THE WELFARE EFFECTS OF EXTREME WEATHER EVENTS – INSIGHTS FROM THREE APEC CASE STUDIES

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PREFACE

The question of how to design economic policies that help economies adapt to a changing climatic environment, while reducing their contributions to it, is at the heart of economic policy making today. To tackle this challenge, the APEC Finance Ministers launched APEC Initiative Number 9 in 2008. This Initiative reviews current fiscal, trade, and investment policies, regulatory frameworks and capacity gaps to address the realities of a changing climate. The implications for human welfare of extreme weather events were further examined, as an input into the broader debate about the costs and benefits of climate change adaptation and mitigation policies. The study was coordinated by the World Bank with the support of the Treasury of Australia. The findings are synthesized in a report entitled "Climate Change and Economic Policies in APEC – Synthesis Report". The report, together with the associated background papers, was presented for feedback to the APEC Senior Finance Officials Meetings in September, 2010 and discussed at the APEC Finance Ministers' Meetings in November, 2010.

The overall study was organized in four pillars: 1) fiscal options to address climate change; 2) technological options and role of trade and investment policies in fostering them; 3) capacity needs assessments; 4) the human welfare effects of extreme weather events. To enable more in depth understanding of the methodologies used and the country specific insights emerging, the background papers underpinning each of the four pillars have been compiled in separate reports. This report provides an in-depth review of the empirical findings emanating from three country case studies examining the welfare effects of extreme weather. It concerns the occurrence of droughts in Indonesia, rainfall and temperature volatility in Mexico and droughts, floods and hurricanes in Vietnam. This pillar was prepared by a team led by Luc Christiaensen (EASER) and Emmanuel Skoufias (PRMPR) under overall guidance of Ahmad Ahsan (Office of the Chief Economist, East Asia and Pacific). The team members included Hector V. Conroy (IADB), Quy Toan Do (DECRG), B. Essama-Nssah (PRMPR), Roy Katayama (PRMPR), Timothy Thomas (IFPRI), Le Dang Trung (Copenhagen University), and Katja Vinha (PRMPR). Syud Amer Ahmed (EASPR/DECAR) and Luc Christiaensen prepared the final version of this synthesis report.

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EXECUTIVE SUMMARY

1. **As the frequency and intensity of natural disasters increases, it is important to better understand how extreme weather events affect economies and their people.** This requires more in depth knowledge about the exposure of different areas to these disasters, the expected costs associated with their occurrence, and the effectiveness of different measures that help households prevent or mitigate the effects of these events or help them cope ex post. To do so, three country case studies (Indonesia, Mexico, and Vietnam) were undertaken, under the umbrella of an overall study on Climate Change and Economic Policies in APEC. This study was commissioned by the APEC Finance Ministers under APEC Initiative number 9 and has been coordinated by the World Bank.

2. **This report uses new measures of extreme weather and methodologies to gauge their welfare effects.** A myriad of methodological issues and data constraints plague empirical work on the effects of extreme weather events on human welfare. The shocks themselves are often poorly measured and the lack of sufficiently long panel data or historical data on past events often forces a focus on effects in the short run. Economy wide effects of local shocks are typically only explored within the context of computable general equilibrium models which are very structural in nature. Proper evaluation of public interventions requires correction for the unobserved characteristics of the areas which receive the programs. The necessary baselines and control groups are also often not present. Even though many of the challenges will remain unaddressed, the three country case studies use innovative measures of extreme weather events derived directly from meteorological records, their historical incidence as well as advanced econometric techniques to overcome some of these shortcomings. They examine the effects of the timing and quantity of rainfall in rural Indonesia, the effects of too much and too little rainfall and growing days in rural Mexico and the effects of droughts, (riverine and flash) floods, and storms in Vietnam.

3. **The key insights emerging from these studies are:**

a) Natural hazard maps derived from meteorological records can be a powerful and relatively inexpensive tool for disaster impact analysis and policy planning.

b) There is enormous geographic variation in exposure to extreme weather events, highlighting the need for tailored analysis and interventions.

c) Households in disaster prone areas tend to be substantially poorer, even though they also tend to be less affected by current events, especially floods.

d) The immediate human welfare effects from extreme events can be substantial (between 15 and 20 percent for shortages of rains and up to 50 percent in case of hurricanes), but differ by event, across space and socio-economic groups, underscoring the need for disaggregated analysis.

e) Irrigation helps substantially in alleviating the effects of droughts.

f) Community based programs to mitigate risks ex ante proved effective in Indonesia.

g) Safety nets and coping strategies may help, but are not always sufficient. More rigorous impact evaluation is needed.

h) Country specific points:

a. Indonesia. The community based approach, especially credit and public work projects, was found to be a promising way forward to moderate the effects of shortfalls in rain in rural Indonesia.

b. Mexico. The heterogeneous impact of rain and temperature variability suggests that a "tailored" approach to designing programs aimed at increasing the capacity of rural households to adapt to climate change is likely most effective.

c. Vietnam. How to better protect households against the damaging forces of hurricanes is an important area in need of more attention in Vietnam.

4. **Despite these important pointers, many questions remain about their robustness under different assumptions and settings.** In particular, important value can be added by building on the work in the following directions.

a) The disaster mapping methodology illustrated in the Vietnam case study provides a useful tool for policy making, project planning and disaster impact analysis. It is relatively inexpensive to apply. Fine-tuning and validating this methodology in other settings is recommended.

b) Despite numerous studies undertaken over the past two decades, including the ones presented here, the empirical (and theoretical) knowledge base for choosing between different strategies to reduce the losses from extreme events (e.g. avoiding floods or learning to live with floods) remains thin, especially when it comes to guiding country specific interventions. A more systematic incorporation of evaluation considerations (baseline data collection, control groups) at the outset of new safety net projects is recommended. The model followed during the launch of the PROGRESA program in Mexico may serve as a practical example.

1. INTRODUCTION

1.1 Getting ready for extremes

1. The available evidence suggests that damage from extreme weather events can be substantial. When winds become too strong, temperatures too hot or cold and rainfall too little or too much, the assumption is that they also cause substantial damage to people, livelihoods and economies alike. That is, they translate into disasters. The damage estimates recorded in the Emergency Database (EM-DAT) [1] bear this out, with the worldwide average economic damage for each storm since 1960 estimated at about half a billion dollar and about 3.7 million people affected on average per drought (Table 1.1). In APEC economies the estimated damage is even more severe. About 4.3 million people are affected by drought, storms cause US$ 0.7 billion in damage on average and the number of people affected by floods is twice this in the rest of the world. The estimates can even rise as high as US$ 125 billion in economic damage for the most pernicious storm ever recorded (Hurricane Katrina, US, 2005), US$ 30 billion for the most damaging flood (China, 1998) and an estimated 300 million people affected by the 1987 drought in India..

Table 1.1: Average costs of natural disasters per reported event (1960-2009)

Disaster type	Number of events*	Average number of people affected	Average economic damage per event (US$)***	Average number of people affected when economic damage reported	Average economic damage per person affected (US$)
World					
Drought	550/155	3,707,569	571,743,265	11,066,609	52
Flood	3536/1255	877,762	346,909,622	2,471,885	140
Storm	3015/1509	280,419	504,035,783	560,280	900
APEC Economies**					
Drought	113/47	4,305,199	1,059,308,362	9,860,772	107
Flood	1095/521	1,631,112	439,063,885	3,425,640	128
Storm	1533/866	399,905	679,829,779	707,913	960

Source: EM-DAT

Note: *Number of events / Number of events for which economic damage is reported; **APEC economies include Australia, Brunei Darussalam, Canada, Chile, People's Republic of China, Hong Kong, China, Indonesia, Japan, Republic of Korea, Malaysia, Mexico, New Zealand, Papua New Guinea, Peru, The Republic of the Philippines, The Russian Federation, Singapore, Chinese Taipei, Thailand, United States of America, and Vietnam; *** the average economic damage per event is calculated by dividing the total economic damage by event by the number of events that are reported with damage. So, if there is a low reporting rate then that increase the average damage per event, as in the case of droughts. It should also be noted that in the case of multi-year droughts, only the first year of the drought is reported as an event.

