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Who perceives what? A demographic analysis of subjective perception in rural Thailand

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Abstract

Rural households that rely on natural resources for their livelihoods are expected to face increased vulnerability due to climate variability. A number of empirical papers have assessed the impact of environmental shocks on these households, including demographic research that has investigated the impact of shocks on migration. To date, few studies have explicitly modeled how individual and household characteristics influence a household respondent's subjective perceptions of environmental or other shocks. My paper uses a unique panel dataset from rural Thailand to predict a respondent's probability of attributing a reduction in income to an environmental shock based on household composition and income, as well as on community-level effects. Preliminary results suggest that household composition influences respondents' perceptions of environmental risk, and that policies aimed at vulnerable communities should consider the life courses of the households within a given community.

1 Introduction

According to current climate models, drought and floods are likely to become more frequent and more severe in the future, and the effects of these extreme events are already being felt by residents in rural developing communities (Bernstein et al. 2007; Coe and Stern 2011; Porter et al. 2014). A substantial literature has emerged that has theorized, conceptualized, and empirically identified the most vulnerable residents in rural areas. However, this literature has largely relied on notions of vulnerability that were formulated by outside researchers and development agencies, while neglecting to examine perceptions of vulnerability among target populations (Heijmans 2001). Objective environmental conditions are defined by meteorological

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data. At the same time, however, an individual's subjective assessment of the financial health of his or her household, and the degree to which he or she perceives environmental risks as a source of environmental stress, can reveal a great deal about the household's level of exposure to environmental perturbations, as well as about the members' resilience and ability to cope in the face of environmental risks (Barrett et al. 2001). To date, few studies have explicitly modeled the determinants of the environmental risk perceptions of people living in vulnerable environments. Policymakers interested in crafting sound policies to address the social impacts of climate change must also address the issues that are most salient to and most likely to be reported by the people living in areas that are increasingly vulnerable to exogenous shocks, such as drought or flooding (Volker et al. 2011).

Previous studies on vulnerability and adaptation to climate change have made considerable progress toward providing us with an understanding of the complex relationships between human and environmental systems in an evolving climate, and toward identifying which populations are most vulnerable to environmental shocks (Cutter et al. 2009; Oliver-Smith 2009). Early research focused on the severity of potential impacts to natural systems under proposed climate scenarios, and tended to move in a linear fashion, examining the potential vulnerability as a relationship that moves in a single 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 and Luers 2006). However, this singular focus gave way to more complex modeling of the linkages between humans and environmental systems (Fussel and Klein 2006; Turner et al. 2003). These more nuanced studies considered not only where impacts are likely to occur; they also sought to answer context-specific questions, such as how these shocks might be dampened or exacerbated by underlying societal conditions, and how the demographic characteristics of specific population groups might be associated with different levels of vulnerability to exogenous shocks like adverse climatic events (Adger 2006; Acosta-Michlik and Espaldon 2008). Although the conceptualization of vulnerability is becoming increasingly complex, few studies have attempted to model how socio-demographic and objective exposure to the environment shape the environmental perceptions of rural residents. This research gap can be explained in part by the lack of questions in household surveys that ask respondents to report the occurrence of a climatic event, and to indicate whether they experienced financial hardship as a result of such an event—despite frequent calls for these kinds of questions to be included (Billsborrow 2009; Sanchez-Pena and Fuchs 2012).

My paper explicitly explores the causes cited by surveyed household members for why the respondent's household had a bad income year, and the associated demographic characteristics across households in which the respondent reported that environmental and other economic problems represented risk factors. In particular, I investigate how the age and gender composition of a household, and access to a variety of capital assets, condition the likelihood that a household respondent attributed a bad income year to an environmental problem or to another 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. To test whether a household member's life course transitions influence his or her perceptions of risk, I explore the demographic characteristics of households in which a member reported having experienced an income shock due to an environmental problem, and compared them with the characteristics of respondents who reported having experienced a good income year or a bad income year due to another type of shock. Conceptually, I draw on the sustainable livelihoods framework and ideas about family life course to explore whether differential access to assets and/or the age structure of the household was significantly associated with the members' perceptions of the environment as a source of livelihood stress. I find that the odds of perceiving that the household was facing an environmental risk to income were higher among the respondents from households in which a majority of the working members were employed in agriculture. Similarly, while larger households were more likely to have reported facing an environmental risk, as the number of older working-age women (aged 25 to 59) and of elderly people in a household increased, the higher the odds were that the respondent reported that the household had experienced a bad income year due to the environment.

2 Theoretical framework and previous studies

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 since been expanded for use in research on sustainability and livelihood (Carney 1998; Eakin and Luers 2006; Scoones 1998). The strength of this framework is that it allows for the exploration of differential access to a series of assets (human, natural, social, physical, and financial)[1] and entitlements that can highlight vulnerability to environmental risk. It also shows how these assets can be used to mediate the impacts of exogenous shocks, including environmental impacts (Bunting et al. 2013; Carney 1998; Eakin and Luers 2006; Scoones 1998). To date, only a few studies have modeled the determinants of subjective risk perceptions of populations in rural areas of

[1] Human capital refers to the skills, the education, and the good health that enable people or households to support themselves. Social capital refers to the relationships or institutions (formal or informal) that people draw upon for social support in times of shocks. Natural capital refers to having access to quality natural resources (for those households that rely on natural resources for daily production). Physical capital refers to the basic infrastructure (i.e. roads) that facilitate daily activities. Finally, financial capital refers to savings or access to credit. See http://www.eldis.org/vfile/upload/1/document/0901/section2.pdf for more information.

the developing world. The results of these studies have indicated that there is heterogeneity in perceptions of livelihood threats among subpopulations within a seemingly homogenous landscape. I have organized the findings in the existing literature according to the five assets conceptualized in the framework to highlight which factors influenced whether a household respondent identified the environment as a main risk to income, and to suggest opportunities for future research.

