If a household respondent had not previously reported the environment as a cause of a bad income year, the probability of attributing a bad income year to the environment is higher for households located in a district with below average NDVI than for households located in districts with average of higher than average NDVI. If a household respondent, living in a district with below average NDVI, previously reported 2 or more years of bad income due to the environment, the probability of reporting an environmental cause of a bad year begins to decline.

Figure 2: Probability of Reporting a Bad Year Due to an Environmental Cause, Conditional on Environmental Condition in Reporting Year and Cumulative Number of Past Reports of an Environmental Cause



Turning to the one-year lag measure of causal attribution, reporting an environmental cause of a bad income year in the previous year also increases the log odds of reporting the same in the current year by 33%. Figure 3 shows the probability of a household respondent reporting a bad income year due to the environment in year t, conditional on the previous year's reporting, and objective environmental condition in year t. Here, the probability of attributing a bad income year to the environment is higher regardless of environmental condition in year t.

Figure 3: Probability of Reporting a Bad Year Due to an Environmental Cause, Given the Environmental Condition in Reporting Year and Response in Year t-1

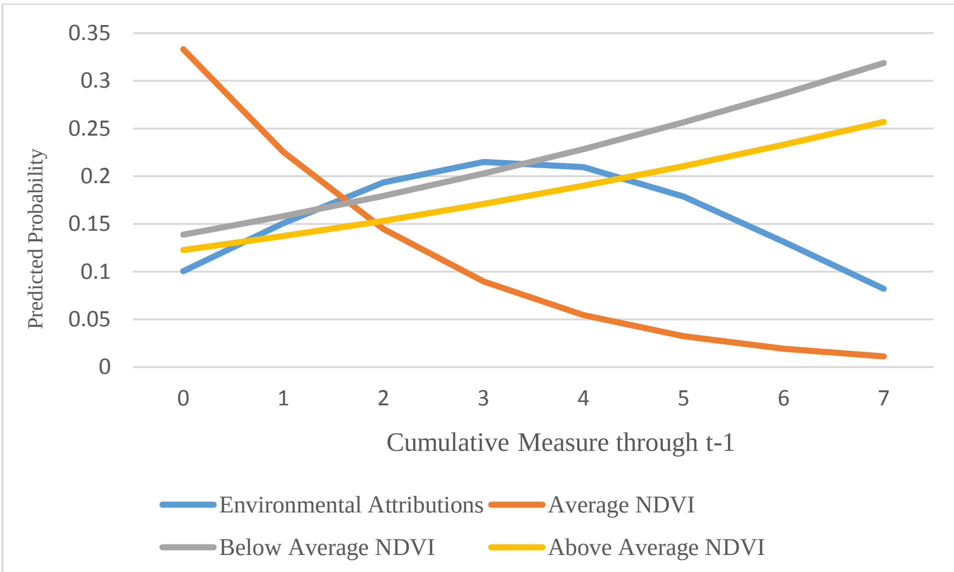


There are a number of possible explanations for the influence of a household respondent's response in t-1 on the current year's response. First, the perceived effects of drought on a household might extend beyond the 12 months that household respondents are asked to reflect upon when answering questions about risks to livelihoods. Second the recency of experiencing and reporting an environmental risk to a household might have a stronger influence of the response in year t, regardless of environmental condition (Taylor et al. 1988). Attention to concern about environmental stresses in the media or within a community might also be at play; the Social Amplification of Risk Framework suggests that social and institutional factors (such as the media) can interact with risk exposure, resulting in dampening or heightening of perceptions (or in this case attributions) (Renn et al. 1992; Kasperson et al. 1998).

It is interesting to note that the lagged objective measures have a much different influence on the likelihood of reporting a bad income year due to an environmental condition than the attributional measures. Below average NDVI (representing less healthy vegetation in the district, typically associated with drought) conditions in year t increases the odds of reporting a bad income year due to the environment, relative to average NDVI in the district, by 45% Above average NDVI (typically wetter) signals in year t reduces the likelihood of a household respondent reporting an environmental cause of a bad income year by 35%, relative to average NDVI year in the district, net of other factors. However, lower than average NDVI, measured at one and two years prior to the household survey, significantly decreases the log odds of reporting an environmental cause of a bad income year by 51 and 33 percent. Above average NDVI measured at one and two years prior to the household survey also decrease the likelihood of reporting an environmental cause of a bad income year by 54% and 46% respectively.

On the other hand, when considering a household's cumulative exposure to average NDVI, below average NDVI, and above average NDVI, along with the cumulative measure of household reports of a bad income year due to the environment, a different picture emerges. Figure 4 shows the predicted probability of a household respondent reporting a bad income year due an environmental cause, by cumulative environmental exposure, and cumulative causal attribution (measured through year t-1). As the number of cumulative years of exposure to average environmental conditions increases, the predicted probability of a household respondent reporting a bad income year due to the environment decreases. However, as the number of years of exposure to below and above average environmental conditions increases, the predicted probability of reporting a bad income year due to the environment increases. When I include the cumulative attribution measure that counts the number of previous reports of a bad income year due to the environment, the predicted probability of attributing a bad income year to the environment initially increases, and then decreases.

Figure 4: Probability of Reporting Environmental Cause of Bad Income Year by Cumulative Environmental Attribution and Objective Measures



Discussion and Conclusions

In this paper, I analyzed how past attributions of the environment as a cause of a bad income year and objective measures of the environment influence a household respondent's likelihood of reporting a bad income year due to the environment. Drawing on the adaptation literature, causal attribution theory, and to some extent, the field of risk perception I argue that examining past attributions might reveal additional information about how people think about the impact of the environment on their livelihoods, net of objective factors. Past theoretical and empirical research suggest that repeat exposure to a hazard might condition an individual to a hazard, perhaps diminishing the view of the hazard as a risk. However, in the existing literature that examines how objective and subjective measures covary, experience and awareness of the hazard is not readily investigated. My paper contributes to this gap by exploring perceptual and objective measures together in a longitudinal study.

To create my perceptual measure, I use the Risk Response module of the Townsend Thai Data an annual resurvey of households in NE and Central Thailand. For my objective measure, I create a standardized measure that captures when households in the survey experience above or below average environmental conditions, using Normalized Difference Vegetation Index (NDVI) data, which measures vegetation health. Households in the Townsend Thai data with household respondents who report hat the previous year was the worst income year, relative to two years ago, are asked to attribute the primary reason for the bad year, and I focus on environmental reasons. I create lagged and cumulative attribution measures and model how these, along with lagged and cumulative vegetation health, influence the likelihood that a household will attribute a bad income year due to the environment.

My findings demonstrate that attribution and objective data reveal different patterns of the likelihood of reporting a bad income year due to the environment. Subjective perceptions of environmental stress tracks proximate below-average objective measures. If a household is located in a district that experienced below-average vegetation health in the 12 months immediately prior to the survey, the odds that a respondent will attribute a bad income year to an environmental cause increases. This finding is similar to prior research that found that more recent weather events are likely to be recalled and match objective weather records (Bryan et al. 2013; Taylor et al. 1988).

However, when considering cumulative measures of exposure and past attributions, a different pattern emerges. Namely that the predicted probability of attributing a bad income year increases with cumulative exposure to above and below average vegetation conditions, net of other factors. However, the predicted probability of attributing a bad income year to the environment initially rises, and then falls, in response to the cumulative number of times a household had previously attributed a bad income year due to the environment. This latter finding suggests that when considering dynamic patterns of risk perceptions, respondents might engage in partial adjustment. This means that following a number years of experiencing environmental stress, familiarity with the hazard might normalize the event and decrease the likelihood that they consider the environment to be a significant threat to their livelihoods. This might occur even when objective measures indicate that the environmental stress continues (Loewenstein and Mather 1990; Slovic et al. 1986). These respondents might still perceive a negative economic outcome, but the probability that the stated cause is the environment decreases.

However, a number of outstanding issues remain that can't be addressed by the structure of the survey instrument used in this study, and should be considered when designing future surveys. For example, while the Risk Response Module of the Townsend Thai survey allows the respondents to report insufficient or too much rainfall as a threat to household livelihood, little is known about the timing and perceived severity of this event, relative to the growing season. Similar to the previous point, the survey only allows respondents to report the cause that they attribute to their reduced income, without opportunity for follow-up questions. This limits my ability to delve deeper into small, but potentially important differences about definitions of environmental stress that might allow me to determine whether the patterns seen in the data might also be attributed to the mental models or causal mechanisms that respondents employ when determining their response to the question about risks to livelihoods. This is a particularly important point when thinking about ways to craft policy in the face of future environmental stress predicted under current climate change scenarios.

Taken together, finer detail about onset and severity about weather, along with information about the cognitive factors that influence attribution would add considerably to this study. Future studies might also incorporate some measure of how household respondents perceive the likelihood of experiencing future environmental risks. A question about future risk perceptions can link whether past experience and attribution of the environment influences how household respondents perceive future vulnerability. A forward-looking question can also assess how people who do not currently see the environment as a risk are incorporating knowledge about climate change into their thinking. A cross-sectional study in Thailand and Vietnam demonstrates this latter point. The researchers find that over 70% of households in Thailand and 90% of households in Vietnam expect to be affected by climatic risks in the future, regardless of whether they had reported experiencing a shock in the past. (Volker et al. 2011). This is an additional way that subjective measures can enrich adaptation studies, enabling policymakers to identify households that might benefit from *ex ante* adaptation strategies.

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Paper Two: Who Perceives What? A Demographic Analysis of Subjective Risk Perception in Rural Thailand”

Abstract

In this study, I explore whether objective environmental exposure, household composition, livelihood assets, occupational diversity and cumulative environment risk perceptions, are highly associated with the likelihood of a household respondent perceiving the environment as a primary source of poor economic outcomes. Rural households that rely on natural resources for livelihoods are expected to face increased vulnerability due to more frequent climate variability. To date, few studies use longitudinal data to explicitly model the characteristics that shape risk assessments among households that experience environmental shocks. Doing so allows researchers to understand how perceptions of environmental risk covary with objective exposure, past risk perceptions, and dynamic household characteristics. I draw on a unique dataset from rural Thailand matched with robust objective environmental data to explore these associations. My results suggest that household size and composition influence environmental risk perceptions, as does occupational diversity of household members, and social learning.

Introduction

The incidence of drought and floods, already a fact of life for residents in rural developing communities, is predicted to become more frequent and severe in the future, according to current climate models (Bernstein et al. 2007; Coe and Stern 2011; Porter et al. 2014). A substantial literature has emerged that theorizes, conceptualizes, and empirically identifies the most vulnerable residents in rural areas. However, this literature largely relies on notions of vulnerability that are assigned by outside researchers and development agencies, rather than assessing perceptions of vulnerability amongst target populations (Heijmans 2001). Objective environmental conditions are defined by meteorological data. On the other hand, a household's subjective assessment of its financial health, and an environmental risk as a source of environmental stress in particular, reveals a lot about the level of exposure to environmental perturbations, as well as a household's resilience and ability to cope in the face of an environmental risk (Barrett at al. 2001). To date, few studies explicitly model the determinants of environmental risk perception of residents living in vulnerable environments. Addressing issues that are most salient to and perceived by residents living in areas that are vulnerable to increases in exogenous shocks, such as drought or flooding, is key for policymakers interested in crafting sound policies to address the social impacts of climate change (Volker et al. 2011).

Vulnerability and adaptation to climate change research has made considerable advances towards understanding the complex relationship between human and environmental systems in an evolving climate and identifying who is most vulnerable to environmental shocks (Cutter et al. 2009; Oliver-Smith 2009). Early research focuses on the severity of potential impacts to natural systems under proposed climate scenarios and tends to move in a linear fashion, examining the potential vulnerability as a relationship that moves in a direction from stressor to impacts, without considering more complex feedback loops that might better encapsulate conditions on the ground (Blaikie et al. 2004; Turner et al. 2003; Eakin & Luers 2006). However, this singular focus gave way to more complex modelling of the linkages between humans and environmental systems (Fussel & Klein 2006; Turner et al. 2003). These more nuanced studies consider not only where potential impacts will occur, but also ask context-specific questions that consider how these shocks might be dampened or exacerbated by underlying societal conditions, and demographic characteristics, that leave an unequal portion of the population vulnerable to exogenous shocks, like adverse climatic events (Adger, 2006; Acosta-Michlik and Espaldon 2008). Despite growing complexity in conceptualizing vulnerability, few studies model how socio-demographic and objective exposure to the environment condition environmental perceptions of rural residents. This is due, in part, to the lack of questions in household surveys that ask respondents to report the occurrence of a climatic event, and to indicate whether this leads to financial hardship, despite calls for their inclusion (Billsborrow 2009; Sanchez-Pena & Fuchs 2012).

My paper explicitly explores household member's causal attributions of a bad income year and the associated demographic characteristics across households whose respondent reports the environment and other economic causes as a risk factor. I use the 1997 to 2006 waves of the Townsend Thai Data, a unique annual economic panel dataset that collects information on self-reported risks to income, as well as household-level information on occupation and other demographic characteristics, to analyze a number of characteristics related to a household respondent's subjective assessments of livelihood risks. I explore demographic characteristics of households with a member who reports an environmental cause of an income shock, compared to respondents who report a good income year, or a bad income year due to some other types of shock, to test whether households with respondents who perceive the environment as a threat to livelihoods are significantly different than other types of households. Conceptually, I draw on the Sustainable Livelihoods Framework and ideas about family life course, to explore whether differential access to assets and/or age structure of the household is significantly associated with the perception of the environment as a source of livelihood stress. I find that the odds of perceiving an environmental risk to income is higher among respondents from households with a majority of working members employed in agriculture. Similarly, as the number of older women, aged 25 to 59, and the number of elderly residents in a household increases, the higher the odds that a respondent perceives a bad income year due to the environment.

Literature Review

My analysis is informed by the Sustainable Livelihoods Framework (SLF), a concept that has been used in the past to explore determinants of poverty in the developing world. The SLF was initially used to study underlying factors that contribute to poverty in the developing world, but has been expanded to sustainability and livelihood studies (Carney 1998; Eakin and Luers 2006; Scoones 1998). The strength of this framework is the exploration of differential access to a series of assets (human, natural, social, physical, and financial) and entitlements that can highlight vulnerability to environmental risk, but also how these assets can be used to mediate the impacts of exogenous shocks, including environmental ones (Bunting et al. 2013; Carney 1998; Eakin and Luers 2006; Scoones 1998). To date, there is small literature that models the determinants of subjective risk perceptions in rural areas situated in the developing world. The results of these studies point to heterogeneity in perceptions of livelihood threats among subpopulations within a seemingly homogenous landscape. I organize the findings in the existing literature according to the five assets conceptualized in the Framework to highlight which factors influence whether a household identifies the environment as a main risk to income, and to suggest opportunities for future research.