2. The EM-DAT data also shows that the impressions left on people and economies differ considerably by type of event. Many more people are affected by droughts than by storms, while floods tend to cause much more economic damage than floods. This results in a widely divergent array of estimated damage per person, going from an average of about US$ 900 per affected person over the past 50 years when it

[1] EM-DAT is the world's most complete and widely consulted database on disasters maintained by the Centre for Research on the Epidemiology of Disasters (CRED) since 1988, with 18,000 mass disasters recorded and records going back to 1900. The database is compiled from various sources, including UN agencies, non-governmental organizations, insurance companies, research institutes and press agencies.

comes to storms around the world to U$140 estimated damage per affected person from floods. The differential effect on human and physical capital from droughts, floods and storms has important implications for their effects on economic growth and human welfare. It also affects the benefits from different measures (risk reduction, risk mitigation, risk coping) in dealing with them.

3. Despite these numbers, our understanding of how much extreme weather affects people, livelihoods and economies and for how long remains poor. While EM-DAT provides the most comprehensive and widely consulted database to date on disasters and their damages, these estimates remain inevitably partial and incomplete. Not only is damage assessment notoriously difficult, it is often largely based on estimates of asset damage, ignoring the complexity and ingenuity of human behavior in the face of natural hazards. More refined answers to the question of the welfare costs associated with extreme weather events are needed to assess the benefits from investments and policies to reduce people's exposure to these events or to strengthen their capacity to cope with them ex post. In designing such interventions it is equally important to better understand the short and long run consequences of extreme weather events and map which population groups and regions are more or less likely to be affected.

4. Better quantification of the effects of extreme weather events is important as they are not singular, and likely to occur more frequently as climate change proceeds. A review of the number of droughts, floods and storms in the APEC economies suggests that the number of events has trended upward over the past five decades (Figure 1.1). Looking forward, as the globe warms up, the frequency of these events and their associated damages are predicted to increase even further (United Nations and World Bank, 2010). Rising sea water levels for example increase flood risks and climate change shortens the return period of large storms, in effect fattening the tail of the damage distributions of large storms. In addition, the occurrence of multiple smaller hardships or disruptions from climate change over a shorter period could erode coping systems and combine to cause even greater damage than the sum of each event on its own. While the timing, bunching and coincidence of the different extreme events remains essentially unknown, their effects could be substantially mitigated through proper preparation. To better appreciate the importance of being prepared, it is important to understand the channels through which extreme weather events affect people, livelihoods and economies and how households, communities and governments have so far managed their impacts.

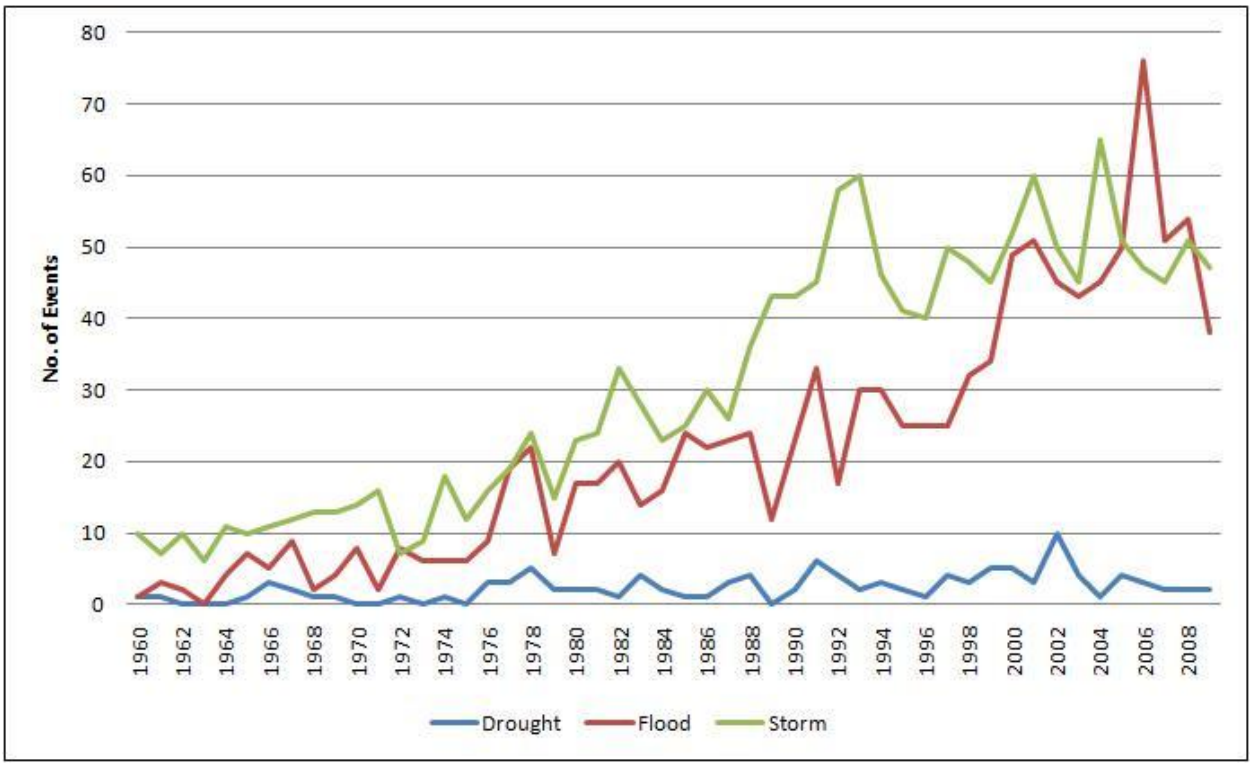
1.2 Extreme events do not necessarily turn into welfare loss

5. A framework is needed to understand whether extreme events translate into welfare loss. The expected losses from extreme events are modulated by government policies and individual responses taken before and after the events occur. Ignoring the implicit or explicit individual, community or government outlays involved in these responses underestimates the true costs associated with extreme weather events. To better grasp the full effect of extreme weather events, a simple framework is proposed to disentangle the channels through which households try to shield themselves from their effects. The organizing framework used here goes back to the social risk-vulnerability chain pioneered by Heitzmann et al. (2002) and Siegel et al (2003).

6. Smoothing incomes through risk prevention: The risk of an extreme weather event happening differs across space. However, even when it materializes, not everybody will be equally affected. The likelihood of an event happening and the sensitivity of a household's income to it determine together the actual exposure of the household. Preventing the event from happening, or more precisely, preventing the event from affecting one's income stream, is one widely applied strategy to reduce exposure to natural hazards. Use of irrigation in drought prone areas is just one example. By taking direct control of the water supply, households insulate their harvests and incomes from the vagaries of the rains. Doing so not only reduces the volatility of their incomes, it may also increase yields on average, for example by enabling multiple

harvests per year. Risk prevention also happens through income and asset portfolio diversification. Such a strategy, however, often comes at the expense of lower average – but more stable – income streams.

Figure 1.1: Number of droughts, floods and storms in APEC economies (1960-2009)



Source: EM-DAT data

7. Smoothing incomes through insurance or risk mitigation: Risk prevention strategies seek to reduce risks by reducing the exposure and sensitivity of one's asset and income portfolio to the event itself. Another set of ex ante strategies seeks to set up arrangements for compensation in case of the event materializes, i.e. it seeks to stabilize incomes ex post by insuring them ex ante. They also go under the name of risk mitigation strategies. This can be done through savings (self-insurance) or through (formal or informal) market insurance arrangements. Insurance markets are however often incomplete, especially in developing economies. Risk prevention and mitigation strategies are in essence aimed at smoothing incomes by taking action ex ante, before the event strikes.

8. Smoothing consumption ex post through risk coping, even when incomes are volatile: In addition to smoothing and insuring incomes ex ante, households often also have to undergo the shock and try to cope with income losses ex post to maintain their consumption. A myriad of strategies have been deployed by households to do so, including temporal migration, drawing down of stocks of social and human capital, or dietary shifts to cheaper calories. Together these individual risk prevention, mitigation and coping strategies help households smooth their consumption and reduce the welfare effects from extreme weather events.

9. Community and government/donor interventions further complement individual/household risk prevention, compensation and coping strategies. Community infrastructure projects can for example reduce the threat of floods and landslides, while the institution of enforceable property rights (e.g. of land and trees) can provide the needed incentives for afforestation and drought reduction as observed in Niger. Extreme weather events tend to cause less damage when capital markets are better developed. In the absence of such markets, savings and credit cooperative associations can facilitate precautionary saving. Catastrophic bonds are increasingly used by governments to insure their outlays in case of extreme

events. To cope with shocks ex post, households often fall back on remittances (domestic and international), especially when public safety nets and disaster relief funds are poorly developed and inadequate. These *can* be effective. Children under two in drought affected communities in Ethiopia saw their growth slow down almost by one centimeter over a 6 month period, though not in communities that also received food aid (Yamano et al., 2005). Yet, many children were left stunted nonetheless because poor targeting rendered food aid rather unresponsive to drought shocks.