The evidence is mixed on how human capital—which is typically measured at the level of the head of the household—influences the likelihood that a household respondent will report perceiving an environmental risk. In a study of East African pastoralists by Barrett et al. (2001), gender and economic activity were found to have strongly influenced risk perception: men were more likely than women to have reported perceiving risks to livestock, water availability, and pasture; factors that were related to men's primary agricultural activities. Similarly, in the South African context, women who were tasked with cooking were more likely to have reported perceiving environmental risks related to water quality and the impacts of wood smoke. (Hunter et al. 2010). In Botswana and Namibia, men and women both said they perceived that the decline in natural resources represented a significant risk to their livelihoods. However, men were slightly more likely to have said they perceived an environmental risk, which is again attributable to the greater participation of men than of women in economic activities that are impacted by flooding and drought (Bunting et al. 2010). However, Doss et al. (2008) found that individual-level characteristics such as age, sex, and education of the head did not significantly affect risk perceptions. The education of the head, which was included to capture the potential for participation in formal labor market, was not found to be significant in the studies that modeled this factor. In Vietnam and Thailand, individuals who were working in agriculture were significantly more likely than non-agricultural workers to have said they perceive climate as a risk (Volker et al. 2011).

Human and financial capital were shown to interact with natural capital in several studies. Respondents who said they consider drought to be a significant risk tended to have greater access to natural capital (on average, higher rainfall amounts). However, this access was found to have been muted by reduced financial and human capital among pastoralists in East Africa. Somewhat surprisingly, household members located in areas that get more rainfall on average were more likely to have reported perceiving rainfall as a main livelihood risk. These households tended to be poorer than other households in the study area, and were more likely to have been engaged in agriculture. Findings such as these further indicate that there is a need to incorporate subjective measures as well as objective data in analyses of these associations (Barrett et al. 2001). A study of villagers in Botswana and Namibia found that subsistence-based farmers were more likely than villagers in more formal labor markets to have ranked drought as a significant risk to their livelihoods. Again, these findings reflect a lack of access to a diversity of human and natural capital in these villages (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 encourage residents to share information about the impact of erratic rainfall amounts, which could in turn influence how individuals perceive rainfall as an environmental risk (Bunting et al. 2013; Lybbert et al. 2007). Doss et al. (2008) found that natural capital variables such as rainfall have significant effects on risk rankings when measured at the community level, and when household and individual-level characteristics are controlled for. Similarly, in Vietnam participation in socio-political organizations has been shown to increase the odds of climate risk perception (Volker et al. 2011).

Physical capital has also been found to influence perceptions, particularly in areas that lack the kind of infrastructure that might mediate such concerns. Hunter et al. (2010) introduced another dimension to the literature by analyzing the spatial proximity of a village to an environmental problem in a study of rural South African residents. An individual was more likely to have reported perceiving the environment as a major concern if he or she was living in a household located in a village in close proximity to an environmental problem, such as polluted water, eroded soil, or refuse.

The existing literature on determinants of risk perceptions has explored a number of key livelihoods concepts that enrich the study of subjective and objective measures of risk. In particular, these studies have highlighted a number of factors that explain the heterogeneity of risk perceptions in areas assumed to be vulnerable to environmental stress, such as access to financial and natural capital. However, the existing studies that examined the determinants of subjective perceptions in the developing world were limited by a number of factors. The first factor was a lack of temporal depth, which limited the ability of researchers to study how risk perceptions vary over time. Doss et al. (2008) analyzed the risk perceptions of a sample population over a period of 27 months, and found that people's risk perceptions varied across time and with the seasons. However, the remaining studies were cross-sectional studies that captured a single time period—an approach that does not allow for observations of temporal variation and past experience, or for analyses of how these factors combine to update or extend risk perceptions. Individual perceptions are influenced by a number of factors that can change over time, including the following: the 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 has been the lack of robust household demographic measures that could show how household composition and structure shape perceived risks to livelihoods. While some existing risk perception studies have incorporated household demographic data, these data have been limited to information about the household head, and the results of these studies have been mixed. Because male and female East African pastoralists engage in different sectors of the economy, the risks they reported perceiving also differed (Barrett et al. 2001). In South Africa, individuals in older households (in which one-third of the members were over age 50) with fewer opportunities to diversify their livelihoods away from a dependence on natural resources were more likely than individuals in younger households (in which one-third of the members were under age 15) to have expressed great concern about water quality; however, this measure was not a consistent metric in the study, and was limited by the cross-sectional nature of the data (Hunter et al. 2010). A more refined measure of age and gender structures within a household might indicate whether household composition is highly associated with a household respondent reporting that he or she perceives that environmental problems threaten his or her livelihood. As a household's composition changes due to life course events (such as births, deaths, or household members leaving for labor market or educational opportunities), the household members' economic opportunities and perceptions of vulnerability might also change (Martine and Schensul 2013). Previous research on household composition and family life course transitions in rural China found that younger households, and younger males in particular, were more likely to have engaged in innovative labor reallocation strategies during a period of reform (Chen and Korinek 2010). In the literature on gender and climate change, women have been shown to perceive disasters differently than men, mainly as a function of gendered social structure, and because men and women have different relationships to agriculture and livestock (Hunter and David 2011; Terry 2009).