The influence of human capital, typically measured at the level of the head of the household, is mixed with regards to how this capital influences the likelihood that a household respondent perceives an environmental risk. In a study of East African pastoralists by Barrett et al. (2001), gender and economic activity strongly influence risk perception. Men are more likely than women to perceive risks to livestock, water availability, and pasture, which are related to agricultural activities that they are primarily engaged in. Similarly, in the South African context, women who are tasked with cooking are more likely to perceive environmental risk with respect to water quality and impacts of wood smoke. (Hunter et al. 2010). In Botswana and Namibia, men and women both perceive declines in natural resources as a significant risk to livelihoods. However, men are slightly more likely to perceive an environmental risk, again related to mens' greater participation in economic activities that are impacted by flooding and drought (Bunting et al. 2010). However, Doss et al. (2008) find little significance between individual-level characteristics such as age, sex, and education of the head and risk perceptions. Education of the head, included to capture potential for participation in formal labor market, is not significant in the studies that modelled this factor. In Vietnam and Thailand, individual's working in agriculture are significantly more likely to perceive climate as a risk (Volker et al. 2011).

Human and financial capital interact with natural capital in several studies. Respondents who consider drought to be a significant risk, have greater access to natural capital (rainfall). However, this access is muted by reduced financial and human capital among pastoralists in East Africa. Somewhat surprisingly, household members located in areas that get, on average, more rainfall, are more likely to perceive rainfall as a main livelihood risk. These households tend to be poorer than other households in the study area, and are more likely to be engaged in agriculture, further motivating the need to incorporate subjective measures in addition to objective data (Barrett et al. 2001). Among villages in Botswana and Namibia, subsistence-based farmers are also more likely to rank drought as a significant risk to livelihoods, relative to participants in more formal labor markets; again reflecting a lack of access to a diversity of human and natural capital (Bunting et al. 2013).

Natural capital also intersects with social capital to shape how individuals form their perceptions of the environment. In particular, participation in social learning might facilitate residents sharing information about the impact of erratic rainfall amounts, which in turn influences how individuals perceive rainfall as an environmental risk (Bunting et al. 2013; Lybbert et al. 2007). Doss et al. (2008) find that natural capital variables, such as rainfall, when measured at the community-level, have a significant effect on risk rankings, when controlling for household and individual-level characteristics. Similarly, in Vietnam, participation in socio-political organizations increases the odds of climate risk perception (Volker et al. 2011).

Physical capital, too, influences perceptions, particularly in areas lacking proper infrastructure that might mediate such concerns. Hunter et al. (2010) introduces additional dimension to the literature by analyzing spatial proximity of a village to an environmental concern in a study of rural South African residents. Individuals are more likely to perceive the environment as a major concern, if they live in households located in villages in close proximity to environmental problems, such water quality, soil erosion, or refuse.

The existing literature on determinants of risk perceptions explores a number of key livelihoods concepts that enrich the study of subjective and objective measures of risk. In particular, they highlight a number of factors that explain heterogeneity of risk perceptions in areas assumed vulnerable to environmental stress, such as access to financial and natural capital. However, the studies that examine determinants of subjective perceptions in the developing world are limited by a number of factors. First is a lack of temporal depth that limits a study of how risk perceptions vary over time. Doss et al. (2008) analyze risk perceptions over 27 months and find that risk perceptions vary across time both seasonally. However, the remaining studies are cross-sectional studies that capture one time period, which does not allow for observations of temporal variation and past experience, and how these combine to update or extend risk perceptions. Individual perceptions are influenced by a number of factors that can change over time, these include: degree of objective exposure to a risk (place-specific, such as rainfall), individual perception (which can be conditioned by previous experience), and whether a respondent can apply *ex ante* mitigation or *ex post* coping strategies (Barrett et al. 2001).

The second limitation is the lack of robust household demographic measures that can reveal how household composition and structure shapes perceived risks to livelihoods. Among the existing risk perception studies that incorporate household demographic data, this is limited to information about the household head, and the results of this influence are mixed. Among East African pastoralists, men and women engage in different sectors of the economy, and this influences the risks they perceive (Barrett et al. 2001). In South Africa, individuals in older households (households where one-third of the members are over the age of 50) with fewer opportunities to diversify livelihoods away from a dependence on natural resources, are more likely to express great concern about water quality than individuals in younger households (one-third of household members under the age of 15), however this measure is not a consistent metric in the study, and is limited by the cross-sectional nature of the data (Hunter et al. 2010). A more refined measure of age and gender structure within a household might indicate whether household composition is highly associated with a household respondent perceiving the environment as a livelihoods threat. As a household's composition changes due to life course events (such as births, deaths, or household members leaving for labor or educational opportunities), household economic opportunities might change, along with perceptions of vulnerability (Martine and Schensul 2013). Previous work on household composition and family life course transitions in rural China finds that younger households, and younger males in particular, are more likely to engage in more innovative labor reallocation strategies during a period of reform (Chen and Korinek 2010). In the literature on gender and climate change, women perceive disasters differently than men do, which is largely a function of gendered social structure, as well as differential relationship to agriculture and livestock (Hunter and David 2011; Terry 2009).

My paper addresses the limitations of previous studies that explicitly model the determinants of perceptions of environmental risk. First, I address the issue of temporal depth by analyzing data from a unique panel study of rural households in two provinces located in the poorer Northeast region and two provinces in the better off Central region. The study collects household-level retrospective subjective measures of perceived risks to income, including environmental causes, as well as detailed data on the age, sex, and occupation of household members, which allow me to model the age, gender and occupational structure of the household. The study also collects data on income, and assets, and social capital, which allow me to model access to capital assets found in the SLF, and. To these rich social data, I add robust objective environmental data that coincides with the time period of the household survey, which allow me to measure natural capital.

Based on my review of previous research, I test a number of hypotheses with these data. First, I explore whether objective environmental data is highly associated with environmental risk perceptions. Next, I explore whether risk perceptions are influenced by the concentration of working age household members who are primarily employed in the agricultural sector. I then explore whether respondents from households with relatively younger age structures report risk perceptions that are significantly different from those reported by respondents in households with relatively older age structures. I also explore whether respondents in households with younger or older males report different risk perceptions than household members in households with younger or older females. Finally, I explore whether social learning and previous reports of an environmental risk are associated with a household perceiving an income risk.

Thailand and Climate Change

Thailand is a suitable area to explore issues of rural households and their vulnerability to climate change. In the past 50 years, the number of rainy days has decreased, and the mean annual temperate between 1981 and 2007 has risen by one degree Celsius (Dore 2005; Marks 2011). Rice, one of the main crops of Thailand, is particularly sensitive to predicted changes in weather under current climate change scenarios, and a large number of farmers in Thailand rely on rainfed irrigation to water their paddies (Marks 2011). Predictions of changes in precipitation in both space and time have the potential for great change in agricultural production in areas that are dependent on rainfall for irrigation. To date, only a small number empirical studies consider the issue of vulnerability in Thailand, despite evidence that the effects of climate change are already being felt. A comparative, cross-sectional study of climate risk in Vietnam and Thailand finds that among individuals in rural agricultural households, a majority reported suffering from a variety of shocks between 2002 and 2008, including: climatic, biological, socio-demographic and economic shocks. Climatic shocks were the most common shocks reported, and experience with these shocks is highly associated with perceptions of future climatic risk, and employment in agriculture is positively correlated with climatic risk perceptions (Volker et al. 2011).

From an agro-climatic perspective, rice production, a mainstay of agricultural production in rural Thailand, is a crop that is sensitive to both quantity and timing of rainfall. The effects of climate change on rice yields are highly speculative, depending on the level of climatic change used in economic impact models. Felkner et al. (2009) estimate the impact of climate change on rice production, using three possible emissions scenarios: neutral to high; neutral to low; and low to high. They also include information about farm inputs, soil quality and household socioeconomic conditions as well as current environmental data (Felkner, et al. 2009). Their analysis indicates that, depending on the level of emissions, a slight increase in rice production may occur due to increases in rainfall at the right stage in the growth cycle, which assumes that farmers are able to respond to climate change if changes aren‘t too great. Their overall conclusion is that at higher emissions levels, with greater changes to rice production, farmers will be unable to mitigate the effects on production yields. At more moderate levels of change, farmers may be able to make adjustments in inputs in order to preserve rice yields, but they conclude that poorer farmers (those with access to fewer resources) will not be able to respond, even at lower levels of climatic impact. Prolonged drought due to climate change may further compound production of rice and the livelihoods of households in the region. Due to the sensitivity of rice to drought, a delay in the start of the rainy season may cause a drop in yields. Hayano et al. (2008) report that when the rainy season began 20 days later than normal, rice production decreased by 20 percent (Hayano, et al. 2008).

In sum, there is limited, but important evidence that individuals living in rural areas of Thailand who are employed in agriculture both experience and perceive climatic factors as a risk to their livelihood. Climate data already indicate that rainfall patterns in the area are changing, and there is evidence that these changing patterns might impact rice, a particularly important cash crop in Thailand.

Description of Data: Townsend Thai Data

The Townsend Thai Data, one of the longest running panel data sets in the developing world that provides rich data on household composition, income, assets, as well as questions about household exposure to a number of exogenous shocks, including the environment. The survey began as a cross-sectional data in 1997 to measure and investigate how informal institutions such as family and social networks mediate exogenous shocks that might otherwise compromise livelihood outcomes. Following the devaluation of the Baht and the subsequent Asian Financial Crisis, Townsend and his colleagues saw a unique opportunity to examine, over time, how an exogenous shock affects households and how members of these households draw on formal and informal institutions to recover. Townsend and his colleagues proposed an annual resurvey that follows a percentage of the households from the original 1997 survey. Households in the study are located in four provinces; two provinces in the poorer Northeast region and two provinces in the better off Central region. 64 villages were randomly chosen, as well as 15 households in each of the villages, totaling 960 villages per year.[2]

Description of Objective Environmental Data: NDVI

Traditional measures of drought and flooding that rely on rainfall amounts, including gridded precipitation data sets, can be inaccurate if rainfall gauges are not evenly distributed in the area of interest (Thenkabail et al. 2004). One way to address potential inaccuracies in rainfall

[2] For more detailed information about the design of the dataset, please see: http://cier.uchicago.edu/data/data-overview.shtml

data is to use a vegetation index product, derived from satellite images, and available over a long time-scale. NDVI is a measure of plant biomass and general health, obtained from satellite remote sensing imagery (Tucker et al. 1985), and is being used more frequently as a way to assess the impact of climate environmental change on plant health versus rainfall alone (Pettorelli et al. 2005).

For my analysis, I use the Global Inventory Modelling and Mapping Studies (GIMMS) normalized difference vegetation (NDVI) dataset, which provides 24-years (1982 to 2006) of global bi-monthly (24 measures each year) vegetation changes, obtained via images produced by National Oceanic and Atmospheric Administration-Advanced Very High Resolution Radiometer (NOAA-AVHRR) satellites and instruments, measured in 8km x 8km pixels. While the spatial resolution is coarser than the resolution of more recent NDVI products, the strength of these data lies in the rich temporal resolution, which combines well with longitudinal social data. NDVI is a ratio of light reflectivity in the red and near-infrared bands of the electromagnetic spectrum, and give an indication of how much of the photosynthetically active bands of light are being absorbed by vegetation on the ground (Tucker 1979): NDVI= (NIR-RED) / (NIR+RED).

Actively growing healthy vegetation tends to reflect less red light, and more near-infrared light, so that a higher NDVI value can be interpreted to mean healthier plan. NDVI can be used to assess drought or flooding by examining the NDVI anomaly, defined as the difference in a monthly or annual measure as compared to a longer-term average for the same time period (Anyamba et al. 2005).

Description of Analysis File

My analysis file is restricted to 10 years of data from the 1997 to 2006 rounds, in order to utilize best available NDVI data (my environmental measure). With these data I construct an analysis file consisting of household-year records.

I use the following question from the Risk Response Survey module to generate my dependent variable: "Comparing this past year (e.g. June 2002 – May 2003) to the year before that (e.g. June 2001 – May 2002), which was the worst year for household income?" Household respondents who indicate the past year to be the worst for income are prompted to supply the most important reason that they believe explains why their income was lower in the past year. The survey question is identical each year, the only change is the years that the questions reference (year t-1 compared to year t-2). For this paper, the outcome variable is whether a respondent indicates a bad income year due the environment, or due to another cause, relative to household respondents who indicate a good income year. For the environmental cause, I combine the following responses: "not enough rainfall", "flooding" or "pests destroyed my crops". The latter category is considered an environmental cause because studies have shown that hot and dry conditions that accompany drought can often favor the proliferation of insects that destroy crops (Mattson and Haack 1987). The majority of household respondents reporting a bad year due to the environment indicate that it is due to "not enough rainfall". All other responses to this question, (non-environmental) are coded as "other". The dependent variable is coded into three categories: 1) last year was a good income year (referent category); 2) last year was a bad income year due to an environmental cause; and 3) last year was a bad income year due to another cause. I include the non-environmental category to determine whether or not household characteristics associated with perceiving an environmental shock are similarly associated with perceiving another type of shock.

To account for my objective exposure data, I create an annual NDVI measure for each amphoe (district) where the households are located is generated. Next, I calculate a period (1997 to 2006) average and then create standardized z-scores to indicate yearly anomalies from the period-average NDVI. This new variable, which I call my standardized NDVI (or sdvi) variable takes the following form: sdvi = (Annual NDVI – Period Average NDVI) / Period Standard Deviation. Table 1 below demonstrates the coding decision used to generate the variable.

Table 1: Standardized NDVI Variable

SDVI Value	Corresponding z-score
0 – Average NDVI	0
1 – Below Average NDVI	-1/-2
2 – Above Average NDVI	1/2

Next, I construct variables that correspond to the various forms of capital introduced in the SLF, to model how these factors mediate a household respondents' perception of risks. Human capital represents the various skill sets and available labor within a household, and depends on the mix of age, education, and labor force participation. To model these factors, I include controls for the age, sex, and education level of the head, as well as a variable that measures whether 50% or more of working aged household members are engaged in agriculture as their primary occupation. To capture the influence of the age and gender effects on household composition, I include a number of variables that measure the influence of younger (aged 15 to 24) and older (aged 25 to 59) working-age males and females present in the household, as well as the number of children (aged 0 to 14) and elders (over age 59).