Table 1.2: Individuals and governments, prevent, insure and cope with extreme weather events

Measure	Individuals/households	Community	Governments
Risk reduction or prevention	Owning multiple assets and diversifying sources of income Irrigation Investments to protect and maintain assets (timely repairs) Permanent migration	Community training Community-based information systems Small scale irrigation and infrastructure projects	Development of better information systems (disaster risk profiles, early warning systems, public awareness raising) Public works Enforceable property rights
Risk mitigation or insurance	Self insurance through saving (cash, livestock, grain storage, durables) Market insurance such as weather/catastrophe based insurance for property, crops	Local borrowing and saving schemes Microfinance Cereal banks	Well functioning markets (e.g. to sell livestock) Sovereign budget insurance and catastrophe bonds Safety nets (cash transfers and public employment guarantee schemes) Deferred Draw Down Options (DDO)
Risk coping or ex-post risk management	Temporal migration or expansion of household labour Drawing on stocks of social capital or human capital Diversifying expenditures towards less expensive calories and goods	Interhousehold transfers and private remittances	Disaster relief

Source: United Nations and the World Bank (2010)

1.3 Innovative tools are needed

10. The effects of natural shocks and the effectiveness of different instruments and strategies in dealing with them remain poorly quantified, because of methodological challenges and data constraints. A myriad of methodological issues and data constraints plague our empirical understanding of the effects of extreme weather events on human welfare. The shocks themselves are often poorly measured and the lack

of sufficiently long panel data or historical data on past events often forces a focus on the short run. Economy wide effects of local shocks are typically only explored within the context of computable general equilibrium models which are very structural in nature. Proper evaluation of public interventions requires correction for the unobserved characteristics of the areas that receive the programs, but baselines and control groups are often not present. The three country case studies presented in this report remedy some of these shortcomings using weather and climate data, though many of the challenges will remain unaddressed. The case country studies focus on the effects of the timing and quantity of rainfall in rural Indonesia, the effects of too much and too little rainfall and growing days in rural Mexico and the effects of droughts, (riverine and flash) floods, and storms in Vietnam.[2]

11. Subjective versus objective measures of extreme weather: Subjective measures of shocks are often used to identify whether households have been affected by extreme weather or not. They consist of self reported declarations of having experienced a shock by the households or communities. Such information is regularly recorded in standard household questionnaires and avoids having to define a cut-off beyond which rain, wind or temperature is considered either too high or too low. Yet, as seen above, whether a household considers a meteorological event a disaster is likely to depend both on its ex-ante exposure to it as well as its ex-post capacity to cope with it. To reduce its exposure it may have adopted less risky portfolio strategies over time. As a result, it may not consider the event a shock because it has already adapted to it, leading to an underestimate of the true welfare loss associated with shocks. Moreover, it is typically also difficult to extrapolate the findings across space and time, as subjective shock measures are usually not available outside the sample, and neither are their probability distributions. The latter are especially useful to explore their long run effects and to simulate the effects of climate change. The country case studies presented here use objective measures of extreme weather, derived directly from the meteorological data, as opposed to subjective measures, based on household reports. This required innovative methods to interpolate the meteorological event data across space and to link them to the economic data sources on household assets, income, and consumption and human development outcomes.

12. Measuring both the long and short of it: The effects of current events may not only be felt today, but also long thereafter. That there is long run detrimental damage of growth retardation during the first 1000 days of life (from conception to the age of 2) has been well documented.[3] There is less evidence and consensus of the long run effects of extreme weather events on economic growth[4] or household welfare[5]. To speak to this issue, the Vietnam case study explores the welfare effects of past weather events, in addition to the current ones. It further examines the welfare effects of regular exposure to extreme events, in effect capturing the cumulative effects of those events as well as those of any adaptation strategies (e.g. more drought resistant varieties, flood proof crops) adopted over time to mitigate their effects.

13. Extreme weather events affect incomes directly as well as indirectly, through their effects on the rest of the economy. Droughts for example, affect farmers' incomes directly through harvest loss. Yet, they may also affect other consumers indirectly, through the food and factor markets. Food prices may increase affecting net rural buyers and urban consumers and the demand for agricultural wage labor may decrease (Jayachandran, 2006). Similarly, while hurricanes destroy assets, they may subsequently also generate employment opportunities in the construction industry, following reconstruction. While the indirect effects may often be more important than the direct effects (Okuyama, 2009), they are typically

[2] Skoufias et al. (2011a), Skoufias et al. (2011b), and Thomas et al. (2010)

[3] One such study is by Maccini and Yang (2009) who find significant (negative) effects of rainfall during early life between 1953 and 1974 on future schooling, health and socio-economic indicators of women in rural Indonesia.

[4] Cavallo and Noy (2010) and Loyaza, Olaberria, Rigolini and Christiaensen (2009) review the literature regarding the effects of natural disasters on economic growth and conclude that it is largely inconclusive, with some studies suggesting a negative effect on growth, others no effect and a few, even a positive effect.

[5] Dercon (2004) forms a welcome exception, reporting that household hit hard by the 1984-5 famine in Ethiopia experienced 16 percentage points less growth in their consumption between 1989 and 1997 compared with those household who weren't hit by the drought.

ignored in the econometric analysis. The importance of controlling for the indirect effects in exploring the direct ones is illustrated in the Vietnam case study.

14. Innovative tools to explore the welfare impacts of weather events and the effectiveness of some of the prevention, mitigation and coping strategies. To examine the welfare effects of extreme events each case country study spatially interpolates the extreme events derived from meteorological data. In doing so, the Vietnam study goes one step further, constructing explicit hazard and event maps. These disaggregated, geo-referenced hazard maps are subsequently coupled with detailed geo-referenced household survey data of income, consumption, and human development measures to statistically estimate the impact of weather shocks on these measures. In Indonesia, the focus is on the timing of the rainfall, and in Mexico both extreme temperatures and rainfall patterns are considered. In each study, the effects on rural households and incomes are analyzed, mainly via the agricultural channel. The Vietnam study is more comprehensive in scope, considering droughts, localized and riverine floods as well as storms and considers both rural and urban areas. Each study further explores differences in impacts across geographical areas and socio-economic groups. In addition, the effectiveness of irrigation and a series of safety net and community relief programs is also explored. Finally, the Vietnam case study also distinguishes between the short and long run effects, controls for indirect effects, and documents some of the channels through which households try to mitigate the effects of extreme weather events (including asset decumulation, reception of domestic and international remittances, and disaster relief).