My paper addresses the limitations of previous studies that explicitly modeled the determinants of perceptions of environmental risk. First, I address the issue of temporal depth by analyzing data from the Townsend Thai Data project, a unique panel study of rural households in two provinces located in the poorer northeast region of Thailand, and in two provinces in the more prosperous central region of the country. The Townsend Thai Data project collected household-level retrospective subjective measures of perceived risks to income, including environmental threats, as well as detailed data on the age, sex, and occupation of household members. These data allow me to model the age, gender, and occupational structure of the household. The Townsend Thai Data project also collected data on income, assets, and social capital, which enable me to model access to capital assets found in the SLF. In order to measure natural capital, I have added to my analysis robust objective environmental data that coincide with the time period of the household survey.

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

2.1 Thailand and climate change

Thailand is a suitable context for examining the vulnerability of rural households to climate change. In the past 50 years, the number of rainy days in Thailand has decreased, and the mean annual temperature between 1981 and 2007 rose by one degree Celsius (Dore 2005; Marks 2011). Rice, which is one of the main crops of Thailand, is particularly sensitive to the kinds of changes in the weather that are predicted in current climate change scenarios. A large number of farmers in Thailand rely on rain-fed irrigation to water their paddies (Marks 2011). The predicted changes in precipitation in both space and time have the potential to greatly change agricultural production in areas that are dependent on rainfall for irrigation. To date, only a small number empirical studies have considered 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 has found that a majority of individuals in rural agricultural households reported having suffered from a variety of shocks between 2002 and 2008, including climatic, biological, socio-demographic, and economic impacts. Climatic shocks were the most common type of shock reported, and having experienced these kinds of shocks was highly associated with perceptions of future climatic risk. Moreover, being employed in agriculture was positively correlated with climatic risk perceptions (Volker et al. 2011).

From an agro-climatic perspective, rice is a crop that is sensitive to both the quantity and the timing of rainfall. Predictions of the effects of climate change on rice yields vary depending on the level of climatic change used in economic impact models. Felkner et al. (2009) estimated the impact of climate change on rice production using three possible emissions scenarios: neutral to high, neutral to low, and low to high. In addition to current environmental data, they included in their model information about farm inputs, soil quality, and household socioeconomic conditions (Felkner, et al. 2009). Their analysis indicated that, depending on the level of emissions, rice production may increase slightly in response to increased rainfall at the right stage in the growth cycle. Their overall conclusion is that while farmers will be able to adapt at lower emissions levels, they will be unable to mitigate the effects on production yields of higher emission levels. They further concluded that some farmers will be able to make adjustments to their inputs in order to preserve rice yields if the effects of climate change remain at moderate levels, but 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 the negative effects on the production of rice and the livelihoods of households in the region. As rice is sensitive to drought, a delay in the start of the rainy season may cause a drop in yields. Hayano et al.

(2008) reported that when the rainy season began 20 days later than normal, rice production decreased by 20% (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 have both experienced and perceive climatic factors as representing risks to their livelihood. Climate data already indicate that rainfall patterns in the area are changing, and there is evidence that these changing patterns might affect rice, a particularly important cash crop in Thailand.

3 Data and measures

3.1 Townsend Thai data

As one of the longest running panel surveys in the developing world, the Townsend Thai Data project provides rich data on household composition, income, and assets; and collects information on the exposure of households to a number of exogenous shocks, including the environment. The project began as a cross-sectional survey in 1997 designed 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 exogenous shocks affect households, and how members of these households make use of formal and informal institutions to recover, by conducting an annual resurvey that would follow a percentage of the households from the original 1997 survey. The households in the study are located in four provinces: two provinces in the poorer northeastern region and two provinces in the more prosperous central region. Within these regions 15 households in 64 villages were randomly chosen, for a total of 960 respondent households per year.[2]

3.2 Objective environmental data – NDVI

Traditional measures of drought and flooding that rely on rainfall amounts, including gridded precipitation datasets, 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, which is derived from satellite images and is available over a long time scale. The normalized difference vegetation index (NDVI) is a measure of plant biomass and general health obtained from satellite remote sensing imagery (Tucker et al. 1985)

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

that is increasingly being used as an alternative to measures of rainfall to assess the impact of climate environmental change on plant health (Pettorelli et al. 2005).