To control for a household's access to financial capital, I include household income measured in quintiles, which measures year-to-year economic well-being. I also include a wealth index measure which provides a measure of longer-term status of the household. Tesliuc and Lindert (2004) in a report on vulnerability to a variety of shocks in Guatemala construct a wealth index using PCA to overcome the potential spurious relationship between poverty and shocks. They find that households with higher scores on the wealth index are less likely to report a welfare shock.

If a household respondent indicated that the previous year was a bad income year, he or she is asked whether they perceived that other households in the village also had a bad year. I use the response to this question (yes/no) to proxy social capital or social learning.

I take advantage of the longitudinal nature of these data by analyzing the impact of past environmental attribution, via a cumulative measure (up to time t) of times that a household had attributed a bad year to an environmental cause. I use this measure to test whether some household respondents might always attribute a bad income year to an environmental cause, thus increasing the odds of reporting the same in year t. Conversely I test whether the cumulative measure indicates familiarity with the risk of the environment on livelihoods which would result in a decrease in the odds of reporting an environmental concern (Meijer-Irons 2015). Table 2 below provides summary statistics for the dependent and independent variables.

Table 2: Means and Standard Deviation of Variables

Dependent Variable Categories (0,1)	Mean	S.D.
HH reports a good income year	0.50	0.50
HH reports a bad income year due to environment	0.20	0.40
HH reports a bad income year due to other cause	0.30	0.46
Independent Variables / Head of Household		
Age	54.21	13.36
Sex	0.72	0.45
No Education	0.13	0.33
Primary Education or Less	0.78	0.41
Some Secondary Education	0.06	0.23
Finished Secondary Education	0.02	0.13
Vocational or Other	0.01	0.11
Household Characteristics / Capital Assets		
Financial Capital		
Household Income Quintile 1	10868.94	34196.12
Household Income Quintile 2	36189.98	9492.7
Household Income Quintile 3	62099.14	14788.2
Household Income Quintile 4	100000	24522
Household Income Quintile 5	320000	410000
Asset Index	-0.02	0.88
Human Capital		
0 to 49% employed in agriculture	0.55	0.50
50% or more employed in agriculture	0.45	0.50
# of Males aged 15 to 24	0.39	0.64
# of Females aged 15 to 24	0.36	0.61
# of Males aged 25 to 59	0.91	0.66
# of Females aged 25 to 59	1.00	0.58
# of Elders	0.59	0.75
# of Children	1.20	1.12
Social Capital		
HH indicated year was bad for others in village	0.56	0.50
Cumulative # of times HH said it was a bad income year due to the environment	0.92	1.21
District Level Natural Capital Variables		
Average NDVI	0.39	0.49
Below Average NDVI	0.27	0.44
Above Average NDVI	0.34	0.47

Methods

I use a random-effects multinomial logit model to assess the effect of household characteristics on three different categories of my dependent variable: last year was a good income year (referent category), last year was a bad income year due to an environmental cause, and last year was a bad income year due to another cause. I include village-level dummies in my model to account for potential unobserved similarities of households in the same villages (not included in output). I selected a random-effects model (at the household-level) in order to examine variability between households over-time, rather than within households, and to model how this variability influences the dependent variable. When I ran a fixed-effects model on these data, households that have no variability on the dependent variable (roughly 25% of my sample) are dropped. I am also interested in controlling for time-invariant variables, such as sex of the head and village location, variables that can't be modelled with a fixed-effects logit. In the multinomial model, the log odds of reporting a bad income year of type j relative to a good income year are given by

$\log\left(\frac{p_{jht}}{p_{Jht}}\right) = \propto_j + \beta_j X_{ht}$, where p_{jit} is the odds of reporting a bad income year due to type *j* for household *h* in year *t*. $\propto_j$ is a constant, and X_{ht} is a vector of independent variables for household *h* in year *t*. β_j is a vector of parameters for the effects of the independent variables on income year type *j*.

I estimate two models: a base model with only household characteristics and a second model that includes an asset index, the district-level measure of NDVI anomaly, as well as the cumulative environmental response variable, and the household's perception of whether the year had been bad for other households in the village.

Results

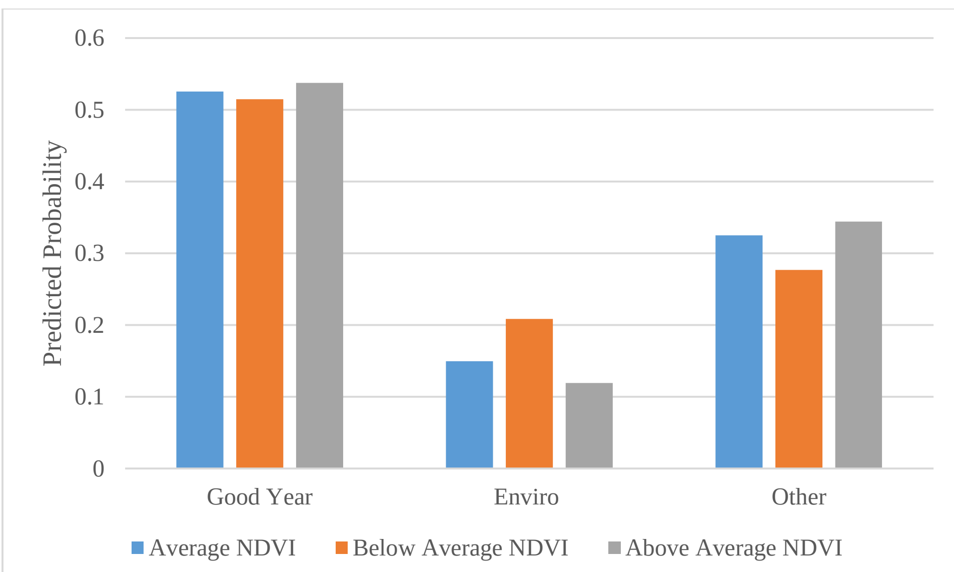
Table 3: Results of Multinomial Logit Models, Including Odds Ratios and Significance Tests

	Environmental Risk	Other Risk		Environmental Risk	Other Risk
Independent Variables / Head of Household					
Sex (female referent)	1.190*	1.117^{+}		1.162^{+}	1.113
Age	1.059***	1.005		1.074**	1.001
Age Squared	0.999***	1.000		0.999***	1.000
Education (Primary Referent)					
No Education	1.047	0.832*		1.262^{+}	0.931
Some Secondary	0.917	0.917		0.785	0.851
Completed Secondary	0.557^{+}	0.940		0.554	0.938
Vocational or Other	0.833	0.835		0.844	0.869
Household Characteristics/Capital Assets					
Financial Capital					
Household Quintile 2	0.714***	0.713***		0.672***	0.687***
Household Quintile 3	0.567***	0.566***		0.535***	0.535***
Household Quintile 4	0.493***	0.470***		0.444***	0.435***
Household Quintile 5	0.371***	0.392***		0.353***	0.363***
Asset Index				1.075	1.088*
Human Capital					
50% of Employed Members in Agriculture	1.386***	0.878*		1.210**	0.811***
# of Males aged 15 to 24	1.030	1.083*		1.007	1.065
# of Females aged 15 to 24	1.109*	1.098*		1.103^{+}	1.086^{+}
# of Males aged 25 to 59	1.083	1.007		1.095	0.992
# of Females Aged 25 to 59	1.319***	1.117*		1.275***	1.080
# of Elders	1.239***	1.053		1.289***	1.046
# of Children	1.067*	1.064*		1.017	1.048^{+}
Social Capital					
HH Indicated year was bad for others in village				9.903***	2.322***
Cumulative Environmental Perception				0.830***	1.123***
District Level Variables/ Natural Capital					
Below Average NDVI				1.422***	0.869*
Above Average NDVI				0.777***	1.035
# of Observations	9570	9570		9380	9380
AIC	18930.06	18930.06		17445.15	17445.15
BIC	20126.85	20126.85		18710.05	18710.05

+p<=.10, *p<=.05, **p<=.01 ***p<=.005

Before I summarize the findings of the effects of household head and household composition characteristics on the likelihood of reporting a bad income year due to the environment or due to another cause, I begin with the results of the objective environmental data. The results indicate that when objective environmental conditions in the district where a household is located are below average, the odds of a household respondent perceiving a bad income year due to the environment increases by 42% relative to average environmental conditions. The odds of perceiving some other cause of a bad income year when environmental conditions are below average decrease by 13%. Figure 1 below shows the predicted probabilities (holding all other variables at their means) of a household reporting one of the three income year types, varying environmental conditions.

Figure 1: Probability of a HH Reporting a Good Income Year, or a Bad Income Year Due to Environmental or Other causes, Controlling for Environmental Condition



Next, I present the results of the head of household characteristics. The sex of the household head is weakly and positively associated with a household respondent perceiving an environmental cause of a bad income year. In addition, an older household head increases the odds of attributing the cause of a bad income year to the environment by 7%, but the squared term indicates this is not a linear relationship and declines as the age of the head increases.

The results of the multinomial logit reveal a number of significant relationships between household composition and a household attributing a bad income year due to the environment or other cause relative to a good income year. To begin, it must be noted that in all cases, larger households increase the odds of reporting a risky income year, regardless of reason, although not all age categories increase these odds in a significant way. The odds of a household respondent perceiving a bad income year due to an environmental cause increases by 28% as the number of females aged 25 to 59 present in the household increases. Similarly, the more elderly residents present in a household increases the odds of a household respondent perceiving an environmental cause increases by 29%. Figures 2 and 3 below show the predicted probabilities of a household respondent perceiving a good income year, or a bad income year due to the environment or other causes, holding all other variables at their means.

Figure 2: Predicted Probability of a Respondent Perceiving a Good Income Year, or a Bad Income Year Due to Environmental or Other Causes, by Number of Elderly Household Members

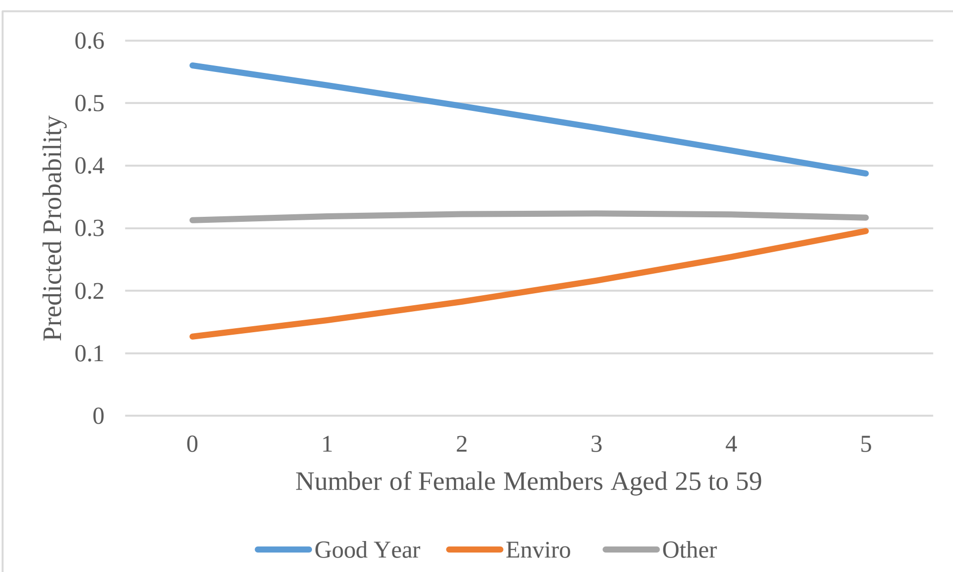
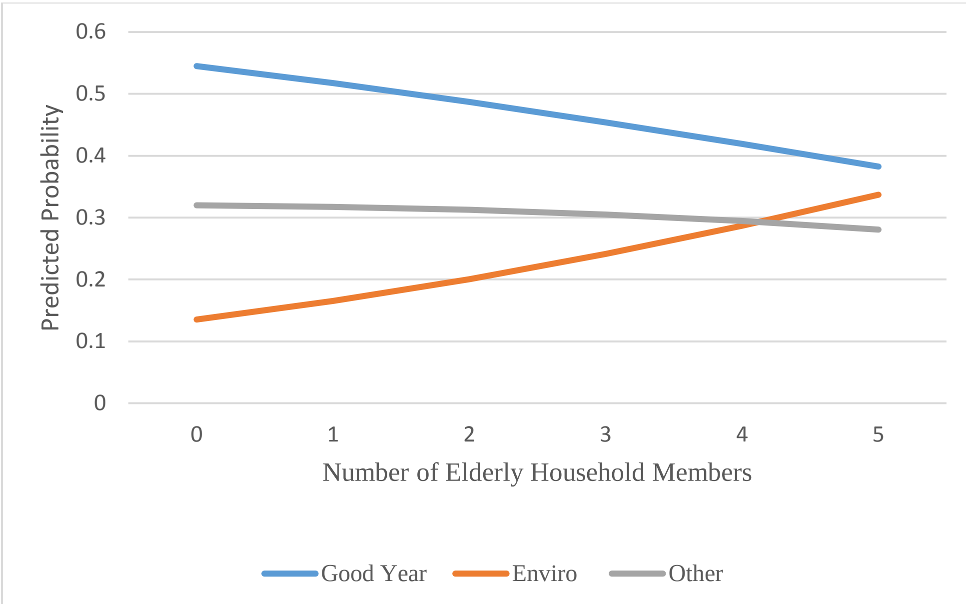
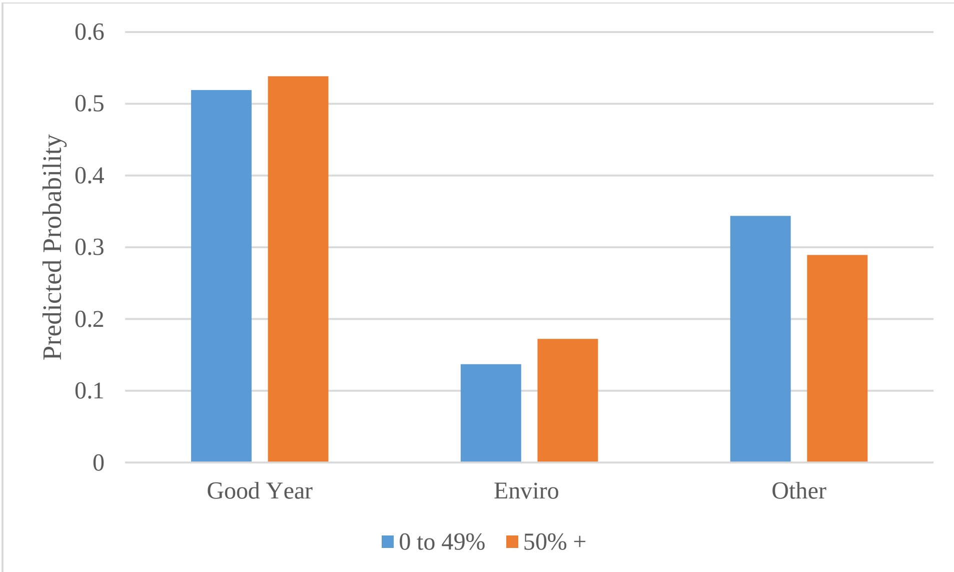