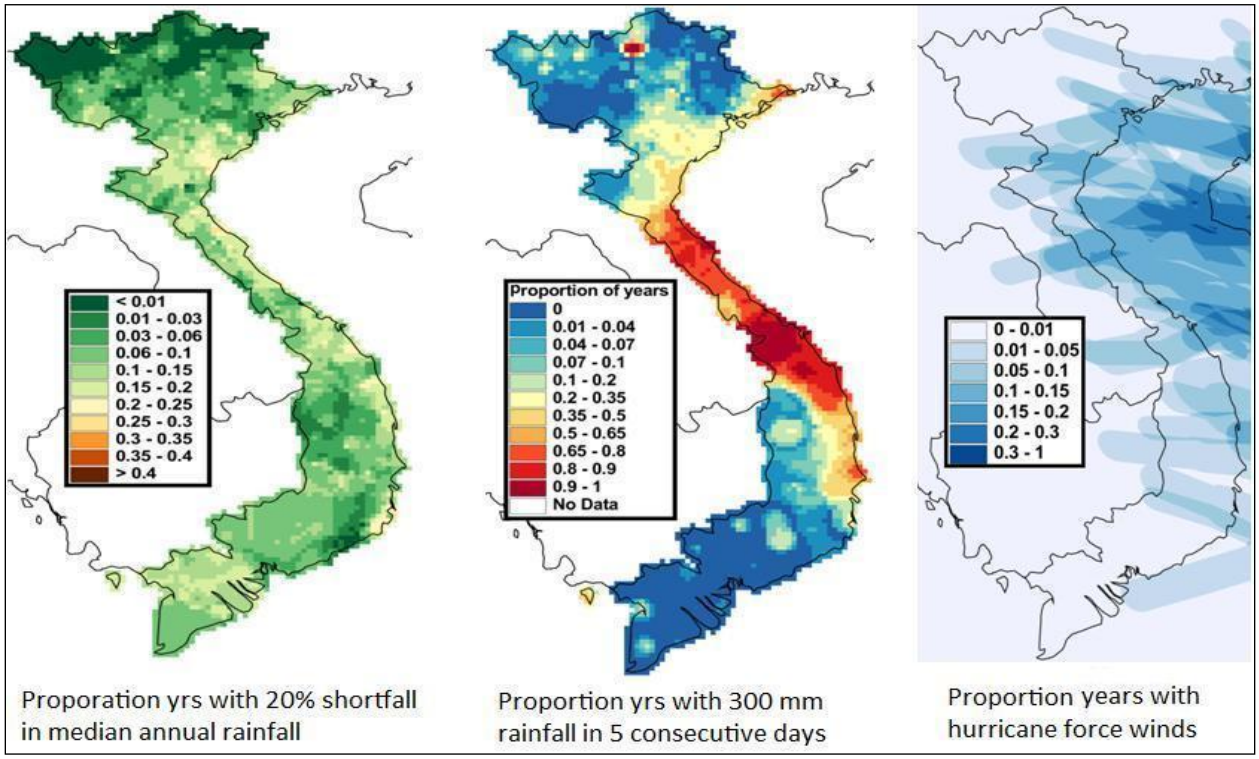
1.4 Emerging insights

15. The natural hazards maps illustrate the enormous geographic variation in exposure to extreme weather events. A recurring finding across the case studies is the spatial variation in exposure to different events. This is best illustrated by the hazard maps constructed for Vietnam (such as Figure 1.2). The maps also provide an important tool for planning and gauging the exposure of interventions to extreme events. In one application, they were overlaid with World Bank sponsored projects, indicating the extent to which the World Bank portfolio was exposed.[6]

16. The human welfare effects from extreme events can be substantial, but differ by event, across space and socio-economic groups, underscoring the need for disaggregated analysis. Focusing on irregular rainfall patterns, the evidence from rural Java, Indonesia suggests for example a decline in per capita consumption by 17 percent among rice farmers, when the rains are two standard deviations below their mean during the 90 day post-monsoon onset period. While negative, the effect on other households was however not statistically significant. Similar declines in welfare following droughts (14-17 percentage points) are reported for Vietnam, at least when the fields are not irrigated. Yet, in Mexico, there was no evidence of consistently negative effects of droughts, heat waves or cold weather, even though significant differences were noted across regions (North versus Center and South) and socio-economic groups (with female headed households for example better able to benefit from positive weather shocks). Hurricanes (explored only in Vietnam) caused most damage, with households in metropolitan centers seeing their welfare go down by 50% when hit by a hurricane. Riverine floods in Vietnam also caused substantial welfare loss in the short run (up to 23 percent). The losses are again smaller the further away from the metropolitan centers households are, possibly because economies are less integrated in more remote settings. Finally, the Mexico case study also explored the effects of extreme precipitation and temperature on child health. Contrary to expectations, it was during wet and hot years that boys (but not girls) saw their nutritional status go down, and then especially in the center and south of Mexico, underscoring the differentiated nature of the impact of extreme events.

[6] http://115.146.126.6:8008/

Figure 1.2: Geographical distribution of the likelihood of extreme weather in Vietnam



Source: Thomas et al. (2010)

17. Irrigation helps substantially in alleviating the effects of droughts. The results from both Indonesia and Vietnam show that irrigation is effective in shielding households from the effects of droughts. They were basically unaffected. This underscores that irrigation may not only increase annual yields (for example by enabling multiple harvests per year), but that an important contribution also comes from helping households smooth their income and consumption over time, an important additional benefit.

18. Households in disaster prone areas tend to be substantially poorer, even though they also tend to be less affected by current events, especially floods. A core finding from the Vietnam study is that regular exposure to disasters poses an important drag on households' welfare. Cumulative asset loss and adaptation likely erode the asset base and induce the adoption of lower risk, lower return portfolios over time. However, in areas where rivers frequently exceed their banks, households appear richer. This is specifically for households in the Mekong River Delta that have learned to live with floods and have built their livelihood systems around them. Yet, regular exposure to shocks also prepares households better for the next event, reducing the immediate effects of extreme events, especially when it comes to floods. This does not apply to hurricanes, with regular exposure in effect exacerbating the already disastrous consequences from current events. Frequent exposure to hurricanes erodes the capacity of households to cope with such events and government relief programs have so far not been very effective in providing relief.

19. Community based programs to mitigate risks ex ante prove effective in Indonesia. It is the availability of credit (provided through the INPRES Poor Villages Program) that proved most effective in reducing the effects of rainfall shocks in Indonesia, followed by the community based infrastructure development programs.

20. Safety nets and coping strategies may help, but are not always sufficient. The community based programs in Indonesia developed in response to the 1997-98 crisis (such as its labor intensive public work programs and its village infrastructure block grant programs) provided a useful cushion to rainfall failure.

The Vietnam study also provides indirect evidence that disaster relief systems are instrumental in mitigating the effects of extreme weather events. The Mexico study on the other hand, concludes that the current risk-coping mechanisms (public and private) are not effective in insulating rural household welfare and child health from erratic weather patterns (as measured by annual precipitation and growing degree days). While providing useful pointers, given data limitations, the case country studies were not able to provide a rigorous assessment of the safety net programs. This is an area in dire need of more in depth analysis, including regarding the effects of the design of such programs on their effectiveness.

1.5 Moving ahead

21. Deepening and fine-tuning our understanding of how natural disasters affect human welfare is a pressing concern, as climate change is set to increase the frequency and severity of weather shocks. This requires more in depth knowledge about the exposure of different areas to these disasters, the expected costs associated with their occurrence, and the effectiveness of different risk prevention, mitigation and coping measures. The following lessons emerge from the three case studies.

a) Geographically disaggregated natural disaster maps from meteorological data provide a useful tool for policy making, project planning and disaster impact analysis. The methodology illustrated here for the Vietnam case study provides a relatively inexpensive and promising method to do so. Fine-tuning and validating this methodology in other settings is thus worthwhile. This is quintessentially a multi-disciplinary (scientists and economists) and cross-sectoral effort, a continuing challenge in our mono-discipline focused world. Nonetheless, the current efforts provide a good starting point to build on.

b) The estimated long run effects are huge, especially for droughts and hurricanes, while the short run effects are highly varied, highlighting the need for a better and more granulated understanding of the relative effectiveness of the different prevention, mitigation and coping options. Despite the numerous studies undertaken over the past two decades, including the ones presented here, the empirical (and theoretical[7]) knowledge base for choosing between different strategies (e.g. avoiding floods or learning to live with floods) remains thin, especially when it comes to guiding country specific interventions. The myriad of safety net and community based initiatives that are being introduced across the APEC economies provide a unique learning opportunity to expand and tailor the knowledge base. It would require a much more systematic incorporation of evaluation considerations (baseline data collection, control groups) at the outset of the projects. This would in turn enable a much more refined response to important questions regarding design issues of safety nets as well as cost benefit analysis. The model followed during the launch of the PROGRESA program in Mexico provides a good example to build on.

c) Country specific insights include:

   a. Indonesia. The community based approach, especially credit and public work projects were found to be a promising way forward to moderate the effects of shortfalls in rain in rural Indonesia.

   b. Mexico. The heterogeneous impact of rain and temperature variability suggests that a "tailored" approach to designing programs aimed at increasing the capacity of rural households to adapt to and mitigate the effects of climate change is likely most effective.

[7] Devarajan and Jack (2007) is an important and insightful exception.

c. Vietnam. While irrigation helps mitigate the effects of droughts, and disaster relief takes some of the sharp edges away from heavy rains and riverine floods, households largely undergo the effects of hurricanes, with little relief from effective adaptation or ex post coping strategies, especially for those in areas close to the metropoles. How to better protect households against the damaging forces of hurricanes is an important area in need of more attention in Vietnam.

The remainder of the report discusses each of the three country case studies in more detail.