For my analysis, I use the Global Inventory Modelling and Mapping Studies (GIMMS) NDVI dataset, which provides global data on 24 years (1982 to 2006) of vegetation changes measured on bi-monthly basis (24 measures each year). The data were 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 of these images is coarser than the resolution of images gathered by more recent NDVI products, the strength of these data lies in their rich temporal resolution, which makes it possible to combine them with longitudinal social data. The NDVI represents a ratio of light reflectivity in the red and near-infrared bands of the electromagnetic spectrum, and thus gives 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).

As actively growing healthy vegetation tends to reflect less red light and more near-infrared light, a higher NDVI value can be interpreted as an indication of healthier plants. Anomalies in the NDVI, or divergences in the monthly or the annual measure from the long-term average for the same time periods, can be used to identify periods of drought or flooding (Anyamba et al. 2005).

3.3 Analysis file

To ensure that my environmental measures match the subjective measures collected in the survey data as well as possible, I restricted my analysis file to 10 years of data from the 1997 to 2006 rounds. Using these data, I constructed an analysis file consisting of household year records.

I used 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 year was worse for household income?” The household respondents who indicated that their household income was lower in the past year than in the previous year were prompted to cite the most important reason why they believe this was the case. The survey question was identical each year, with the only change being the years referenced (year $t-1$ compared to year $t-2$). For this paper, the outcome variable is whether a respondent indicated that the household’s income had decreased due to an environmental problem or another factor, or that the household’s income had not been negatively affected. For the environmental cause, I combined the following responses: ‘not enough rainfall’, ‘flooding’, or ‘pests destroyed my crops’. The last category is considered an environmental cause because studies have shown that the 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 who reported having experienced a bad year because of the environment said that

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

‘not enough rainfall’ was the cause. All of the other responses to this question (non-environmental) were coded as ‘other’. The dependent variable was coded into three categories: (1) last year was a good income year (reference category), (2) last year was a bad income year due to an environmental problem, and (3) last year was a bad income year for some other reasons. I included the non-environmental category to determine whether the household characteristics associated with having perceived an environmental shock were also associated with having perceived another type of shock.

To account for my objective exposure data, I created an annual NDVI measure for each amphoe (district) where the households are located. Next, I calculated a period (1997 to 2006) average and then created standardized z-scores to indicate yearly anomalies in 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 demonstrates the coding decision used to generate the variable.

Next, to model how these factors mediate a household respondent’s perceptions of risks, I constructed variables that correspond to the various forms of capital introduced in the SLF. Human capital represents the various skill sets and available labor within a household, and is based on a mix of factors related to age, education, and labor force participation. To model these factors, I included controls for age, sex, and education level of the head, as well as a variable that measures whether 50% or more of working-age household members were engaged in agriculture as their primary occupation. To capture the influence of the age and gender effects on household composition, I included a number of variables that measured 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 elderly people (over age 59).

To test for the influence of financial capital on a household’s response to the income question, I generated an ‘income changed’ variable, or a dummy that indicates whether a household’s current year income fell in the same quintile as the year before, or was in a higher or a lower income quintile relative to the year before. I also included a wealth index measure that provides a measure of the longer-term status of the household. In a study on the population’s vulnerability to a variety of shocks in Guatemala, Tesliuc and Lindert (2004) constructed a wealth index using PCA. The goal of this approach was to overcome the potentially spurious relationship between poverty and shocks. They found that households with higher scores on the wealth index were less likely to have reported experiencing a welfare shock.

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

Taking advantage of the longitudinal nature of these data, I analyzed the impact of past environmental problems via a cumulative measure (up to time t) of the number of times a household had attributed a bad year to an environmental problem. I used this measure to test whether some household respondents always attributed a bad income year to an environmental problem, thus increasing the odds of making the same report in year t. Conversely, I tested whether the cumulative measure indicated familiarity with environmental risks to livelihoods, which would result in a decrease in the odds of reporting an environmental concern (Meijer-Irons, 2015). Table 2 provides summary statistics for the dependent and independent variables.

3.4 Statistical model

I fitted a mixed model with random intercepts (i.e. fixed effects) and random coefficients (i.e. random effects) using GSEM in Stata 13 in order to assess the effects of household characteristics on three different categories of my dependent variable: last year's household income was good (reference category), last year's household income was bad due to an environmental problem, and last year's household income was bad due to another factor. I included village-level dummies in my model to account for potential unobserved similarities of the households in each village (not included in output). I selected a random-effects model (at the household level) in order to examine variability between (rather than within) households over time, and to model how this variability influenced the dependent variable. 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

$$\log\left(\frac{p_{jht}}{p_{Jht}}\right) = \alpha_j + \beta_j X_{ht}$$

where p_{jit} is the odds of reporting a bad income year due to type of income shock j for household h in year t. α_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 estimated two models: a base model that included household characteristics only; and a second model that included an asset index, the district-level measure of NDVI anomalies, the cumulative environmental response variable, and the

Table 2:
Means and standard deviation of variables

Dependent variable categories (0, 1)	**Mean**	**S.D.**
HH reported a good income year	0.50	0.50
HH reported a bad income year due to environment	0.20	0.40
HH reported a bad income year due to another 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

Table 3:
Results of multinomial logit models, including odds ratios and significance tests