Figure 3: Probability of a HH Reporting a Good Income Year, or a Bad Income Year Due to Environmental or Other causes, by Number of Elderly HH Members



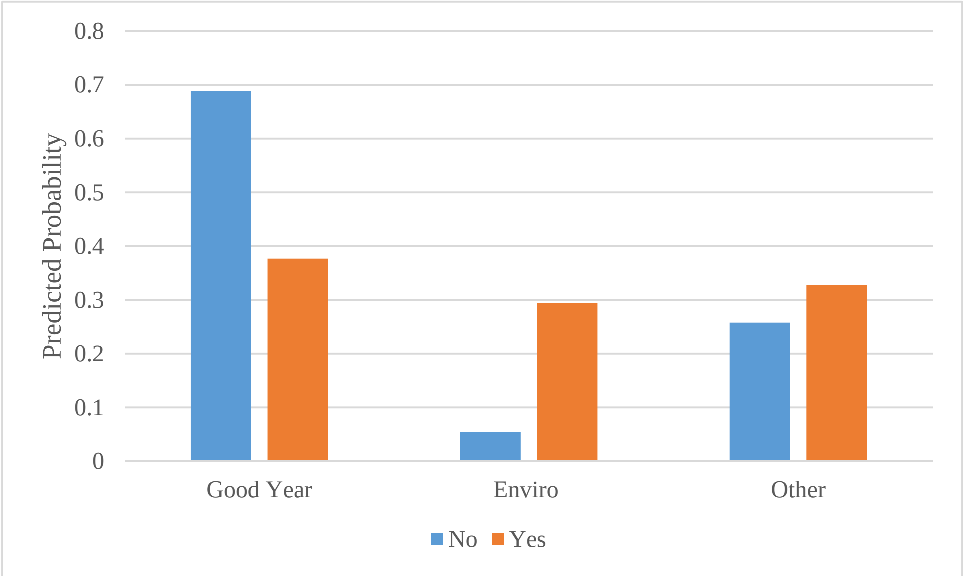
Next, households that have more than 50% of their members engaged in agriculture have an increases the odds of a household respondent perceiving an environmental risk by 21%, relative to a good income year. However, the odds of a household respondent perceiving a bad income year due to some other decreases by 19% if the percent of household members engaged in agriculture exceeds 50%. Figure 4 displays the predicted probabilities of a household respondent perceiving a good income year, or a bad income year due to environmental or other causes, based on the concentration of agricultural labor in the household.

Figure 4: Probability of a HH Reporting a Good Income Year, or a Bad Income Year Due to Environmental or Other causes, by Percentage of HH Members in Agriculture



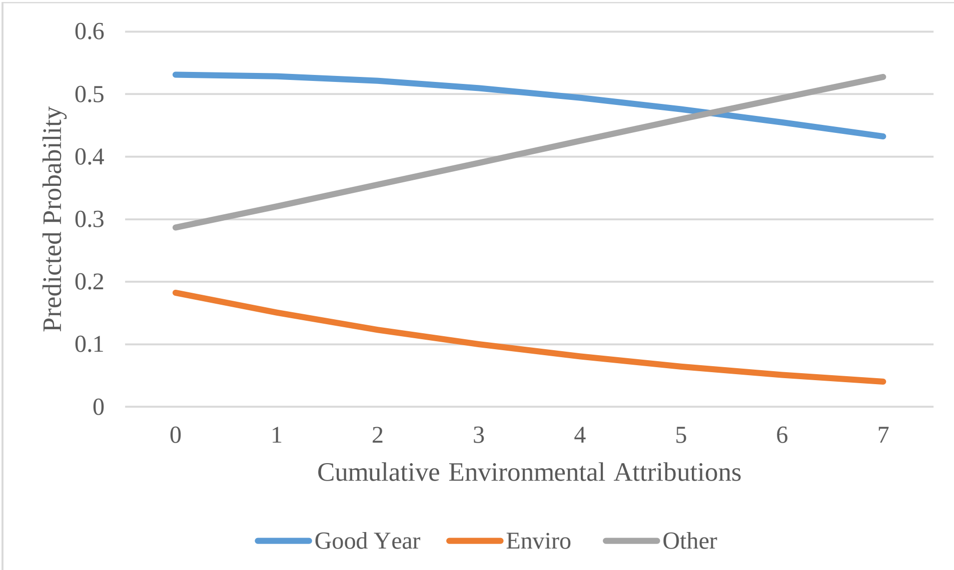
A household respondent's perception that other households in the village also had a bad income year significantly increases the odds of a household respondent perceiving a bad income year due to the environment or other cause. Figure 5 illustrates the predicted probabilities of a household respondent reporting a bad income year based on the perception of others in the village also having a bad income year. For household respondents who attribute a bad year due to the environment, a large proportion of those respondents perceive that others in the village also had a bad year. Household respondents who attribute a bad income year due to some other cause are split in their response to the question about whether others in the village also had a bad income year. While in both cases, the perception that others in the village had also experienced a bad year increased the odds of a household reporting a bad income year, the differential distribution of the village-wide perception variable depending on reported cause of a bad income year might hint at covariant and idiosyncratic shocks. The former are shocks that affect most people in a village, while the latter tend to affect only a few members of a community.

Figure 5: Probability of a HH Reporting a Good Income Year, or a Bad Income Year Due to Environmental or Other causes, by Perception that Others in Village Had Bad Year



Finally, the cumulative number of times a household respondent has attributed a bad income year due to the environment in the past (measured up to year t), decreases the odds that a household respondent will attribute an environmental cause in year t by 17%. The odds of a household reporting some other reason for a bad income year increases by 12% as the cumulative number of environmental attributions increase. This switch in attribution suggests that some household respondents might regularly indicate a bad income year, but a change in the attribution might represent adaptation to repeated environmental exposure.

Figure 6: Probability of a HH Reporting a Good Income Year, or a Bad Income Year Due to Environmental or Other causes, by # of Prior Reports of an Environmental Cause



Discussion and Conclusions

My study set out to explicitly model whether access to household assets and household composition are highly associated with the likelihood of a household respondent perceiving the environment as a primary source of decreased economic health. I use the Sustainable Livelihoods Framework as a conceptual model, to organize findings of past research, and to select the appropriate variables for my analysis. The strength of this framework is the ability to parse out how differential access to capital assets influences both how vulnerable a household might be to exogenous risks, but also how they access to these assets might condition perceptions of vulnerability. Indeed, past research finds that individuals living in areas with similar objectively measured environmental conditions have different perceptions of the risk that the environment presents to their financial well-being. These differences are related to the availability and access to natural, financial, physical, social, and human capital present within a household. These past findings point to the need to better understand how these factors influence risk perception, which research has shown might influence human behavior more than objective measures of the environment alone.

While this past research has added to our understanding of individual and household-level determinants that shape risk perceptions, they are limited in a number of key ways. First, the majority of the studies that model determinants of risk perceptions in the developing world are cross-sectional. These cross-sectional data do not allow researchers to account for how accumulated experience with the environment, and changing economic and household compositions shape dynamic risk perceptions. Second, the data analyzed in past research do not include robust measures of household demographic data or income and asset data. Using a unique panel data set from Thailand, my paper addresses a number of the gaps in these previous studies.

I select Thailand as the site for my study site because previous research on vulnerability and risk perception in Thailand finds that household members already perceive climatic risks to their livelihoods, particularly those engaged in agriculture. Finally, there is evidence to suggest that under future climate scenarios, rice, a staple crop in Thailand, will be impacted by changing precipitation patterns. To test my research questions, I take advantage of the 1997 to 2006 waves of the Townsend Thai Data, a unique economic panel dataset that includes data on self-reported risks to income, including environmental causes, and household composition data. I add robust objective environmental data that coincides with the time period of the social data, to control for the effect of objective environmental conditions on risk perceptions. My dependent variable includes three categories: a respondent perceived the previous year to be a good income year; a respondent perceived a bad income year due to an environmental cause; and a respondent perceived a bad income year due to some other cause. I construct my dependent variable this way to determine whether there are significant differences in household composition between respondents who perceive an environmental or other cause of a bad income year.

The results of my study show that respondents from larger households have higher odds of indicating a bad income year, regardless of cause, relative to a good income year. However, respondents who live in households with higher numbers of elderly and older (age 25 to 59) women have significantly higher odds of perceiving an environmental cause of a bad income year. One possible explanation is that the older females in these households are more likely to be tied to the household via agriculture. However, while men and women in Thailand have different roles and expectations within a rural household, there is evidence that these strict gender roles that had previously tied women to rice growing and other agricultural duties within the household is waning as non-farm economic opportunities expand. (Curran and Saguy 2001:63; Curran et al. 2005; Garip and Curran 2010). This finding requires further study to determine possible mechanisms, including additional modelling of interaction between occupation, gender, and age.

I also find that occupational diversity within a household influences how respondents think about their livelihoods. These findings are consistent with previous research in Thailand that find that respondents engaged in agricultural employment significantly perceive environmental risks to their livelihood. In the Townsend Thai Data, respondents from households where 50% of working aged members are engaged in agriculture as a primary occupation (relative to households with less than 50% of total members engaged in agriculture) show significantly increased odds of reporting lack of rainfall, floods, or pests as a threat to their livelihoods. Households where members are engaged in off-farm employment might be able to maintain more stable income in years when the environment is compromised. As a result, policies that help create these opportunities might help increase adaptive capacity on the ground.

On the other hand, the cumulative measure that counts the number of times that a household had previously reported an environmental cause for a bad year decreased the odds of a respondent reporting an additional cause of a bad income year, but increases the odds of reporting a bad income year due to some other cause. This finding might be a form of psychological adaption to environmental stress. Repeated exposure to environmental shocks might reset a household's reference point of a normal condition, dampening the effect of an environmental shock. However, it does not reduce a feeling of income risk, just the perceive cause (Loewenstein & Mather 1990).

Perceiving that others in the village had a bad income year increased the odds that a respondent reports a bad income year, regardless of cause, although if a respondent reported a bad year due to environment, she largely reported that others in the village were impacted as well. The reason for the patterns requires some additional research. The pattern could indicate that when an environmental shock hits, it is likely to impact almost everyone in the village, or at the very least, be a dominant topic of informal conversation among villagers. A mixed methods approach that includes both detailed demographic data, but also qualitative surveys that allow for more in-depth analysis of these perceptual responses would help shed light on a number of the questions analyzed in this paper.

Despite some of the limitations and need for further research, I argue that the preliminary results add to our understanding of the characteristics of households are likely to report an environmental shock, such as insufficient rainfall, which is common in the study area.

Respondents from households that are less dependent on agriculture, have a younger mix of residents, and have higher incomes may live in areas with insufficient rainfall, but they appear to be less likely to either report a bad income year, or attribute a bad year to the environment. Policy recommendations based on this research might include mechanisms to help diversify occupational opportunities to buffer against reduced livelihoods during times of environmental shocks. A number of studies point to the role of seasonal migration and remittances as an adaptive response to environmental shock, providing a needed buffer to help supplement households via off-farm income. This preliminary work also points to the need to consider a life course approach in development work focused on rural households and response to climate change. This approach pushes for a solid understanding of the structure and composition of rural households, as well as the role that individuals play within these households. Rather than assume that all households are identical in their experience of a given shock, this more nuanced study of the make-up of a household can help guide policy and development work meant to assist the most vulnerable in a community.

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Paper Three: Environmental Migration: The Role of Proximate and Cumulative Subjective and Objective Environmental Measures on Mobility in Rural Thailand

Abstract

I assess whether migration events within a household are highly associated with proximate and cumulative experience and exposure to environmental stress. Past research finds that migration following environmental stress may be a household risk-minimizing strategy employed by household members in the absence of credit and insurance markets. This household decision to send a migrant may, in turn, be mediated by a household's access to capital endowments and capital entitlements. To date, few studies consider how subjective perceptions of the environment interact with objective measures influence migration decisions. I take advantage of a unique longitudinal dataset that includes data on migration, as well as data on a household's subjective assessment of the environment as a cause of a poor economic outcome. I find that in the near-term, objective and subjective environmental measures reduce the odds of a household sending a migrant. However, after cumulative exposure to environmental shocks, a differential pattern emerges, one that is conditioned on subjective measures of environmental risk.

Introduction

Climate scientists predict significant impacts of increasing temperatures on world food production, including reduced yields for wheat, maize, and rice. Households in rural areas of the developing world often rely on these major crops for food supply and as a source of income; reductions in yield without adopting adaptation practices represent a significant impact to their future well-being (Porter et al. 2014). In response to initial concern about large increases in rural to urban migration in direct response to unprecedented climate change (El-Hinnawi 1985; IPCC 1990), a new line of inquiry in migration studies has emerged (Bates 2002; Homer-Dixon 1991; Hugo 1996; Myers 2002; Suhrke 1994).

Social scientists argue that is difficult to parse out the independent role that environmental change plays in inducing out-migration, particularly in areas where slow-onset environmental change, such as drought, is more likely to occur (Castles 2002; Hugo 2008). Instead, researchers suggest that migration might be employed as a household strategy to diversify risk due to environmental shocks, in response to decreases in agricultural income, particularly when access to credit is limited, a concept introduced in the New Economics of Labor Migration (Stark and Bloom 1985). In addition, researchers also consider how households can draw on available capital endowments and capital entitlements to mediate migration decisions in the face of environmental shocks (Carney 1998; Scoones 1998). More recently, discussion has turned towards a more elaborated understanding of how household members experience and perceive environmental risk and how this in turn conditions migration response (Hunter 2005; Jonnson 2010; Sanchez Peña & Fuchs 2013; Volker et al. 2011).