2. INDONESIA

2.1 Introduction

1. The adverse impacts of climate change[8] and extremes represent a serious challenge to development efforts around the globe and are likely to exacerbate the incidence, severity and persistence of poverty in many countries. The global mean surface temperature of the earth has been rising as a result of increased emission of greenhouse gases, particularly carbon dioxide (DFID 2004). Climate change and extremes are expected to affect mostly climate-sensitive sectors of the economy and in turn influence the pattern of household income and consumption. It is estimated that three-quarters of the world's poorest whose standard of living falls below $2 per day rely mostly on natural resources for their livelihoods (WRI, 2008). The degradation of natural resources induced by climate change thus places significant stress on these livelihoods. As for agriculture, an important sector of activity for the poor, yields from rain-fed agriculture could be cut by half by 2020 in some parts of the world. It is feared that climate change could reduce soil fertility by 2 to 8 percent, inducing a significant reduction in yields for a variety of crops.

2. However, very little is known about the welfare losses that households experience from these phenomena. Households at low levels of income are believed to be the most vulnerable to the impacts of climate change and extremes. This is due to their geographical locations, limited assets, limited access to resources and services, low human capital and high dependence upon natural resources for income and consumption. While there is wide recognition of this impending threat of climate change upon the poor, limited attention is given upon quantifying the poverty and distributional effects of climate change and identifying adaptation strategies and targeted measures that could mitigate the poverty impacts.

3. This chapter analyzes the potential welfare impacts of rainfall shocks in rural Indonesia, and draws relevant policy lessons. With an estimated population of 237.5 million, Indonesia is the largest archipelago and the fourth most populous nation in the world. Located in Southeastern Asia between the Indian and the Pacific Oceans, the country has a tropical climate with two distinct seasons, monsoon wet and dry, and is endowed with high levels of biodiversity. The country has been experiencing change in both mean temperature and precipitation. Since 1900, it is estimated that the annual mean temperature has increased about 0.3^{o} C. 1998 was the warmest year in the century as the temperature rose 1° C above the 1961-1990 average (PEACE 2007). The increase in average temperature is projected to lie between 0.36 and 0.47^{o} C by the year 2020. It is reported that overall annual precipitation has decreased by 2 to 3 percent, but there are significant regional differences (WWF, 2007). Southern regions such as Java, Lampung, South Sumatra, South Sulawesi, and Nusa Tenggara have seen a decline in annual rainfall. Northern regions on the other hand have experienced an increase in precipitation. These include most of Kalimantan and North Sulawesi. These changes in precipitation are strongly influenced by El Niño Southern Oscillation (ENSO). Indonesia tends to experience droughts during the warm phase of ENSO (i.e. El Niño) and excessive rain in the cool phase (i.e. La Niña). With the possible exception of southern Indonesia annual rainfall is expected to increase across the rest of the country (Naylor et al., 2002).

[8] According to the Intergovernmental Panel on Climate Change (IPCC) a narrow definition of climate refers to the statistical description in terms of the mean and variability of quantities such as temperature, precipitation and wind over a period of time ranging from months to thousands of years. The norm is 30 years as defined by the World Meteorological Organization (WMO). In a wider sense, climate refers to the *state* and the *statistical description* of a system composed of the following five components: atmosphere (gaseous envelope around the Earth), hydrosphere, cryosphere (snow and ice), land surface, and biosphere (all ecosystems and living organisms). For more details, please see Parry et al. (2007). Climate is different from weather which refers to atmospheric conditions in a given place at a specific time. The term "climate change" is used to indicate a significant variation (in a statistical sense) in either the mean state of the climate or in its variability for an extended period of time, usually decades or longer (Wilkinson 2006).

4. These observed and expected changes in climate are bound to have adverse impacts on the ecosystems, the associated resources and the lives of people who rely on these resources and on agricultural activities. The 1997-1998 droughts associated with El Niño led to massive crop failures, water shortages and forest fires in parts of Indonesia, and likely exacerbated the impacts of the financial crisis at that time. El Niño events tend to delay rainfall, leading to a decrease in rice planting in the main rice-growing regions in Indonesia such as Java and Bali. Adapting projections by the IPCC to local conditions, Naylor et al. (2007) predict that by 2050 change in the mean climate will increase the probability of a 30-day delay in monsoon from 9-18 percent currently to 30-40 percent. This delay combined with increased temperature could reduce the yield of rice and soybean by as much as 10 percent. The analysis presented here considers the welfare implications of both a late monsoon onset and low level of rainfall. As noted later, a certain amount of rainfall is needed in the 90 day post-onset for rice to grow properly.

5. The chapter is organized as follows. Section 2.2 presents the methodology focusing on the estimation of the impacts of rainfall variability on household expenditure per capita, our measure of welfare. The guiding view here is that the distribution of welfare losses associated with such events depends on the degree of household and community level vulnerability and the moderating impact of existing assets and social protection institutions. Understanding these factors plays an important role in designing policies to minimize exposure to and the impact of these shocks. Section 2.3 describes the available data while analytical results are presented in section 2.4. Concluding remarks are made in section 2.5.

2.2 Methodology

6. This section describes the methodology and analytical frameworks used in estimating the impacts of rainfall variability on household welfare in rural Indonesia and the potential moderating effects of community-based programs and infrastructure. We need to make our analytical framework consistent with the logic of vulnerability, the bedrock concept for the study of the welfare impacts of climate change and extremes. The distribution of economic welfare in any given society hinges crucially on individual endowments and behavior and the socio-political arrangements that govern social interaction. These factors (endowments, behavior and social interaction) also determine the distribution of vulnerability[9]. Adger (1999) emphasizes the connection between individual and collective vulnerability because it is impossible to consider individual achievement in isolation from the natural and social environment. Vulnerability of an individual or a household to livelihood stress depends crucially on both exposure and the ability to cope with and recover from the shock. Exposure is a function of, inter alia, climatic and topographical factors. The ability to cope is largely determined by access to resources, the diversity of income sources and social status within the community[10]. Increased exposure combined with a reduced capacity to cope with, recover from or adapt to any exogenous stress on livelihood leads to increased vulnerability.

7. Given data limitations, we focus on exploiting cross-sectional variation in the data and linking some welfare indicator (e.g. consumption per capita) or some component thereof (food versus non-food expenditure) to a climate-related shock defined on the basis of available rainfall data focusing mainly on rural households. As noted earlier, the yield of crops such as rice (staple food in Indonesia) and soybean is very much affected by changes in precipitation patterns which are strongly influenced by ENSO.

8. Given the importance of rice farming in the rural economy of Indonesia, we define climate shocks with reference to this activity. Naylor et al. (2007) explain that El Niño events can cause a delay in monsoon

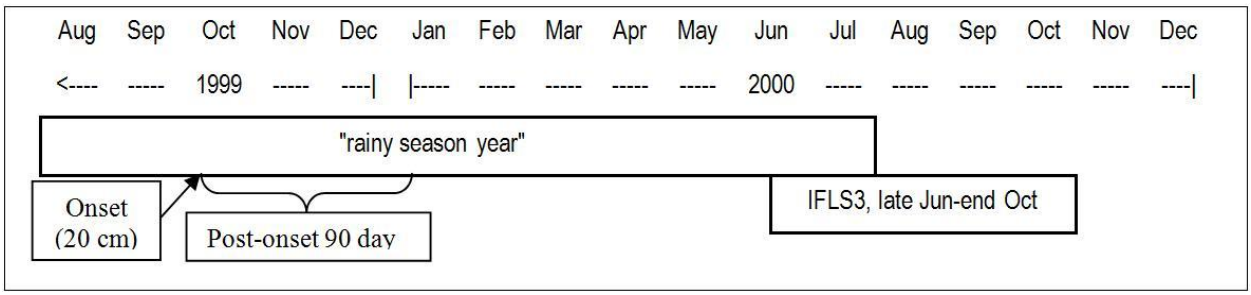
[9] Vulnerability is usually taken as the likelihood that, at a given point in time, individual welfare will fall short of some socially acceptable benchmark (Hoddinott and Quisumbing 2008).

[10] Hoddinott and Quisumbing (2008) make essentially the same point by noting that, at the household level, vulnerability is determined by the nature of the shock, the availability of additional sources of income, the functioning of labor, credit and insurance markets, and the extent of public assistance.

onset of up to 60 days. The same authors define "onset" as the number of days after August 1 when cumulative rainfall reaches 20 cm [11], and "delay" as the number of days above the mean onset date over the 1979-2004 period. Since farmers will typically begin planting after monsoon onset, late onset may affect prospects for a second harvest later in the season and possibly change crop combinations (with potentially significant consequences on production and market prices).