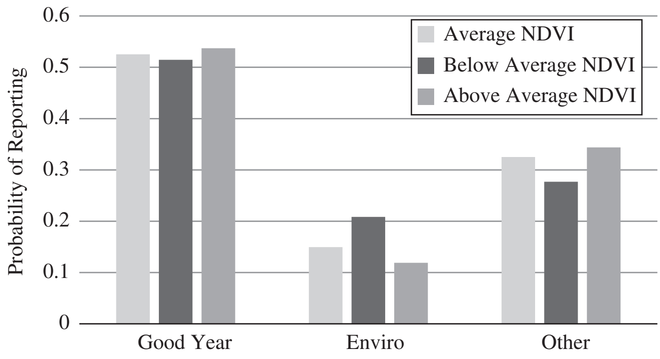
	Model 1				Model 2			
	Environmental risk		Other risk		Environmental risk		Other risk	
Independent variables/ head of household								
Sex (female referent)	1.240	**	1.144	*	1.218	*	1.134	*
Age	1.033		0.984		1.055	*	0.986	
Age squared	0.999	*	0.999		0.999	*	0.999	
Education (no education referent)								
Primary	0.865		1.067		0.746	*	0.976	
Some secondary	0.585	***	0.825		0.495	**	0.771	+
Household characteristics/ Capital assets								
Financial capital								
Income Change Indicator (referent is income quintile same both years)								
Income last year better than year before	0.777	***	0.658	***	0.780	**	0.656	***
Income last year worse than year before	2.468	***	2.450	***	2.596	***	2.482	***
Asset Index					0.927		0.964	
Human capital								
50% of employed members in agriculture	1.425	***	0.944	+	1.248	**	0.885	+
# of males aged 15 to 24	1.036		1.082		1.005		1.060	
# of females aged 15 to 24	1.054		1.021		1.040		1.026	
# of Males aged 25 to 59	1.042		0.955		1.064		0.954	
# of females aged 25 to 59	1.267	***	1.015		1.263	***	1.006	
# of elders	1.164	*	0.967		1.251	***	0.981	
# of children	1.085	*	1.083	***	1.025		1.061	*
Social capital								
HH indicated year was bad for others					12.329	***	2.674	***
in village					12.329	***	2.674	***
Cumulative environmental perception					0.766	***	0.982	
District level variables/ natural capital								
Below average NDVI	1.192	*	0.813		1.353	***	0.845	*
Above average NDVI	1.014		1.216		0.840	**	1.161	**
# of observations	8404				8404			
AIC	16451.13				15271.91			
BIC	17598.08				16461.08			

Note: $+p <= .10$, $^{*}p <= .05$, $^{**}p <= .01$, $^{***}p <= .005$.

respondent's perception of whether the year had been bad for other households in the village. The results of these two models are provided in Table 3.

Before summarizing the findings of the effects of the characteristics of the household head and of other household members on the likelihood of reporting a bad income year due to the environment or due to another factor, I present the results of

Figure 1:
Probability of a HH attributing a good income year or a bad income year to an environmental problem or another cause, controlling for environmental conditions



the objective environmental analysis.[3] The results indicate that when the objective environmental conditions in the district where a household was located were below average, the odds of a household respondent reporting having experienced a bad income year due to the environment increased by 35%, while the odds of a respondent citing another reason for a bad income year decreased by 16%. Figure 1 shows the predicted probabilities (holding all other variables at their means) of a household respondent reporting one of the three income year types across a range of environmental conditions.

Next, I present the results of the analysis of the characteristics of the household heads. In households headed by men respondents were slightly more likely than average to have cited an environmental problem as the cause of a bad income year. In addition, the odds of attributing a bad income year to the environment was 5% higher than average among older household heads, but the squared term indicates this was not a linear relationship, and that it declined as the age of the head increased.

The results of the multinomial logit reveal a number of significant relationships between household composition and the likelihood that a household respondent would attribute a bad income or a good income year to the environment or another factor. It should be noted that respondents in larger households had higher odds of attributing a bad income year to the environment, although these odds were not significantly elevated in all age categories. The odds of a respondent reporting that the household experienced a bad income year due to an environmental problem increased by 26% as the number of females aged 25 to 59 present in the household

[3] The model fit criteria (AIC and BIC) indicate that the full model (Model 2) better fits the data. I report on the results of this full model in this discussion section.

Figure 2:
Predicted probability of a respondent attributing a good income year or a bad income year to an environmental problem or another cause, by number of female household members aged 25–59

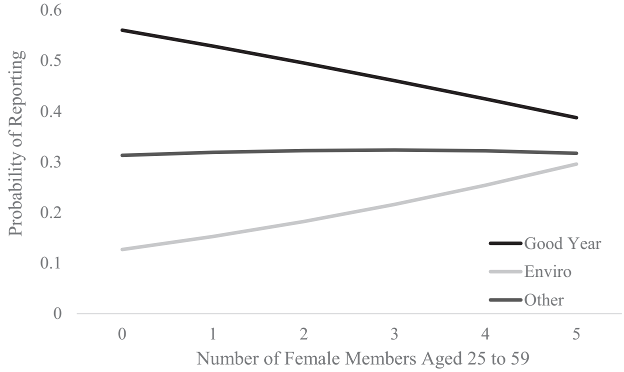
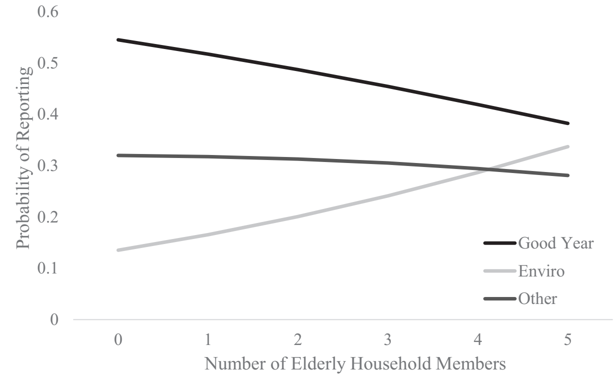