My paper represents a theoretical and empirical contribution to the small, but growing literature that examines migration as a possible adaptation strategy in the face of environmental shocks in the developing world (Curran and Meijer-Irons 2014; Findley 1994; Gray 2009; Gray and Billsborrow 2013; Gray and Mueller 2012a; Gray and Mueller 2012b; Halliday 2006; Henry et al. 2004; Hunter 2005; Massey et al. 2007; Saldana-Zarillo and Sandberg 2009). The conceptual model used in my paper draws on the mechanisms developed in the New Economics of Labor Migration theory and the Sustainable Livelihoods Framework that recognize migration as a household risk-minimizing strategy, and expands on these ideas by incorporating aspects of the vulnerability literature that argue for inclusion of perceptions of risk to better examine and understand human-environment interactions (Adger et al. 2009; Volker et al. 2011). I argue that the inclusion of subjective measures of environmental risk enhances migration models by incorporating local knowledge and perceptions of the environment and providing a mechanism to explain when migration behavior differs from what one might anticipate based on objective data alone (IPCC 2014, Chapter 12; Meijer-Irons 2015; Volker et al. 2011).

In response to the need for multi-level analyses to properly assess the complex and independent relationship between environmental degradation and mobility (Curran 2002; Kniveton et al. 2008 Piguet 2008), I use a unique longitudinal dataset of rural households in NE and Central Thailand that includes rich data on household composition and subjective measures of risk, in addition to migration data. I then combine these data with objective environmental data that matches the time period covered in my social data. Using these data, I model proximate and cumulative objective exposure and perspective measures to test whether differences in lagged and repeat exposure to environmental stress are statistically associated with household migration strategies. Doing so, I consider both the near-term and longer-term impacts of rainfall variability, the latter measure being of particular importance in the case of drought (Bardsley and Hugo 2010; Chen 1991).

Literature Review

Early research in the field of environmental migration is rooted in the neo-classical theories of migration that emphasize push and pull factors in the origin and destination that compel an individual's decision to move. Within this neo-classical framework, an individual migrates, usually in an attempt to maximize wages, from rural to industrial areas in the direction of higher wages. (Lee 1966; Todaro 1969; Ravenstein 1885; 1889). When the push-pull framework is applied to studies linking the environment to migration, researchers rely on neo-Malthusian arguments that over-intensification of the land and population pressures lead to environmental degradation that compels or "pushes" people to engage in out-migration (de Haas 2010; de Sherbinin et al. 2007; Myers 2002). Conversely, the environment might serve as a pull factor as resource abundance and labor opportunities in the frontier attracts individuals from areas of high fertility and resource depletion. This migration in turn can have environmental consequences if new settlements result in deforestation and degradation of fragile ecosystems (Carr 2004; Carr et al. 2005).

In the environment-migration literature that is concerned with future impacts of climate change on population mobility, research that assumes a direct relationship between the environment and migration is classified as maximalist research, and it draws heavily on the push-pull framework. Studies that fall within the maximalist designation have been criticized for focusing on defining, quantifying (with questionable accuracy), and classifying migrants as passive environmental refugees. These studies do not always employ empirical studies that model correlations between climate change and migration, as the direct role of the environment is assumed. (El-Hinnawi 1985; Myers 2002; Perch-Nielsen et al. 2008; Suhrke 1994). While rapid and sudden-onset degradation has been linked to internal migration around the globe, the unique role of the environment in these movements is hard to disentangle from other social or political factors operating at the same time (Lonergan 1998). This is especially true in the case of slower-onset environmental changes such as drought.

Despite similar complexity in the land use mechanisms that contribute to floods and droughts (i.e. deforestation), the time scale of flooding and drought events are decidedly different. A flood and its attendant impacts are felt close to the weather event, as seen during heavy rain events such as monsoons or hurricanes. In contrast, the effects of drought and desertification occur slowly over time. This slower onset environmental degradation can make it difficult to make direct causal linkages between drought and migration decisions made by people living in the area. As Herrmann and Hutchison state “on the ground, droughts manifest themselves in vegetation stress and ultimately loss of green vegetation cover, decreases in stream flow, and the dying out and cracking of soil surfaces” (c.f. Leighton 2009). From their description one could assume that people living in these areas will adopt a series of adaptation strategies up until a tipping point, when they might be forced to abandon the land and engage in out-migration.

Given the challenges of making explicit the direct relationship between slower onset environmental conditions and migration, the work of the maximalists have been mostly discounted by social scientists, particularly demographers (Hugo 1996; Meze-Hausken 2000; Perch-Nielsen et al. 2008; Piguet 2008; Tacoli 2009). In response to these short-comings in the maximalist literature, minimalist studies emerged that argue a more complex relationship between the environment and intervening social factors that contribute to migration (Jonnson 2010; Suhrke 1994), including the household as the unit of decision-making, drawing on concepts introduced in the New Economics of Labor Migration Theory.

The New Economics of Labor Migration (NELM) theory represents a departure from neo-classical migration theories that highlight migration as an individual decision to maximize income. In NELM, migration is a household-decision used as a risk-minimization strategy to maintain income levels and overcome lack of access to credit and insurance markets (Stark and Bloom 1985; de Haas 2010). Temporary and permanent migration is used as a strategy to buffer household exposure to risk, sending members of households to earn additional income that is later remitted back to the family of origin (de Haan 1999; Kniveton et al. 2008; Stark and Taylor 1989; Tacoli 2009). In the case of the environment, migration can be used by households to diversify income streams and weather leaner years by relying on remittances to supplement lost farm income (Stark and Bloom 1985). To date, a number of papers that examine the impact of drought on mobility begin from a premise of migration as a household strategy to reduce risk, and the results suggest an internally differentiated pattern of migration, depending on context and gender roles within the household (Tacoli 2009). A pre-post study of migrants in the Upper Senegal River Valley in Mali, where rain fed agriculture and livestock are major economic outputs, suggests that aggregate levels of migration remained the same during the 1983-1985 droughts, although the composition of the migrations changed. Compared to pre-drought levels, international moves, typically more costly, declined. Shorter distance temporary labor migration increased, as did women and child migrations increased. These increases in migration among women and children may have served as a means to reduce pressures on households during declining agricultural outputs (Findley 1994), a commonly utilized strategy when population pressure is high (Davis 1963). Differentiated migration in response to climate stress is also seen in Burkina Faso, where households are routinely subject to fluctuations in rainfall declines and harvest yields. Results of a longitudinal study indicate that men and women who live in drier regions are far more likely to make a temporary move, but generally only to a neighboring rural area. Longer distance moves are generally not considered by migrants from rain-scarce regions, instead these moves are more likely to come from people living in wetter regions where water availability is less of an issue. (Henry et al. 2004).

However, migration is just one of a number of adaptation options employed by people who rely on natural resources as a source of livelihood (Meze-Hausken 2000; Perch-Nielsen et al. 2008). In fact, a few papers demonstrate that migration is reduced when households face environmental stress such as drought (Guttman et al. 2005; Munshi 2003) or in the case of floods (Gray and Mueller 2012). A number of recent papers has also pointed to the possibility that disasters might reduce the ability to migrate, creating vulnerable or trapped populations that might be unable to employ migration as a coping mechanism (Black et al. 2013). Still other papers suggest that the benefits of positive rainfall shocks might be used to fund migrations, suggesting positive migration response to environmental conditions (Gray and Billsborrow 2013; Gray and Mueller 2012). Finally, evidence from a longitudinal study in NE Thailand suggests that migration follows a period of exposure to environmental stress, but might not be an immediate response, and depends on gender of migrant and land-holdings (Curran and Meijer-Irons 2014). These findings suggest that additional factors present within the household should be considered as mediating factors when a household experiences a shock such as climate variability. Black et al. (2008) argue that an individual's vulnerability to climate change and her resultant decision to migrate is a function of available capital endowments and capital entitlements —rather than simply the availability of jobs, food or housing in a particular area. The Sustainable Livelihoods Framework captures the ideas argued by Black et al. (2008) and builds on the household as decision-making nucleus developed in NELM, recognizing the role of migration as a livelihoods strategy.

The use of the SLF more fully elaborates migrant selectivity in the literature on environment and migration by acknowledging the use of migration as an income diversification strategy in the face of risk, but also as a way to overcome other capital constraints in the origin, such as social and institutional capital (Carney 1998). Conversely, households can postpone or forego migration by drawing on available social, institutional, natural, physical and human capital within the household or community in response to a shock to adapt. The Sustainable Livelihoods Framework (SLF), like NELM, recognizes out-migration as a household strategy to reduce risk, but the concepts found within the SLF can be used to help explain why some households in the same area send migrants in response to an environmental shock, while others do not. (Bunting et al. 2013; Carney 1998; Eakin and Luers 2006; Scoones 1998).

A number of empirical papers that examine the relationship between environmental change and migration can be summarized and organized according to the SLF. Research to date demonstrates that the presence of established social networks, a form of social capital, in the destination can also lower the cost of migration, tipping the decision to migrate in response to environmental degradation in coastal communities and in cases of sudden onset disasters (Curran 2002; Raleigh et al. 2008), as well as slower onset disasters (Findley, 1994; McLeman and Smit 2006). At the same time, participation in social networks in the origin might serve as an adaptive strategy that allows households to remain intact, particularly in the absence of formal institutions (Adger 2003; Gilbert and McLeman 2010).

Similarly, access to institutional capital in the sending area can mediate the need to migrate, by reducing vulnerability to the immediate effects of environmental degradation, particularly among vulnerable groups within a society (Tacoli 2009). Government or international aid organizations provided food and relief supplies when sources of livelihoods were temporarily disrupted during the Dust Bowl, a drought in Burkina Faso, and following a tornado in Bangladesh, likely reducing the number of migrants from these areas (Gilbert and McLeman 2010; Henry et al. 2004; Paul 2005). On the other hand, loss of institutional capital can also lead to an increased risk of out-migration, a point made in a study conducted in Mexico that highlights the removal of governmental protections and agricultural subsidies following natural disasters as a key driver in out-migration (Saldaña-Zorrilla and Sandberg 2009).

With respect to natural capital Nawrotzki et al. (2012), in a paper that investigates differences in capital assets between migrants and non-migrants find that in general, migrants in Madagascar had better access to natural capital, which they might be able to draw on generate income. Gray and Billsborrow (2013) find that migration follows extended periods of normal to above normal rainfall, suggesting that additional agricultural production may fund additional migrants.

Migrant selectivity is also determined by access to economic, physical and human capital. Several studies pointed to a lack of property rights as a disincentive to remain on the land when agricultural productivity declined, suggesting that a lack of physical capital may be a driver of environmental migration, or at the very least, is sensitive to climate change (Adamo 2009; Black, et al. 2008; Curran and Meijer-Irons 2014). Landless farmers might lack incentives to employ land use methods that stress conservation, leading to migration to urban areas when land loses productivity during drought conditions (Barrios et al. 2006). Landless farmers might also be ineligible for government aid that provides incentives to remove land from production (Gutmann et al. 2005: McLeman and Smit 2006). Finally, landownership is used in a number of cases to fund labor migrations during agricultural shocks as a way to self-insure against declining yields (Gray 2009; Halliday 2006).

Finally, human capital, such as education and available labor, is an additional source of capital that influences who migrates from a household in response to environmental change. In a study on climate-related disasters in Mexico, areas that saw declining agricultural income in the ten years prior to the study, that had pockets of higher levels of education were significant factors determining who migrated following prolonged drought (Saldaña-Zorrilla and Sandberg 2009). On the other hand, poor households might be restricted in their ability to migrate, resulting in households where would-be migrants are unable to finance a migration and are forced to remain where they are (Adamo 2009). Availability of labor in a household is also a predictor of out migration in resource dependent households. In the Chitwan Valley, a decline in natural resources results in increased time spent collecting firewood. Households with sufficient labor to cover the increased time collecting firewood were better able to send labor migrants to supplement household income. (Shrestha and Bhandari 2007).

Despite increasingly complex conceptualizations of the environment-migration nexus, few migration studies consider perceptions of environmental change among household members to explain migration patterns. While NELM and the SLF recognize migration as a strategy employed by households in response to risk, including environmental stress, the studies to date rely on objective environmental data to proxy environmental risk. Hunter (2005) in a review of household migration and hazards suggests that "outsider" perceptions of risk may be completely different from the perceptions of residents in the study area, and urges inclusion of "insider" perceptions to more fully elaborate the environmental-migration relationship. Further, Slovic (1987) argues that people will respond to a risk if they perceive one, and this can only be ascertained by asking people to assess the impact of the environment on their livelihoods. To date, only a small number of longitudinal studies that focus on environmental migration analyze data from surveys that explicitly ask respondents about their perceptions of environmental stress as a source of livelihood risk. Gray (2009) examines the role of drought on three types of migration destinations in the southern Andes region of Ecuador, and finds that a household reporting unusually good or bad harvest increases the odds of local and internal migration. Perceived decline in agricultural productivity in the Chitwan Valley significantly raises the odds of local moves among men and women in the sample (Massey et al. 2007). On the other hand, Gray (2010) found that reports of soil degradation resulted in reduced migration, particularly among women. Finally, Gray and Mueller find that households in rural Ethiopia that reported experiencing drought in the previous year had increased odds of out of district labor migration among men (Gray and Mueller 2012).

Perceptions of change, not just absolute change, might be a key factor that explains migration decisions (Jonnson 2010), and subjective perceptions may provide considerable information on their own, even when they differ from objective measures. A household's decision to send a migrant might be influenced more by perceptions of environmental conditions than by objective measures of the environment, resulting in responses that seem out of character or unexpected given objective conditions (Taylor et al. 1988). Households might respond proactively by sending a migrant if they anticipate a shock that they have experienced in the past, rather than wait to see if conditions improve (Sanchez Peña & Fuchs 2013). Conversely, studies that incorporate both subjective measures of the environment and objective environmental data might reveal resilience or adaptive capacity previously overlooked (Barrett et al. 2001). Households that have experienced climate variability in the past might practice a wait-and-see approach and delay sending a migrant; repeat exposure to a hazard conditions subjective perceptions, possibly normalizing the event in the eyes of local community members, while objective data, with narrower definitions of hazard might identify a given year as "dangerous" (Casimir 2008; Slovic et al. 1986).