9. While delayed onset is an important determinant of harvest, we also need to consider the amount of rainfall after the onset. After farmers plant the rice fields, 60-120 cm of rainfall are needed during the 3-4 month grow-out period (Naylor et al., 2002). Thus, the second dimension of the shock involves the deviation of the amount of post-onset rainfall from the 25 year mean for each weather station. The amount of post-onset rainfall is defined as the total amount of rainfall during the 90 day period following the monsoon onset date.

Figure 2.1 Timing of typical climate events and the IFLS3



10. The timing of these events in relation to the IFLS3 survey is illustrated in Figure 2.1. Considering that the degree of rainfall variability can differ across areas and that households may adjust farming practices accordingly, we use standard deviations from the inter-temporal mean to help account for such spatial differences. In terms of delay of monsoon onset, a negative shock is defined as being more than one standard deviation above the 25 year mean. In terms of the amount of post-onset rainfall, a negative shock is defined as being more than two standard deviations below the 25 year mean.

11. Given the interconnection between individual and collective vulnerability and adaptive capacity, the empirical analysis uses regressions to link an indicator of household welfare (real per capita total expenditure or its food and nonfood components) to some climate shock while controlling for household characteristics, and for the province of residence. A regression equation of the form described in equation 2.1 below is estimated, where Y_{ij} represents per capita household expenditure of household i in community j, and X_i represents various control variables. S_j represents the covariate rainfall shocks, and F_i is a binary variable representing rice farming households.

$$y_{ij} = \beta_0 + \beta_1 X_i + \beta_2 X_j + \beta_3 (S_j * F_i) \qquad (2.1)$$

12. After analyzing the effects of rainfall shocks on welfare, we consider the potential moderating effect of various community level programs. As Pitt et al. (1993) have argued, the placement of government programs is not likely to be random. One consequence of the endogeneity in program placement is that it is likely to result in biased estimates of program effects, especially when using cross-sectional data. Recognizing that government assistance programs are often targeted to poor areas, we use propensity score matching to investigate the difference that some community programs make with respect to mitigating the impact of the shock on household welfare. In particular, the sample is restricted to

[11] This is the amount of rainfall needed to moisten ground sufficiently for planting. It is believed that about 100 cm of rain are needed throughout the season for cultivation.

households exposed to the post-onset low rainfall shock. In line with treatment response literature, the treatment group consists of affected households residing in communities with a specific program or infrastructure (e.g. technical irrigation, safety net programs, access to credit, etc.) while the comparison group is made of affected households living in communities without such a program. Assuming that, conditional on observable community characteristics, program placement is as good as random we can consider two households with the same propensity score as observationally equivalent. Let one of these reside in a community with the program.

13. The outcome of the other affected household residing in a community without the program represents a counterfactual outcome for the one in a community with the program. Here the propensity score is the probability of observing an affected household in a community with the program of interest as a function of some covariates. We estimate propensity scores on covariates using probit and retrieve their predicted values for matching "treated" observations with those in the comparison group. Specifically, for each program, a separate stepwise estimation of the probit specification was performed such that variables with a p-value less than 0.5 were added to the right hand side. The list of possible right hand side variables for the stepwise estimation included household and community variables. The household variables included: household size, age of head, marital status of head, gender of head, education level of head, household use of electricity, ownership of farmland, household nonfarm business, and household farm business. The community variables included: availability of public transport, availability of piped water, predominance of asphalt roads, share of households with electricity, distance to provincial capital, distance to district capital, and the shares of household heads with elementary, junior high, high school, and university level education.

14. Each treatment household is matched to its "nearest neighbor" based on propensity scores, restricting matches to the same year of the survey. We then compare average outcomes for affected households in the treatment group (i.e. in communities with a specific program or infrastructure) to the average outcome for similarly affected households in the comparison group (i.e. living in communities without the program under consideration).

15. To describe this somewhat more formally, let Y_i (1) denote the per capita expenditure outcome of household i in the presence of some "treatment" attribute in the local community, such as a safety net program or type of infrastructure, and Y_i (0) denote the per capita expenditure outcome of household i in the absence of the attribute in the local community. As both Yi (1) and Yi (0) are not observable, we use bias-corrected matching estimators, $\hat{Y}_i(0)$, in place of Yi (0) (see Abadie and Imbens, 2002, and Abadie et al., 2004) and estimate the sample average treatment effect for the subpopulation of the treated (SATT), as in equation 2.2, where Wi=1 indicates that a household is in a community with the treatment attribute, and n1 is the sample size of the treated.

$$SATT = \frac{1}{n_1} \sum_{i|W_i=1} \left\{ Y_i(1) - \hat{Y}_i(0) \right\} \tag{2.2}$$

2.3 Data

16. We are able to study the impacts of extreme weather events on rural households by merging household and community level data from the Indonesian Family Life Survey (IFLS) with daily rainfall data covering a 25 year period. The combined data set contains information on rainfall, household expenditures, household level socio-economic characteristics, and community level attributes.

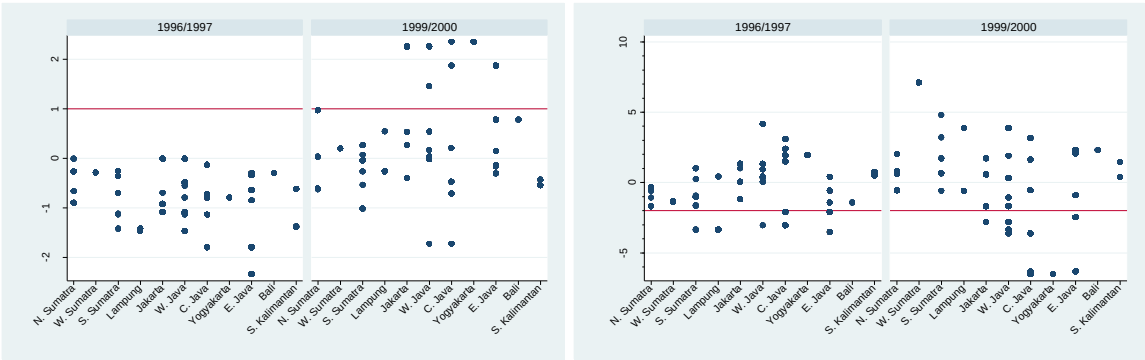
17. Household and community surveys were fielded from late June to the end of October 2000 for IFLS3 and from August 1997 to January 1998 for IFLS2. The surveys include village-level data which allows

the determination of the extent to which access to better infrastructure or social programs increases resiliency. The consumption aggregate consists of food and nonfood components. The food component consists of 37 food items (purchases and the value of own production or gifts) consumed within the last week. The nonfood component consists of frequently purchased goods and services (utilities, personal toiletries, household items, domestic services, recreation and entertainment, transport, sweepstakes), less frequent purchases and durables (clothing, furniture, medical, ceremonies, tax), housing, and educational expenditures for children living in the household. Transfers out of the household were excluded. All values are monthly figures and are in real terms. To obtain real values, both temporal and spatial deflators were used, using prices in December 2000 in Jakarta as the base.[12]

18. Using daily rainfall data from 1979 to 2004, we calculated the 25 year mean and standard deviations for monsoon onset and the amount of post-onset rainfall for 32 weather stations. The rainfall data from these weather stations were then matched to communities in IFLS. Weather data were merged with household survey data at the community level based on proximity. Only weather stations with complete data for the 25 year period were used. The matched data contained a total of 267 communities and 32 WMO stations. In rural areas, 106 communities in 9 provinces were matched to 27 stations. In rural Java, 66 communities in 4 provinces were matched to 18 stations. The number of communities per WMO station ranged from 1 to 10 in rural areas. 3,290 households were matched to 27 stations in rural areas, and 2,159 households were matched to 18 stations in rural Java.

19. After merging available precipitation data and dropping observations with missing data, the sample size in the 2000 IFLS3 for our analysis was reduced to 6,188 households from a total of 10, 292. 3,290 households in our 2000 sample were located in rural areas, and of these 2,159 were located on Java. Data from additional weather stations would benefit this analysis by improving the level of disaggregation of weather data, but this data could not be obtained.

Figure 2.2 Variation in monsoon onset and post-onset rainfall



20. Figure 2.2 shows variation by province in monsoon onset and post-onset rainfall. With respect to delays in monsoon onset, only provinces in Java experienced a delay greater than one standard deviation from the 25 year mean in 1999/2000. As for the amount of rainfall during the 90 day post-onset period, the data indicate that only provinces in Java experienced rainfall below two standard deviations from the 25 year mean in 1999/2000.