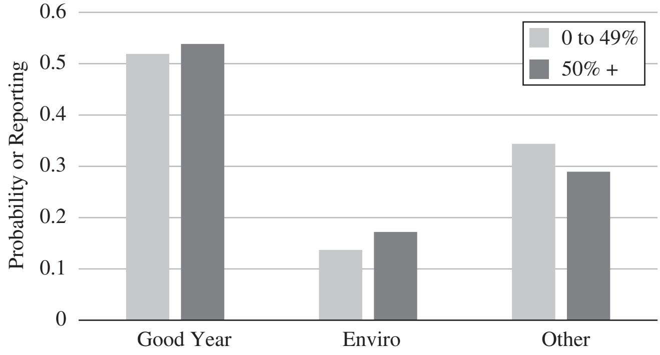
Figure 3:
Probability of a HH attributing a good income year or a bad income year to an environmental problem or another cause, by number of elderly HH members



increased. Similarly, the presence of a large number of elderly members in the household increased by 25% the odds that a respondent would attribute a bad income year to an environmental problem. Figures 2 and 3 show the predicted probabilities of a household respondent reporting having experienced a good or a bad income year due to the environment or another factor, holding all other variables at their means.

My results also show that in households in which more than 50% of the members were engaged in agriculture the odds that the respondent reported perceiving

Figure 4:
Probability of a HH attributing a good income year or a bad income year to an environmental problem or another cause, by percentage of HH members in agriculture

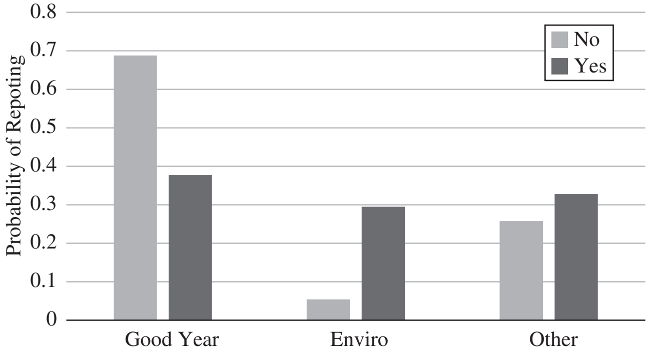


an environmental problem was 25% higher in a bad income year than a good income year. However, the odds that a respondent attributed a bad income year to another reason decreased 12% if the share of household members engaged in agriculture exceeded 50%. Figure 4 displays the predicted probabilities of a household respondent attributing a good income year or a bad income year to environmental or other factors, based on the concentration of agricultural labor in the household.

If a respondent perceived that other households in the village also had a bad income year, the odds were significantly higher that the respondent attributed the bad income year to the environment or to another factor. Figure 5 illustrates the predicted probabilities of a household respondent reporting a bad income year based on his or her perceptions that others in the village also had a bad income year. Of the household respondents who attributed a bad income year to the environment, a large share reported that others in the village also had a bad year. However, the household respondents who attributed a bad income year to another factor were split in their responses to the question about whether others in the village had 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 respondent reporting that his or her own household had experienced a bad income year, the differential distribution of the village-wide perception variable depending on the reported cause of a bad income year might hint at the presence of covariant and idiosyncratic shocks. Covariant shocks affect most people in a village, while idiosyncratic shocks tend to affect only a few members of a community.

The cumulative number of times a household respondent attributed a bad income year to the environment (measured up to year t) decreased the odds by 23% that

Figure 5:
Probability of a HH attributing a good income year or a bad income year to an environmental problem or another cause, by perception that others in the village had a bad year



the respondent would attribute a bad income year to an environmental problem in year *t*. This result suggests that a psychological adaptation might be at play. Prior research suggests that a household respondent's perceptions that environmental factors pose a risk to the household's income change as his or her familiarity with environmental stresses increases; or that having had earlier experiences with a hazard might decrease the likelihood that the respondent would attribute a bad year to the environment, even if the hazard remained (Casimir 2008; Loewenstein and Mather 1990).

Finally, I interacted the income change variable with the NDVI variable to determine whether there is a differential pattern of causal attribution dependent on both income and environmental condition; the results of this model are included in Table A.2 in the appendix. Figures 6 and 7 illustrate the predicted probability of a household respondent attributing a bad income year to the environment or another factor, conditional on his or her income and environmental conditions. The predicted probabilities can be found in Table A.1 of the appendix.