Finally, subjective data might reveal local-level heterogeneity in climate that objective data, due to issues of scale, obscure (Byg and Salick 2009; Hunter 2005). The result might be reports of localized stresses that are not revealed in aggregate physical measures captured at a coarser-scale. Meze-Hauzken argues that objective measures of adequate or insufficient rainfall should be compared to idealized expectations and past experience of famers, which play a part in determining whether or not the amount of rainfall is perceived as problematic. In her 2004 fieldwork, she finds that farmer's expectation of some idealized rainfall amount determines whether or not a year is "good or bad" and this ideal might not square with the scientific community's idea of a healthy year. She does propose a measure of caution when relying on perceptions, however, and underscores the need for a broader analysis of social contextual factors. In some cases she argues people may assign more significance to the environment, ignoring social factors that may explain reductions in livelihoods (Meze-Hauzken 2004).

Finally a study exploring the impact of rising sea level on the residents of the island of Funafuti and their willingness to migrate in the future further supports the importance of understanding perception and how it relates to migration. Funafuti is the capital and main island of Tuvalu, which is predicted to suffer from major and permanent inundation due to rising sea-levels as a result of climate change (Stern 2006). While the prevailing assumption of the international community is that the residents of Funafuti should migrate, survey results reveal that many residents do not indicate climate change as a reason to migrate, they are choosing instead to remain on the island due to a strong sense of cultural identity. For those who do choose to leave, economic concerns are their first priority. These residents express knowledge of climate change, but their desires to migrate are more closely tied to their relative employment status than their immediate concerns over climate change (Mortreux and Barnett 2009).

Figure 1 below summarizes the conceptual review of the environmental migration literature, including the fourth box that motivates my study.

<u>Figure 1: Summary of Key Concepts in Environmental Migration Literature</u>

Push-pull factors	environment →migration migration → environment
Push factors + NELM	environment → Household income and assets →migration
Push factors + NELM + SLF	environment→ Household income and assets + access to social, natural, physical, financial, human, social capital →migration
Push factors +NELM + SLF + Perceptions	(proximate and cumulative measures) environment → environmental perception → Income and assets + access to social, natural, physical, financial, human, social capital →migration

From a methodological perspective, while there is agreement on the need for robust empirical work to better understand the impact of environmental change on migration, there is a dearth of high-quality longitudinal datasets in the developing world that researchers can use to study the these interactions (Piguet 2010; Fussell et al. 2014). Among existing studies, there is also considerable heterogeneity in the data, measures, and methods employed. Earlier work focused on relatively short time periods (two to four years) that involved surveys taken in response to a single event, (Findley 1994), or a single measure of environmental change at the beginning of the survey period is used to model all future migration events (Massey et al. 2010). Studies that incorporate multi-level methods are growing in number, and these studies often rely on life history calendars to record individual migration histories, that are linked with objective environmental data allowing researchers to understand longer-term trends in migration (Curran and Meijer-Irons 2014; Gray 2009; Gray and Billsborrow 2013; Gray and Mueller 2012a; Gray and Mueller 2012b; Gutmann et al. 2005; Henry et al. 2004; Massey et al. 2010).

With respect to environmental data, researchers have operationalized environmental conditions in a number of ways and to varying degrees of complexity. In Findley's study on Mali, no objective data is used, rather the study draws on migration surveys conducted before and after the drought there (Findley 1994). Rainfall data is used in a number of studies, either obtained from rainfall gauges within the study area, or from gridded satellite rainfall data, or by asking household members about exposure to drought or flood-related damage (Gray 2009; Gray and Billsborrow 2013; Gray and Mueller 2012a; Gray and Mueller 2012b). Finally, El Nino year effects are used as proxies for drier and wetter than average seasonal fluctuations (Curran and Meijer-Irons 2014). To the extent that subjective measures of the environment are included, the questions range from "quality of harvest" to reports of experiencing a drought in the previous year.

Rainfall as a variable to measure climatic change captures only one measure of environmental stress to an agricultural system; incorporating land use data and remote sensing data overtime can add additional insight into the effects of these dynamic measures on migration patterns. Normalized Difference Vegetation Index (NDVI) is a technique that measures vegetation conditions relative to some normalized values. The presence of deteriorating vegetation conditions over time, measured along with rainfall data, can give a more accurate picture of how drought impacts agriculture (Peters et al. 2002). To date, only a few studies use NDVI to proxy environmental conditions in migration studies. A study in Ghana compares NDVI time series trends to census data in the study area to make observations about how the two measures covary, but does not explicitly model migration in response to changes in NDVI (van der Geest and Dietz 2010). A second study employs NDVI values as a measure of natural capital at the sub-village level in South Africa and how this measure relates to out-migration, but largely deals with issues of scale in measuring NDVI (Leyk et al. 2012).

Finally, with respect to the length of exposure of an environmental stress relative to the migration event, most studies only measure proximate objective exposure. This suggests that an environmental stress in t-1 results in a migration in t, and ignores important temporal dimensions that should be considered when exploring the impacts of slower-onset environmental stress on households. Chen, in her work on seasonality and drought in India, argues that household impacts and subsequent adaptation responses are quite different during single-year droughts versus prolonged droughts (Chen 1991). On the other hand, Gray and Billsborrow point to prolonged exposure of average to above average rainfall amounts as a potential driver of out-migration (2013). Bardsley and Hugo argue that migration might be employed as a longer-term adaptation strategy in response to long-term declines in livelihood, but in the near-term, households might employ other adaptive strategies to remain intact (2010).

In sum, early studies of environmental stress suggested direct links between the environment and individual-level migration, but these studies neglected household-level contextual factors, such as income and asset levels, and capital endowments that mediate migration decision-making, particularly in the case of slower onset environmental stress. Further, incorporating concepts of the perception of the environment among household members into environment-migration models is needed in order to more fully elaborate if and when households employ migration as an adaptation strategy. Longitudinal datasets drawn from household surveys that collect data on migration and subjective perceptions of the environment, coupled with robust longitudinal environmental data will allow researchers to construct proximate and cumulative measures of objective and subjective data to determine whether there is a temporal as well as spatial dimension to the decision of a household to send a migrant in response to environmental stress.

In my study, I take advantage of a unique longitudinal dataset, the Townsend Thai Data that asks questions about household perceptions of risk exposure over a 10-year period, and collects detailed household information, including migration data. I couple these data with objective environmental to extend previous migration research by explicitly modelling migration as a function of both objective environmental data and subjective perceptual measures of environmental risk over a 10-year period. I construct income and asset variables to capture concepts presented in NELM, as well as proxies for social, natural, physical, natural, and financial capital in the SLF, factors that might mediate migration decision-making. I relax the assumption that migration is a function of immediate stress, and include both lagged and cumulative measures of environmental exposure and perspectives. Doing so, I argue that migration in the face of climate change may be in response to longer-term declines in livelihood, rather than in response to a more proximate environmental stress, and may also be mediated by perceptions of environmental stress.

Thailand and Climate Change

Thailand is a suitable area to explore migration, climate change, and subjective measures for a number of reasons that include: a history of labor migration in rural areas; a perception of climatic risk among households; and the sensitivity of cash crops to climatic variability. First, internal migration is readily employed in Thailand, and there is already some evidence that households are employing migration as a response to the environment in Thailand. Miller and Paulson (1999) find that remittances are higher when rainfall in the receiving household is lower. Paulson (2000) also finds that remitting migrants from rural areas that experience rainfall shocks tend to move to areas unaffected by rainfall shocks, improving the odds of finding employment in the receiving area. A series of empirical studies using Nang Rong Migration data, a 16-year longitudinal study, describe patterns of migration among household members who engage in rainfed agriculture. Lacking other natural resources in the area, and in many cases a lack of access to credit markets, off-farm labor migration is employed to reduce risk among households, with a portion of the earnings from this supplemental labor remitted back to the household members left behind (Curran et al. 2005; Entwisle, et al. 2008; Garip and Curran 2009; VanWey 2005; Walsh et al. 2005). More recently, a study by Curran and Meijer-Irons (2014) explicitly models environment and migration and provides evidence that longer-term exposure to drought conditions increases the probability of out-migration, and this differs by gender and land tenure. Following 24 months of El Niño (droughty) conditions, men from households with smaller landholdings are more likely to migrate, while women are less likely to migrate regardless of land tenure and environmental conditions.

Second, there is empirical evidence that suggests that rural Thai households' prior experience with climatic shocks influence subjective risk perceptions of climate change, and that this perception in turn influences household decision-making. Volker et al. (2011), in a survey of risk perceptions in rural households in Thailand and Vietnam, find that a household is more likely to engage in collective action (i.e. digging irrigation ditches to hold water in cases of drought) or attempt to diversify their source of income as their perception of risk increased (Volker et al. 2011). In this study, members of 4400 rural households in NE Thailand and Central Vietnam were asked to recall experience with climatic, biological, socio-demographic and economic shocks between 2002 and 2008, and to assess the severity of these shocks in terms of impacts to their livelihood. They were also asked about current risk perception, and past experience with climatic shock positively influences their perception that climate shocks will occur in the future.

Finally, from an agro-climatic perspective, rice is a mainstay of agricultural production in rural Thailand, and is sensitive to both quantity and timing of rainfall, and a large number of farmers in Thailand rely on rain fed irrigation to water their paddies (Marks 2011). Recent weather trends indicate that the climate is already changing; in the past 50 years, the number of rainy days has decreased, and the mean annual temperate between 1981 and 2007 has risen by one degree Celsius (Dore 2005; Marks 2011). Felkner et al. (2009) estimate the impact of climate change on rice production, using three possible emissions scenarios: neutral to high; neutral to low; and low to high. They also include information about farm inputs, soil quality and household socioeconomic conditions as well as current environmental data. Their analysis indicates that, depending on the level of emissions, a slight increase in rice production may occur due to increases in rainfall at the right stage in the growth cycle, which assumes that farmers are able to respond to climate change if changes aren‘t too great. Their overall conclusion is that at higher emissions levels, with greater changes to rice production, farmers will be unable to mitigate the effects on production yields. At more moderate levels of change, farmers may be able to make adjustments in inputs in order to preserve rice yields, but they conclude that poorer farmers (those with access to fewer resources) will not be able to respond, even at lower levels of climatic impact. Prolonged drought due to climate change may further compound production of rice and the livelihoods of households in the region. Due to the sensitivity of rice to drought, a delay in the start of the rainy season may cause a drop in yields. Hayano et al. (2008) report that when the rainy season began 20 days later than normal, rice production decreased by 20 percent (Hayano, et al. 2008).

In sum, rural out-migration is already taking place in resource-dependent areas of Thailand, and there is some evidence to suggest that migration is, in part, a response to climatic shocks. To the extent that the impact of the environment has been measured in the research reviewed above, most studies rely on objective data, such as rainfall or El Niño year effects. However, Volker et al.'s study on perceptions suggests that past experience with a climatic shock influences risk-minimization and other adaptive responses. Finally, climate change is anticipated to impact rice yields in an area highly dependent on rice for income. My study extends previous research on migration among resource-dependent households by incorporating household risk experience and perceptions along with environmental data to more fully explore the impact of environmental stress on rural Thai households. Based on previous empirical work in NE Thailand, I expect that a household's decision to engage members in migration as an adaptive response to environmental variability is a function of both objective exposure to climatic shocks, as well as perceived experience with climatic shocks.

Data and Measures

I take advantage of the Townsend Thai Data, a unique dataset that annually measures a household's migration activity, income and assets, and access to capital endowments, as well as a household's perceived cause of an income risk. To this rich dataset, I add robust objective environmental data that coincides with the time period of the household survey. Together, this analysis file allows me to model migration as a function of cumulative and proximate measures of objective and perceptual measures of the environment, along with measures captured in the New Economics of Migration and Sustainable Livelihoods Framework. Doing so, I add additional complexity to the discussion of environmentally-induced migration in the developing world.

<u>Description of Data: Townsend Thai Data</u>

The Townsend Thai Data, one of the longest running panel data sets in the developing world that provides rich data on household composition, income, assets, as well as questions about household exposure to a number of exogenous shocks, including the environment. The survey began as a cross-sectional data in 1997 to measure and investigate how informal institutions such as family and social networks mediate exogenous shocks that might otherwise compromise livelihood outcomes. Following the devaluation of the Baht and the subsequent Asian Financial Crisis, Townsend and his colleagues saw a unique opportunity to examine, over time, how an exogenous shock affects households and how members of these households draw on formal and informal institutions to recover. Townsend and his colleagues proposed an annual resurvey that follows a percentage of the households from the original 1997 survey. Households in the study are located in four provinces; two provinces in the poorer Northeast region and two provinces in the better off Central region. 64 villages were randomly chosen, as well as 15 households in each of the villages, totaling 960 villages per year.[3]

Description of Objective Environmental Data: NDVI

Traditional measures of drought and flooding that rely on rainfall amounts, including gridded precipitation data sets, can be inaccurate if rainfall gauges are not evenly distributed in the area of interest (Thenkabail et al. 2004). One way to address potential inaccuracies in rainfall data is to use a vegetation index product, derived from satellite images, and available over a long time-scale. NDVI is a measure of plant biomass and general health, obtained from satellite remote sensing imagery (Tucker et al. 1985), and is being used more frequently as a way to assess the impact of climate environmental change on plant health versus rainfall alone (Pettorelli et al. 2005).

For my analysis, I use the Global Inventory Modelling and Mapping Studies (GIMMS) normalized difference vegetation (NDVI) dataset, which provides 24-years (1982 to 2006) of global bi-monthly (24 measures each year) vegetation changes, obtained via images produced by National Oceanic and Atmospheric Administration-Advanced Very High Resolution Radiometer (NOAA-AVHRR) satellites and instruments, measured in 8km x 8km pixels. While the spatial resolution is coarser than the resolution of more recent NDVI products, the strength of these data lies in the rich temporal resolution, which combines well with longitudinal social data. NDVI is a ratio of light reflectivity in the red and near-infrared bands of the electromagnetic spectrum, and

[3] For more detailed information about the design of the dataset, please see: http://cier.uchicago.edu/data/data-overview.shtml

give an indication of how much of the photosynthetically active bands of light are being absorbed by vegetation on the ground (Tucker 1979): NDVI= (NIR-RED) / (NIR+RED).