[12] The spatial deflator used is the ratio of the location (province, urban/rural area) poverty line (in December 2000 prices) to the Jakarta poverty line. Thus the spatial deflator used converts the local December 2000 values into Jakarta December 2000 values.

21. The summary statistics of household expenditures, household characteristics, and rainfall shock exposure in rural Java are shown in Table 2.1. The majority of household heads were married males who did not have more than an elementary education. The vast majority of households utilized electricity. Half of the households owned farmland, and 44 percent were engaged in non-farm businesses. Nearly 60 percent of households were engaged in a farm business, 38 percent with rice as the most valuable crop and 22 percent with another crop as the most valuable. 34 percent of households in our sample were exposed to the delay of onset shock and 45 percent were exposed to the post-onset low rainfall shock. The correlation coefficient between these two shock variables for our sample was not large at 0.38.

2.4 Empirical Results

22. We present our findings on (i) the impact of rainfall shocks on per capita household consumption levels and (ii) the role that various social programs may have played in mitigating the negative welfare impacts of the rainfall shocks. For the first part, we used regression analysis to quantify the average reduction in household welfare levels for those exposed to low rainfall shocks. For the second part, we used propensity score matching to estimate the extent of moderating effects offered by the various community-based programs.

Welfare Impacts of Rainfall Shocks

23. Given the importance of rain-fed agriculture, in particular rice farming, to rural livelihoods in Indonesia, we study the potential impact of rainfall shocks on per capita total household expenditure, and its food and nonfood components. We focus on rural Java, the predominant rice production area in Indonesia, and use regression analysis to estimate the impacts on household expenditures.

24. We include in our regressions two binary variables representing the two rainfall shocks defined earlier, delayed monsoon onset and post-onset low rainfall. We interact these shock variables with a binary variable for rice farming households, specifically households engaged in a farm business with rice as the most valuable crop. This is done to differentiate the effect of the shocks between households that have and do not have a farm business with rice as the most valuable crop. In the regressions, we control for various household characteristics: household size, age of household head, sex and marital status of head, level of education of the head (binary variables for elementary, junior high, high school, and university), access to electricity, ownership of farm land, and household farm and nonfarm business activity, whether or not rice is the most valuable crop, and province of residence. The reference case is a household in rural West Java province, with an uneducated, single, male head, that has no access to electricity, no farm land, and no household farm or nonfarm businesses.

25. Using the two rainfall shock variables separately as well as together, we used three different specifications for our regressions. The first includes a binary variable for delayed monsoon onset along with its interaction term with the binary variable for rice farming household. The second substitutes the post-onset low rainfall variable as the shock variable. The third includes both rainfall shocks along their interaction terms. This third variation was used with different dependent variables, that is, per capital total household expenditure and its food and nonfood components.

Table 2.1 Summary Statistics for Households in Rural Java (1999/2000 IFLS)

Variables	Mean	Std. Err.
total pce (Rupiah per capita per month)	257273	7660
food pce (Rupiah per capita per month)	154389	4332
nonfood pce (Rupiah per capita per month)	102885	4745
household size	3.06	0.09
age of head	48.41	0.45
married head	0.84	0.01
female head	0.18	0.01
highest education of head: elementary	0.58	0.02
highest education of head: jr. high school	0.07	0.01
highest education of head: high school	0.05	0.01
highest education of head: university	0.08	0.01
hh utilizes electricity	0.90	0.03
hh owns farmland	0.50	0.03
hh non-farm business	0.44	0.03
hh farm business - rice most valuable crop	0.38	0.03
hh farm business - other crop most valuable	0.22	0.03
shock: delay of monsoon onset (>1 sd)	0.34	0.06
shock: delay of monsoon onset (>2 sd)	0.16	0.04
shock: post-onset low rainfall (<-1 sd)	0.57	0.06
shock: post-onset low rainfall (<-2 sd)	0.45	0.06
N=2159		

26. As might have been expected, there is a strong positive correlation between household per capita expenditure and assets; education and ownership of farmland. All education coefficients are positive and significantly different from zero. For all five of the regressions reported in Table 2.2, the magnitude of these coefficients increase with the level of education up to high school, but the coefficients for university education are less than those associated with high school, which is a rather unusual. In general, the province of residence does not seem to matter in the explanation of variations in household welfare as the associated coefficients are not significantly different from zero. Having electricity is certainly an indication of wealth. This is manifested by a positive and significant effect on per capita expenditure. Similarly, owning farmland or a non-farm business has a positive and significant impact on household expenditure and its components (food and nonfood).

27. In the absence of a weather shock, our results show that there is no statistically significant difference between the average welfare of households for which rice is the most valuable crop and that of the reference household (Table 2.2). On the other hand, we find that households running a farm business with non-rice crops as the most valuable had per capita nonfood expenditures about 12 percent lower than the reference household.

28. The definition of the rainfall shock variable is important in our specifications. While a shock defined by the delay in the monsoon onset has a negative effect on the per capita total expenditures of rural households of Java, it is not statistically significant. This is contrary to that reported in Korkeala et al. (2009) based on panel data. However, when we look at the food component of expenditures, a delay of

monsoon onset shock is associated with a 13 percent drop in per capita food expenditures relative to the reference household.

Table 2.2 Regression Results of Shocks on Household Consumption in Rural Java, 1999/2000

Dependent Variable (log):	total pce			nonfood pce	food pce
	delay of onset shock (1)	post-onset low rainfall shock (2)	both shocks (3)	both shocks (4)	both shocks (5)
household size	-0.145 ***	-0.145 ***	-0.145 ***	-0.136 ***	-0.148 ***
	(0.008)	(0.009)	(0.008)	(0.011)	(0.008)
age of head	0.015 **	0.015 **	0.015 **	0.017 **	0.016 ***
	(0.006)	(0.006)	(0.006)	(0.008)	(0.006)
age of head^2 (1/100)	-0.015 ***	-0.015 ***	-0.015 ***	-0.019 **	-0.015 ***
	(0.005)	(0.005)	(0.005)	(0.007)	(0.005)
married head	0.036	0.042	0.041	0.016	0.102
	(0.077)	(0.076)	(0.077)	(0.086)	(0.078)
female head	-0.019	-0.015	-0.016	0.007	0.012
	(0.077)	(0.076)	(0.076)	(0.079)	(0.079)
highest education of head: elementary	0.091 **	0.086 **	0.087 **	0.172 ***	0.039
	(0.044)	(0.042)	(0.042)	(0.051)	(0.045)
highest education of head: jr. high school	0.214 ***	0.206 ***	0.207 ***	0.358 ***	0.123
	(0.071)	(0.070)	(0.070)	(0.085)	(0.075)
highest education of head: high school	0.506 ***	0.502 ***	0.503 ***	0.786 ***	0.300 ***
	(0.084)	(0.083)	(0.083)	(0.093)	(0.087)
highest education of head: university	0.212 **	0.205 **	0.205 **	0.350 ***	0.098
	(0.099)	(0.095)	(0.095)	(0.117)	(0.088)
Central Java province (33)	-0.072	-0.055	-0.057	-0.007	-0.075
	(0.076)	(0.073)	(0.073)	(0.097)	(0.068)
Yogyakarta province (34)	-0.038	0.004	0.005	0.044	-0.023
	(0.114)	(0.106)	(0.112)	(0.134)	(0.115)
East Java province (35)	-0.071	-0.063	-0.061	-0.016	-0.106 **
	(0.058)	(0.057)	(0.056)	(0.088)	(0.047)
hh utilizes electricity	0.158 **	0.188 ***	0.188 ***	0.441 ***	0.060
	(0.066)	(0.062)	(0.062)	(0.106)	(0.063)
hh owns farmland	0.114 ***	0.117 ***	0.116 ***	0.131 ***	0.080 **
	(0.032)	(0.032)	(0.032)	(0.046)	(0.033)
hh non-farm business	0.172 ***	0.170 ***	0.170 ***	0.228 ***	0.131 ***
	(0.035)	(0.034)	(0.034)	(0.044)	(0.034)
hh farm business - rice most valuable crop	0.002	0.056	0.041	0.072	0.034
	(0.042)	(0.047)	(0.046)	(0.065)	(0.042)
hh farm business - other crop most valuable	-0.046	-0.047	-0.046	-0.117 **	0.003
	(0.044)	(0.046)	(0.045)	(0.054)	(0.048)
shock: delay of monsoon onset (>1sd)	-0.042		-0.035	0.103	-0.132 **
	(0.064)		(0.065)	(0.084)	(0.061)
shock: post-onset low rainfall (<-2sd)		-0.036	-0.027	-0.034	-0.019
		(0.054)	(0.055)	(0.076)	(0.049)
hh farm rice X delay shock	0.024		0.072	0.037	0.118 *
	(0.062)		(0.072)	(0.114)	(0.063)
hh farm rice X low rainfall shock		-0.120 **	-0.142 **	-0.256 **	-0.083
		(0.059)	(0.067)	(0.104)	(0.057)
constant	11.972 ***	11.946 ***	11.952 ***	10.431 ***	11.574 ***
	(0.199)	(0.193)	(0.191)	(0.277)	(0.170)
N	2159	2159	2159	2159	2159
r2	0.196	0.2	0.201	0.189	0.175
legend: p<0.10 *, p<0.05 **, p<0.01 * ; standard errors in parentheses above**					