The interaction results from Figures 6 and 7 show that the probability of a respondent attributing a bad income year to both an environmental problem and another factor was substantially higher if the household income in the previous year was lower than it was two years ago. However, those respondents whose income in the previous year was higher than it was two years ago, when the NDVI was below average, were even more likely to have reported experiencing a bad income year due to environmental problems. Indeed, having experienced poor environmental conditions may have altered a household respondent's perception of his or her economic situation, even though the household's income did not suffer. Meanwhile, the probability of attributing a bad income year to some other cause was higher when

Figure 6:
Probability of a household respondent attributing a bad income year to an environmental problem, conditional on income and environmental conditions

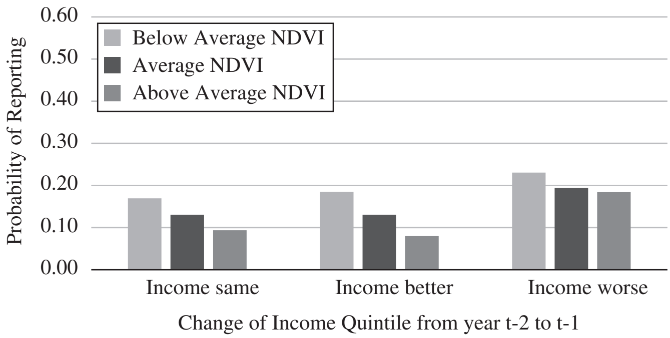
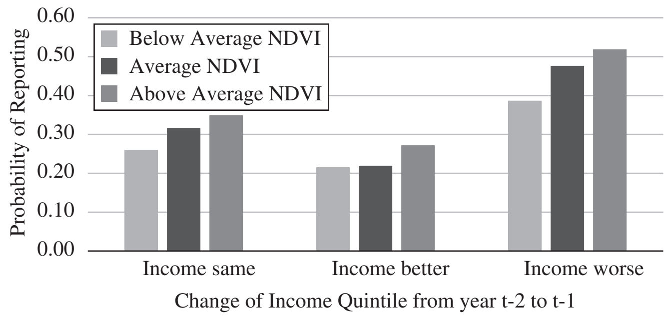


Figure 7:
Probability of a household respondent attributing a bad income year to another factor, conditional on income and environmental conditions



the NDVI was above average, regardless of the actual income change. This implies that these respondents perceived that factors unrelated to environmental conditions posed greater risks than environmental problems, but further research is needed to investigate the exact mechanisms underlying these results.

4 Discussion and future research

In my study I set out to explicitly model whether access to household assets and household composition are highly associated with the likelihood that a household respondent would attribute a decline in household income primarily to the environment. I used the sustainable livelihoods framework as a conceptual model to organize the findings of past research, and to select the appropriate variables for my analysis. The strength of this framework is that it makes it possible to parse out how differential access to capital assets influences both how vulnerable a given household is to exogenous risks, and how the household members' access to these assets might condition their perceptions of vulnerability. Indeed, past research has shown that individuals who were living in areas with similar objectively measured environmental conditions had different perceptions of the risks posed by environmental hazards to their financial well-being. These differences were related to the availability of and the household members' access to natural, financial, physical, social, and human capital. These past findings suggest that we should seek to gain a better understanding of how these factors influence risk perception, as they might influence human behavior even more than objective measures of the environment.

While this past research has added to our understanding of the individual-level and the household-level determinants that shape risk perceptions, these studies were limited in a number of key ways. First, the majority of the studies that modeled determinants of risk perceptions in the developing world were cross-sectional. These cross-sectional approaches did not allow researchers to account for how accumulated experiences with the environment, or changes in economic conditions or household composition, might shape the risk perceptions of individuals over time. Second, the data analyzed in past research did not include robust measures of household demographic data or of income and asset data. Using a unique panel dataset from Thailand, I attempted to close a number of the gaps in these previous studies.

I selected Thailand as the site for my study because previous research on vulnerability and risk perception in the country has shown that many Thais—and particularly those engaged in agriculture—already believe that climate change is affecting their livelihood. Finally, there is evidence to suggest that under future climate scenarios, rice, which is a staple crop in Thailand, will be affected by changing precipitation patterns. To test my research questions, I used the 1997 to 2006 waves of the Townsend Thai Data, a unique economic panel survey that contains data on self-reported risks to income, including environmental causes, and household composition data. To control for the effects of objective environmental conditions on risk perceptions, I added to my analysis robust objective environmental data that coincided with the time period of the social data. My dependent variable included three categories: the respondent perceived that the previous year was a good income year; the respondent perceived that the previous year was a bad income year due to an environmental problem; and the respondent perceived that the previous year was a bad income year due to another factor. I constructed my dependent variable in this way to determine whether there were significant differences in terms of household composition between the respondents who attributed a bad income year to an environmental problem or to another factor.

The results of my study showed that respondents from larger households had higher odds of reporting a bad income year, regardless of cause, than of reporting a good income year. However, the respondents who were living in a household in which the numbers of members who were elderly and older working-age (age 25 to 59) women were high had significantly greater odds of attributing a bad income year to an environmental problem. One possible explanation for this finding is that the households that are more vulnerable to environmental shocks are also those in which many of the male members work elsewhere for part of the year, leaving behind older household members and older women who remain tied to the household via agriculture (Klasen et al. 2015). However, while men and women in rural households in Thailand have different roles and expectations, there is evidence that these strict gender roles that had previously tied women to rice growing and other agricultural duties within the household are 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 its possible underlying mechanisms, including additional modeling of the interactions between occupation, gender, and age.