Actively growing healthy vegetation tends to reflect less red light, and more near-infrared light, so that a higher NDVI value can be interpreted to mean healthier plan. NDVI can be used to assess drought or flooding by examining the NDVI anomaly, defined as the difference in a monthly or annual measure as compared to a longer-term average for the same time period (Anyamba et al. 2005).

Description of Analysis File

My analysis file is restricted to 10 years of data from the 1997 to 2006 rounds, in order to utilize best available NDVI data (my environmental measure). With these data I construct an analysis file of household-year-migrant records. For each household, I have information about migration out of the village, measured as any move out of the village in the past 12 months, as well as a count of how many migrants left from each household.

To account for my objective exposure data, I create an annual NDVI measure for each amphoe (district) where the households are located is generated. Next, I calculate a period (1997 to 2006) average and then create standardized z-scores to indicate yearly anomalies from the period-average NDVI. This new variable, which I call my standardized NDVI (or sdvi) variables takes the following form: sdvi = (Annual NDVI – Period Average NDVI) / Period Standard Deviation

Table 1: Standardized NDVI Variable

SDVI Value	Corresponding z-score
0 – Average NDVI	0
1 – Below Average NDVI	-1/-2
2 – Above Average NDVI	1/2

To test migration decisions due to proximate environmental exposure, I create a lagged variable that captures the environmental condition in t-1. In addition, I created three cumulative variables, meant to capture a household's accumulated exposure to average, below average, and above average environmental conditions, to test for longer-term exposure's influence on livelihoods.

My subjective perceptual measures of the environment, are constructed based on answers to this question from the Risk Response Survey Module: "Comparing this past year (e.g. June 2002 – May 2003) to the year before that (June 2001 – May 2002), which was the worst year for household income?" Households that indicate the past year to be the worst for income are prompted to supply the first and second most important reasons that they believe explains why their income was lower in the past year. The survey question is identical each year, the only change is the years that the questions reference (year t-1 compared to year t-2). For this analysis, I assign a household-year a code of "1" when a households attributes a bad income year to the environment if they indicated "flood", "not enough water", or "pests destroy my crops" as their main reason to explain that their income was lower in the previous year. Household-years where a household indicated a good income year or gave a non-environmental cause of a bad income year are coded "0". I create two measures of self-reported environmental risk to livelihoods in t-1 to test whether households that attribute a bad income year to the environment engage in migration as an adaptation strategy. The first measure is whether the household attributed a bad income year to environment in t-1, and it tests whether migration is a proximate response to this risk. The second measure is the cumulative number of environmental attributions through t-1, and is meant to capture how repeated measures of attribution influence likelihood of reporting a migrant.

Next, I construct variables that correspond to concepts presented in the NELM and SLF, to model how these mediate migration response. First, I include information about the household head, including age (and a squared-term to test non-linear relationships between age and migration) and sex. With respect to the age of the household head, Nawrotzki et al. (2013) point out that the literature is limited on the influence that this demographic information might have on the household-level decision to send a migrant. Older heads may be in a better financial position to help fund a migration, or an older head might indicate a household where younger people no longer reside, decreasing the odds that sufficient labor exists to migrate (Nawrotzki et al. 2013). With respect to the sex of the household head, Terry (2009), in a study of small farmers in South Africa finds that perceptions of climate risk differ between men and women, with men more likely to indicate drought as a risk, compare to women who indicate heavy rainfall (Terry 2009).

To understand how fluctuations in household income influences a household's decision to send a migrant, I include a household income variable (measured in quintiles) derived from comprehensive household income measure that includes all revenue sources (including remittances received) minus business and farm expenses, for each member living in the household. I also include a measure of physical household assets, a continuous variable, to capture non-liquid resources that a household can use to fund migrations, or perhaps sell-off when income dips (Montgomery et al. 2000).

The amount of human capital available in a household influences the number of people available to migrate. I include information about household size, as well as the ratio of working age to dependents. Larger households might be more likely to send a migrant, both due to available labor, but also as a means to reduce pressures on the household during shocks (Davis 1963). However, this variable may be mediated by the number of children and the elderly in a household relative to working aged household members. A higher dependency ratio might reduce the amount of labor in a household free to migrate.

I include two measures of social capital in my models. First, I create a 0/1 variable called "Household Previously Reported a Migrant". I predict that households that have reported a migrant in the past will have a higher odds of reporting a migrant in year t. Second, I create a 0/1 variable "Household Shares Labor" that captures how connected the household is to other households in the village. Access to this local network might serve as a proxy for other sharing that can help offset the need to migrate in case of environmental shocks. On the other hand, this sharing of labor might free up a household member to migrate and secure non-farm employment.

To capture potential influence of institutional support on the odds of a household reporting a migrant, I include a 0/1 variable that indicates whether the households is a BAAC member in t-1. BAAC, the Bank for Agriculture and Agricultural Cooperatives, provides agricultural loans, and has historically provided extended repayment periods during times of drought, and BAAC membership might help mediate migration during environmental shocks.

The land variable is based on the question in The Townsend Thai Data survey that asks households to provide an estimate for land cultivated, regardless of whether the land is owned by the household. While a land ownership variable might be a better measure of natural capital, the amount of land a household has access to might still inform whether or not it is able to send a migrant. I predict that the more land a household has under cultivation, the less likely they will be able to send a migrant.

I include a number of summary tables of the variables in my analysis file. Table 2 presents the number of households reporting a migrant by survey year. Table 3 presents household objective exposure by year, while Table 4 presents the number of households who identified an environmental risk to their livelihood. Finally, Table 5 presents the means and standard deviations for the pooled dataset.

Table 2: Number of Households Reporting a Migrant(s) by Survey Year

HH Sent Migrant	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**
No	782	770	752	724	641	601	715	730	739
Yes	177	186	208	234	319	359	245	230	221
Total	959	956	960	958	960	960	960	960	960

Table 3: Household Objective Environmental Exposure by Survey Year

NDVI	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**
Average	175	299	299	120	719	480	240	660	0	720
Below Average	59	480	0	60	179	300	240	60	960	240
Above Average	709	180	657	780	60	180	480	240	0	0
Total HH	943	959	956	960	958	960	960	960	960	960

Table 4: Household Attributes Bad Year to the Environment

HH Response	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**
No	791	672	641	702	827	816	890	826	717	751
Yes	152	287	315	258	131	144	70	134	243	209
Total	943	959	956	960	958	960	960	960	960	960

Table 5: Mean and Standard Deviation of Variables (pooled sample)

HH Reported Migrant	Mean	Std. Dev.
No	0.75	0.43
Yes	0.25	0.43
Age of Head of Household	54.21	13.36
Sex of Head of Household		
Female	0.28	0.45
Male	0.72	0.45
Proximate Objective Environmental Measure		
Average NDVI	0.35	0.48
Below Average NDVI	0.27	0.45
Above Average NDVI	0.38	0.49
Cumulative Number of Years of Below Average NDVI	0.84	1.04
Cumulative Number of Years of Above Average NDVI	1.89	1.32
Proximate Perceptual Measure of Environmental Risk		
No	0.80	0.40
Yes	0.20	0.40
Cumulative Perceptual Measure of Environmental Risk	0.92	1.21
Financial Capital		
Household Income Quintile 1	10868.94	34196.12
Household Income Quintile 2	36189.98	9492.7
Household Income Quintile 3	62099.14	14788.2
Household Income Quintile 4	100000	24522
Household Income Qunitile 5	320000	410000
Asset Index	-0.02	0.88
Human Capital		
Household Size	4.49	1.84
Dependency Ratio	0.79	0.80
Social Capital		
Household Previously Reported a Migrant		
No	0.53	0.50
Yes	0.47	0.50
Household Shared Labor in Village		
No	0.51	0.50
Yes	0.49	0.50
Institutional Capital		
Household Member of BAAC		
No	0.67	0.47
Yes	0.33	0.47
Natural Capital		
Land Cultivated	22.94	29.91

Statistical Model and Results

The data are analyzed using a random-effects logit model (the random-effect is measured at the household-level to account for any correlated errors related to repeat observations of households). I also include village-level dummies (fixed effects) to control for any differences across villages. In this model, the log odds of a household reporting someone leaving the village in the past 12 months, relative to not reporting a migrant are given by:

$P(mig_{it})$ = f(objective environmental conditions$_{t-1}$ + perceptual environmental attribution$_{t-1}$ + household characteristics from NELM and SLF$_{t-1}$).

I run six models, beginning with the base model that contains the household characteristics based on the NELM and SLF. To this base model, I test a series of additive models to test the independent effects of proximate and cumulative objective and perceptual environmental measures, before running my full model that incorporates these measures. The results of these models are found in Table 5.

Table 6: Results from Logit Models of Migration (odds ratio and significance)

	Base Model	Proximate Objective Measure	Proximate and Cumulative Objective Measure	Proximate Perceptual Measure	Proximate and Cumulative Perceptual Measure	Full Model
Age of Head of Household	1.117***	1.119***	1.116***	1.118***	1.112***	1.114***
Age of Head Squared	0.999***	0.999***	0.999***	0.999***	0.999***	0.999***
Sex of Head (female referent)	0.696***	0.692***	0.694***	0.699***	0.694****	0.691***
NDVI (Average Referent)						
Below Average		0.780***	0.833**			0.836*
Above Average		0.805***	0.741***			0.759***
Cumulative Exposure to Below Average NDVI			0.893*			0.891*
Cumulative Exposure to Above Average NDVI			1.313***			1.262***
Environmental Attribution				0.853*	0.768***	0.836*
Cumulative Environmental Attributions					1.194***	1.116**
Household Income Quintiles						
2	1.093	1.088	1.078	1.087	1.082	1.073
3	1.178+	1.168+	1.166+	1.162+	1.157	1.151
4	1.174	1.165	1.154	1.157	1.162	1.146
5	1.242*	1.231*	1.216+	1.216+	1.220+	1.203+
Asset Index	0.938	0.936	0.933	0.937	0.949	0.940
Household Size	1.571***	1.574***	1.611***	1.573***	1.589***	1.615***
Household Dependency Ratio	0.740***	0.739***	0.731***	0.740***	0.734***	0.729***
Household Previously Sent a Migrant	1.609***	1.592***	1.192*	1.589***	1.374***	1.141
Shared labor	1.079	0.952	0.967	0.941	0.935	0.956
BAAC Membership	0.946	1.082	0.991	1.081	1.017	0.972
Land Cultivated	0.997*	0.997*	0.998+	0.998+	0.997*	0.997+
Constant	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
Rho	0.171***	0.172***	0.211***	0.172***	0.196***	0.219***
AIC	10764.3	10750.1	10689.0	10760.5	10731.8	10680.5
BIC	11332.9	11333.1	11286.4	11336.3	11314.7	11292.2

*+p<=.10, *p<=.05, **<=.01 ***p<=.001*

Before summarizing the findings of household migration response to objective and perceptual measures of the environment I first begin with a discussion of the results of the household characteristics modelled after concepts introduced in the NELM and SLF. As the age of the household increases, a household is more likely to send a migrant, although this relationship is non-linear and begins to decline at older ages. Female-headed households are more likely to report sending a migrant out of the village. The relationship between sending a migrant and household income is linear, households with income in higher quintiles are more likely to send a migrant, relative to the lowest income quintile, but this is only significant for the middle and highest quintiles. Households with a greater number of assets are less likely to send a migrant, although this variable is not significant.

Next, I tested the effects of access to capital endowments on the likelihood of a household sending a migrant out of the village. Human capital is captured by testing the size of the household and the dependency ratio. Larger households are more likely to send a migrant, but households with a greater number of elders and children relative to working aged members are less likely to send a migrant. Households with higher numbers of elders and children might not be able to afford losing a productive family member to off-farm employment.

With respect to social capital, households that had previously reported a migrant are statistically more likely to send a migrant, a finding that is line with the literature on reduced costs of migration for households that already have established networks in the receiving area. Sharing labor in the village is a test for the role of social capital to retain household members, and sharing labor decreases the odds that a household sends a migrant, although this effect is not significant.

Where natural capital is concerned, as the amount of land a household has under cultivation increases, the less likely that household is to send a migrant. It might be that the more land a household has available to cultivate, the more likely they are to generate enough farm income to keep their household afloat, even in periods of reduced production. While most studies consider land ownership versus cultivation, these results match previous research that finds that the more landed a household is, the less likely a household member is to migrate. Finally, access to and membership in formal institutions, such as the BAAC reduces the likelihood of a household sending a migrant in the full model, but this is not significant.

Migration response to both the objective and perceptual measures of the environmental had significant effects on the odds of migration, controlling for income, assets, and capital endowments. However, these results differ for proximate and cumulative measures. Households that experienced below average environmental conditions in the previous year are 16.4% less likely to send a migrant, relative to a year in which households experienced average environmental conditions. Above average conditions in the previous year reduces the odds of sending a migrant by 24.1%. If a household attributed a bad income year to the environment in the previous year, they were also 16.4% less likely to report sending a migrant than households that indicated either a good income year or some other attribution. Modelling the independent effects of an environmental shock in the previous year alone, indicates that households might be able to adapt in place, immediately following a shock. However, adding in cumulative exposure to above or below average conditions reveal slightly different results. As the number of years a household is exposed to below average conditions, the odds of sending a migrant decreases by 10.9%, but cumulative exposure to above average conditions increases the odds of sending a migrant by 26.2%. Similarly, the more a household has attributed a bad income year to the environment, the odds of sending a migrant increases by 11.6%.

It is a bit surprising to see that cumulative exposure to below average conditions reduces the odds of a household sending a migrant. Although a number of factors might be at play that suggest the need for further investigation. First, the NDVI measures I use in my model are aggregated to the district-level. The migration question asks only about people who migrate out of the village, and it is possible that if they are migrating within the district, possibly for other agricultural work, a district-wide longer-term drought might mean it does not make sense for a household to react to environmental conditions by sending a migrant (Chen 1991: 219) In order to unpack this result a bit more, I run an interaction between cumulative exposure to below average conditions and a household's attribution in the previous year (Interaction 1 in Table 6 below). I also calculate predicted probabilities of a household sending a migrant, given cumulative exposure to below average environmental and a household's proximate environmental perceptual measure (Figure 1 below). As cumulative exposure to below average environmental conditions increases, households that attributed an environmental reason for a bad year in the previous year have a higher probability of sending a migrant compared to households that either had a good income year in t-1, or who to some other cause. This result underscores the need to consider how households perceive and experience environmental conditions, rather than just rely on objective measures that might obscure these differences.