The results also indicate that occupational diversity within a household influenced whether respondents reported risks to their livelihoods. These findings are consistent with previous research in Thailand that found that respondents employed in agricultural employment described the environmental risks to their livelihood as significant. In the Townsend Thai Data, the respondents from households in which 50% of the working-age members were primarily employed in agriculture had much higher odds than the respondents in households in which less than 50% of the working-age members were primarily employed in agriculture of reporting that a lack of rainfall, floods, or pests represented threats to their livelihood. Households in which the members were engaged in off-farm employment might have been able to maintain more stable income in years in which the environment was compromised. It thus appears that policies designed to foster these opportunities might help increase the adaptive capacity of these households.

On the other hand, the cumulative measure that counts the number of times a household respondent had previously attributed a bad income year to an environmental problem decreased the odds that he or she would attribute a bad income year to environmental shocks, but increased the odds that he or she would attribute a bad income year to another factor instead. This finding might be indicative of a form of psychological adaptation to environmental stress. Repeated exposure to environmental shocks might reset an individual's reference point regarding what constitutes normal conditions, thereby dampening the effect of an environmental shock. However, exposure does not appear to reduce the individual's feeling that his or her income is at risk; just the perceived cause (Loewenstein and Mather 1990).

Perceiving that others in the village had a bad income year increased the odds that a respondent would report a bad income year, regardless of cause; although if a respondent attributed a bad income year to the environment, she or he was also likely to have reported that others in the village were impacted as well. Identifying the reasons for these patterns will require some additional research. This pattern could indicate that when an environmental shock hits, it is likely to affect almost everyone in the village; or, at the very least, be a topic of informal conversation among villagers. The use of a mixed methods approach that includes both detailed demographic data and qualitative survey data, which 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 these limitations and the need for further research, I argue that the results add to our understanding of the characteristics of the household respondents who are likely to report an environmental shock, such as insufficient rainfall, which is common in the study area. The respondents from households that were less dependent on agriculture, had a younger mix of members, and had higher incomes were less likely to have reported having experienced a bad income year or attributed a bad year to the environment, even if they lived in areas with insufficient rainfall. Policy recommendations based on this research might include mechanisms to diversify occupational opportunities in order to buffer individuals and households from reduced livelihoods during times of environmental shocks. A number of studies have shown that seasonal migration and remittances can serve as adaptive responses to environmental shocks, providing needed buffers to help households supplement their non-farm income. This preliminary work also points to the need to consider a life course approach in the development of research on the responses of rural households to climate change. This approach would allow us to gain a solid understanding of the structure and composition of rural households, as well as of the roles individuals play within these households. Rather than assuming that all households experience a given shock in the same way, this more nuanced examination of the make-up of a household could help to guide policy and development work intended to assist the most vulnerable in a community.

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Appendix

Table A.1:
Predicted probability of attributing a good income year or a bad income year to an environmental problem or another cause, conditional on income and environment

	Income same	Income better	Income worse
Reports an enviro risk			
Below average NDVI	0.17	0.19	0.23
Average NDVI	0.13	0.13	0.19
Above average NDVI	0.09	0.08	0.18
Reports other risk			
Below average NDVI	0.26	0.22	0.39
Average NDVI	0.32	0.22	0.48
Above average NDVI	0.35	0.27	0.52

Table A.2:
Results of interaction of income and vegetation

	Environmental risk		Other risk	
Independent variables / head of household				
Sex (female referent)	1.221	*	1.135	
Age	1.056		0.987	
Age squared	0.999		1.000	
Education (no education referent)				
Primary	0.925	*	0.975	
Some secondary	0.500	***	0.774	
Household characteristics / capital assets				
Financial capital				
Income change Indicator (referent is income quintile same both years)				
Income last year better than year before	0.651	***	0.567	
Income last year worse than year before	2.496	***	2.524	
Asset Index	0.925		0.962	
Human capital				
50% of employed members in agriculture	1.250	**	0.889	+
# of males aged 15 to 24	1.010		1.063	
# of females aged 15 to 24	1.042		1.028	
# of males aged 25 to 59	1.072		0.958	
# of females aged 25 to 59	1.262	***	1.005	
# of elders	1.258	***	0.983	
# of children	1.028		1.062	*
Social capital				
HH indicated year was bad for others in village	12.326	***	2.683	***
Cumulative environmental perception	0.764	***	0.980	
District level variables/ natural capital				
Below average NDVI	1.258	+	0.796	*
Above average NDVI	0.713	*	1.095	
Interactions				
Income * Vegetation				
Income last year better than year before * below average NDVI	1.597	*	1.390	*
Income last year better than year before * above average NDVI	1.123		1.179	
Income last year worse than year before * below average NDVI	0.813		0.878	
Income last year worse than year before * above average NDVI	1.475	+	1.104	

$+p <= .10$, $^{*}p <= .05$, $^{**}p <= .01$, $^{***}p <= .005$