Increased odds of a household sending a migrant following a number of years of above average conditions is similar to findings in Gray and Billsborrow's (2013) work in Ecuador, where they find an increase in internal migration following normal-to-high rainfall. In the Ecuadorian context, internal migrants are the most likely to be the poorest in their study, and increases in rainfall provide additional resources that might fund additional migrations. I also include an interaction between a household's cumulative above average exposure and a household's proximate environmental perceptual measure and I calculated predicted probabilities of a household sending a migrant (Figure 2) although this interaction is not significant.

Table 7: Results from Models of Interactions between Cumulative Objective and Proximate Perceptual Measures

	Cumulative exposure to below average * proximate perceptual measure	**Cumulative exposure to above average * proximate perceptual measure**
Age of Head of Household	1.115***	1.114***
Age of Head Squared	0.999***	0.999***
Sex of Head (female referent)	0.689***	0.691***
NDVI (Average Referent)		
Below Average	0.816***	0.836**
Above Average	0.759***	0.759***
Cumulative Exposure to Below Average NDVI	0.876**	0.892*
Cumulative Exposure to Above Average NDVI	1.259***	1.259***
Environmental Attribution	0.732***	0.814
Cumulative Environmental Attributions	1.101**	1.114**
Household Income Quintiles		
2	1.071	1.073
3	1.147	1.151
4	1.147	1.146
5	1.200+	1.202+
Asset Index	0.940	0.940
Household Size	1.615***	1.615***
Household Dependency Ratio	0.728***	0.729***
Household Previously Sent a Migrant	1.151+	1.141
Shared labor	0.974	0.972
BAAC Membership	0.953	0.956
Land Cultivated	0.997+	0.997+
Cumulative exposure to below average objective measure * proximate perceptual measure	1.188*	
Cumulative exposure to above average objective measure * proximate perceptual measure		1.013

Figure 2: Probability of Household Sending a Migrant, Given Cumulative Exposure to Below Average NDVI and Proximate Environmental Perceptual Measures in t-1

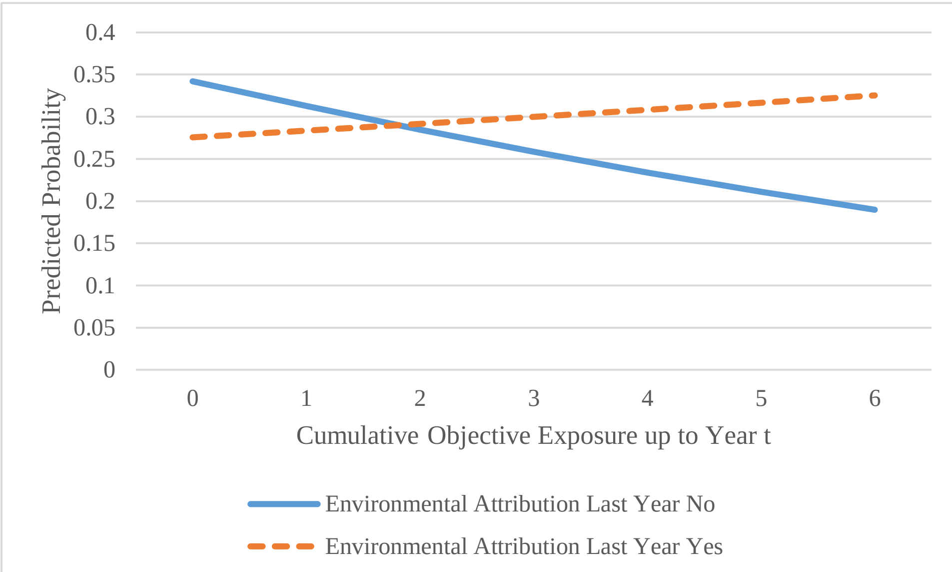
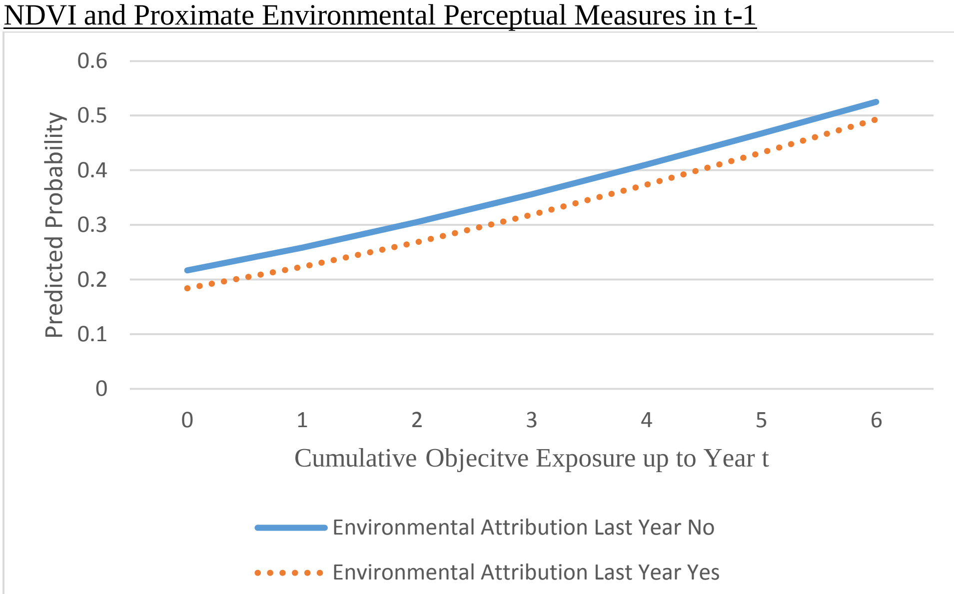


Figure 3: Probability of Household Sending a Migrant, Given Cumulative Exposure to Above Average NDVI and Proximate Environmental Perceptual Measures in t-1



Discussion and Conclusion

My study set out to investigate the role that proximate and cumulative subjective and objective measures of the environment play in migration decisions among rural households located in resource dependent areas of NE and Central Thailand. Past research finds that migration following environmental stress may be a household risk-minimizing strategy employed by household members in the absence of credit and insurance markets. This household decision to send a migrant may, in turn, be mediated by a household's access to capital endowments and capital entitlements. This prior research has largely relied on objective data as a proxy for climate variability, while vulnerability and adaptation researchers argue the importance of also incorporating household member's past experience with environmental stress to better understand how this lived experience conditions reactions to future climate variability, including migration. There are a number of reasons to include subjective data: first, people who live in areas already experiencing climate variability might experience the environment differently than researchers expect, and objective data alone can obscure local experience; next, people might anticipate future environmental stress based on past experience and proactively engage in migration; lastly, the scale at which objective data is measured might obscure heterogeneity at the local-level, and subjective measures may capture a more localized experience. Finally, I model these environmental variables as proximate (lagged) and cumulative measures to determine if migration is a result of recent environmental stress (lagged) or rather, is initiated after a certain threshold of diminished livelihood has been achieved (cumulative).

I select Thailand as the site for my study, because previous research in Thailand points to migration already being employed as an adaptation strategy among households in rural areas that are resource-dependent, and that these moves may be, in part, due to rainfall variability.

Additional research on vulnerability and risk perception in NE Thailand finds that households are more likely to engage in proactive adaptation strategies as their perception of past climatic shocks increased. Finally, there is evidence to suggest that under future climate scenarios, rice, a staple crop in Thailand, will be impacted by changing precipitation patterns. To test my research questions, I draw on a unique annual longitudinal dataset, the Townsend Thai Data, a rich dataset that has data on household migration, composition, income and assets, and access to capital endowments conceptualized in the Sustainable Livelihoods Framework. In addition, the dataset contains data on perceptions of risk to income, including environmental shocks. To these data I attach annual measures of objective environmental data that taken together, allow me to explicitly model the odds of a household sending a migrant as a function of proximate and cumulative household perceptions of the environment as a risk to livelihoods, along with proximate and cumulative objective measures of the environment.

The results of my study show that deviations from average conditions and attributing a bad income year to the environment, in the year before the survey, reduce the odds of a household sending a migrant. This might suggest that in the near-term, households are able to adapt locally, or perhaps choose a wait-and-see approach, before deciding to engage in migration in response to the environment. Modelling longer-term, cumulative exposure to the environment also reveals how repeated exposure to a shock influences the decision to migrate, and these results differ depending on the shock. Cumulative exposure to below average environmental conditions reduces odds of migration, but increases the odds of migration when a household's proximate environmental perceptual measure is also considered, suggesting that household's decision to migrate is not based solely on objective environmental conditions. Cumulative exposure to above average environmental conditions increases migration, although it is unclear whether this is because of financial gains due to increases in agricultural production following higher levels of rainfall, or due to flooding that makes it difficult to maintain crops. Finally, the odds of a household sending a migrant is influenced by subjective measures of environmental perception, although like the objective measures, follow different patterns depending on proximate and cumulative measures. In the former case, a household's proximate subjective perception that the environment was a risk to their livelihood reduces the odds of a household sending a migrant. However, as the cumulative number of previous times a household reported an environmental shock increases, so do the odds of a household sending a migrant.

From an empirical and methodological perspective, I make a number of contributions that build on and extend previous studies of environmentally-induced migration. Key among these contributions are: 1) I use a dataset that allows me to generate a number of measures that have not been previously considered in the literature. The main contribution I make is the use of subjective perceptual measures about household exposure to risk, in addition to objective environmental data that is more typically used. In addition, I am able to include both income and asset measures, as well as measures of natural, social, institutional, physical, and human capital endowments; 2) I link my social data to NDVI, a measure of vegetation health, which has been shown to be a good proxy for rainfall data, which can be difficult to obtain for certain regions of the world; 3) I include both lagged and cumulative measures of both my objective and subjective data. This allows me to test proximate effects versus potentially prolonged effects, and the notion that households might adopt *in situ* adaptation strategies up to a threshold point, after which out-migration becomes a more viable response to environmental shocks. 4) I model a household's access to a variety of capital endowments to incorporate how this access mediates migration.

My initial findings provide some guidance for policymakers who are concerned with the potential for future population displacement under climate change. My work suggests that people are not immediately moving following a deviation from normal environmental conditions, at least not in the case of drought-like conditions. These results challenge assumptions that environmental stress will immediately lead to out-migration. Rather, these assumptions should be reconsidered, particularly in the case of slower-onset environmental shocks where the impact might not be immediately felt. One could assume that people living in areas with frequent drought will adopt a series of adaptation strategies up until a tipping point, when they might be forced to abandon the land and engage in out-migration (Le Houérou 1996; Leighton 2009).

Also, among policymakers, more emphasis should be placed on how people living in areas with variable climate perceive their environment and its impact on their livelihoods. The Fifth Working Group of the IPCC (IPCC 2014) has made explicit the need to consider perceptions and local knowledge in national adaptation plans:

> There is high agreement among researchers that involvement of local people and their local, traditional, or indigenous forms of knowledge in decision-making is critical for ensuring human security (Ellemor, 2005; Kesavan and Swaminathan, 2006; Burningham et al., 2008; Mercer et al., 2009; Pearce et al., 2009; Anik and Khan, 2012). Such forms of knowledge include categories such as traditional ecological knowledge, indigenous science and ethnoscience (Nakashima and Roué, 2002). Collectively they are defined as 'a cumulative body of knowledge, practice and belief, evolving by adaptive processes and handed down through generations' (Berkes 2012: 7). In addition to reasserting culture, identity and traditional values, such forms of knowledge are experiential, dynamic and highly context dependent, developed through interactions with other forms of knowledge (Ford et al., 2006; Orlove et al., 2010; Sánchez-Cortés and Chavero, 2011; Eira et al., 2013).

Taken together, the results of my study push for a more refined understanding by policymakers of who is at risk, who perceives that risk, and ultimately who is able to counter these risks by employing selective migration. In the future, migration may be employed as an adaptive strategy, but this may be limited by the capital assets that a household is able to draw on. Households with the available capital to fund a migration might be less of a concern in the face of future climate change scenarios than so-called “trapped populations” that might want to make a move but are unable to do so (Black et al. 2013). The IPCC Fifth’s Working Group recognizes suggests a number of strategies policymakers can employ:

> Strategies that have been documented as promoting well-being include 1) diversification of income generating activities in agricultural and fishing systems (Tolossa, 2008; Coulthard, 2008; Paavola, 2008; Galvin, 2009; Badjeck et al., 2010; West and Hovelsrud, 2010); 2) migration as a risk management strategy, for example, among pastoralists and farmers in rain-fed areas (Galvin, 2009) and amongst fishing communities (Perry and Sumaila, 2007; Badjeck et al., 2009); 3) the development of insurance systems, particularly amongst vulnerable groups (Badjeck et al., 2010; Linneroth-Bayer and Vari, 2008); and 4) the education of women (Boyle et al., 2006, Rammohan and Johar, 2009).

Migration, then, can be considered as part of a broader adaptation package that also includes policies that target existing inequalities at the origin that might be exacerbated by future environmental stress.

My study is limited by three factors that might reduce the generalizability of the results presented here, or at the very least are points that should be considered in future studies and surveys that incorporate subjective perceptions. First, when respondents report an environmental cause of a bad income year due, they aren’t asked to indicate anything about timing or severity of the event, only that an event occurred. Therefore, I can’t say anything about when “not enough rainfall” or “flooding” occurred in the year, or whether it was a severe event. This also limits my ability to take advantage of the bi-monthly NDVI measures, to more carefully pinpoint timing of subjective and objective events. Second, I do not know what time of year the migrant left the household, only that a migrant left within the past 12 months. Here, too, a sense of timing of the move relative to the environmental event might better link the two phenomena, as would information about whether the migrant returned in the same period. Finally, the rainfall and soil data that were collected at the village-level by the Townsend Thai Data researchers wasn’t available in a public-use format at the time I requested to use these data. It might have been instructive to incorporate rainfall data alongside the NDVI data.

Future research would benefit from rectifying these limitations by including more detail in the survey instrument. In addition, including questions about past environmental experience, as well as perceptions about future impacts, and any future mitigation plans. Doing so would allow researchers to more fully explore whether people living in areas already subject to climate variability take steps to mitigate future shocks based on past experience. In addition, future work might explore migrant destinations and possibly stated reason for the move, although previously discussed, the environment is rarely the sole reason a person migrates. Finally, a study of perceptual and objective data and return migration, while beyond the scope of this current project, would be an interesting addition to the discussion around environment and migration. In particular, when might the environment serve as a pull for migrants to return home?

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