Source: Skoufias et al. (2011a)

29. If the amount of rainfall during the 90 day post-onset period is below 2 standard deviations away from the 25 year mean, the coefficients associated with the interaction between the post-onset low rainfall shock and rice farming are negative and significantly different from zero (at a 5 percent level of significance) for total and nonfood expenditures. With exposure to the low rainfall shock, the per capita

total expenditure of households engaged in rice farming is 12 to 14 percent lower than that of the reference household and the per capita nonfood expenditure is 26 percent lower, controlling for household attributes and province of residence. In contrast, we find that the interaction of the low rainfall shock with the binary variable identifying households engaged in rice farming does not have a statistically significant effect on food consumption. This result, which is frequently observed among rural households in different countries (Skoufias and Quisumbing, 2005), suggests that rice farm households are able to protect their food consumption in the face of weather shocks. Thus, households manage to protect their food consumption at the expense of nonfood consumption. To the extent that reduced expenditures on nonfood are accompanied by lower expenditures on children's education, weather-related shocks may also be associated with reduced investment in the human capital of children (Jacoby and Skoufias, 1997).

Role of Community Programs

30. As noted earlier, vulnerability of an individual or a household to livelihood stress depends on both exposure and the ability to cope with and recover from the shock. The ability to cope is largely determined by access to resources including community-level infrastructure and assistance programs. We explored the role of the following seven community level resources or programs in mitigating negative welfare impacts of shocks in rural areas of Java: (1) presence of technical irrigation in the community[13], (2) Kampung Improvement Program (an informal housing area upgrading program that provided basic services and infrastructure through community based organizations), (3) Infrastructure Development Program (a community-based infrastructure development program), and (4) availability of credit through the INPRES Poor Villages Program, (5) the village has a Padat Karya program, a loose collection of labor-intensive programs sponsored by various government departments (Sumarto et al. 2002), (6) the village had a PDM-DKE (Regional Empowerment to Overcome the Impact of Economic Crisis) program, a block grant program for villages to support public works or revolving funds for credit (Sumarto et al., 2002), and (7) the Inpres Desa Tertinggal (IDT) (Program for Underdeveloped Villages), another block grant program targeting extremely poor villages (Sumarto et al., 2002). Data on the first four community level programs above were available in both the 1997 and 2000 IFLS surveys, so we pooled the data to increase the number of observations. However, data on the last three community-based programs above were only available in the 2000 IFLS survey, so we could only use the single year of observations in evaluating those programs.

30. As discussed earlier, recognizing that government assistance programs are often targeted to poor areas, we use propensity score matching to infer the moderating impact of some community level interventions on the impact of the shock. For each of the community-based programs, we estimate the average treatment effect of the intervention on per capita household expenditures components (total, nonfood, and food) among households exposed to the shock and located in communities with the program of interest (i.e. SATT, or the sample average treatment effect for the treated). The results in Table 2.3 are shown as the percent difference in mean per capita expenditures between the treatment and comparison groups. The panel on the left side of Table 2.3 relates to the sample of households of rural Java that were exposed to the post-onset low rainfall shock regardless of occupational status, while the panel on the right focuses on the sub-sample of households exposed to the shock that were engaged in a farm business.[14]

[13]Data only indicated whether technical irrigation existed in the community, not household use of technical irrigation.

[14] We also attempted to extend this analysis to only farmers indicating rice as the most valuable crop, but the data thinned out and precluded application of this approach to this sub-sample

Table 2.3 Moderating Effects of Community-Based Programs for Households in Rural Java Exposed to Post-Onset Low Rainfall Shocks: Average Treatment Effects based on Propensity Score Matching

	Average Treatment Effect of Community-Based Programs (percent difference between treatment and comparison groups)					
Sub-sample:	All households exposed to low rainfall shock			Households engaged in farm business and exposed to low rainfall shock		
Components of per capita expenditure:	Total	Nonfood	Food	Total	Nonfood	Food
Technical Irrigation ‡	12.6 **	27.0 *** n=884	3.1	24.3 ***	46.7 *** n=575	8.9
Kampung Improvement Program ‡ (community-based)	8.0 *	20.7 *** n=1107	-0.9	6.9	17.4 ** n=838	-3.0
Infrastructure Development Program ‡ (community-based)	13.9 **	10.3 n=632	18.5 ***	-5.0	-9.9 n=509	-2.5
INPRES Poor Villages Program ‡ (credit)	25.0 ***	4.6 n=1390	38.2 ***	11.0	-12.8 n=959	28.8 ***
Padat Karya Program † (public works)	16.3 ***	23.5 *** n=1033	13.8 **	2.7	15.7 n=632	-4.0
PDM-DKE Program † (block grants)	18.9 ***	23.9 *** n=544	18.6 **	9.5	21.5 n=216	9.1
Either of the two programs above †	28.3 ***	31.4 *** n=722	30.0 ***	14.7 *	20.5 * n=514	14.5 *
IDT Program † (block grants)	17.7 ***	14.5 * n=978	18.2 ***	33.4 ***	39.2 *** n=352	35.9 ***

legend: p < 0.1 *, p < 0.05 ** , p < 0.01 ***
‡ Pooled data from 1997 IFLS2 and 2000 IFLS3 ; † Data from 2000 IFLS3 data only

Source: Skoufias et al. (2011a)

31. Focusing on the sample of households of rural Java, we find that households exposed to the rainfall shock but residing in communities with the infrastructure or programs mentioned above have on average a significantly higher level of per capita expenditure than households in the comparison group. Households in communities with the INPRES credit program had an average of 25% higher total per capita expenditure and 38% higher food per capita expenditure than comparison households, suggesting that the program furnished an important coping mechanism to households affected by the shocks. The Padat Karya (public works) and PDM-DKE (public works / credit) safety net programs also appear to have helped households cope with the impacts of the shocks. The difference in average total per capita expenditure between households with and without Padat Karya in their community was 16.3%, and for PDM-DKE, the difference was 18.9%. The differences in the food component of per capita expenditure were 13.8% and 18.6% for Padat Karya and PDM-DKE respectively, while the differences in the nonfood component were about 24% for both programs. If either of these safety net programs are available in the community, the average treatment effect is 28.3% for total per capital expenditure, 31.4% for the nonfood component, and 30% for the food component. The average treatment effects for the IDT program were 18% for both total and food per capita expenditure.

32. The presence of technical irrigation in the community appears to have helped mitigate the impact of the shocks, as the difference in average per capita expenditure between treatment and comparison groups were 12.6% and 27% for total and nonfood per capita expenditure respectively. The community-based programs to improve local infrastructure also appear to have helped households. The average treatment effect for the Infrastructure Development Program was 13.9% for total per capita expenditure (18.5% for food component) and for the Kampung Improvement Program, about 27% for nonfood per capita expenditure and no significant difference for total and food per capita expenditure.

33. As for the subsample of households engaged in farm businesses in rural Java, the right side of Table 2.3 reveals a few community characteristics with statistically significant results in moderating the impacts of the shocks. First, technical irrigation in the community amounted to an average 24.3% higher total per capita expenditure (and 46.7% higher nonfood per capita expenditure) among farm households than the comparison group. Second, the Kampung program facilitated higher nonfood per capita expenditure (17.4%) but no significant differences for total and food per capita expenditure. Third, farm households with the INPRES program in their community had 28.8% higher average food per capita expenditure relative to the comparison group, again suggesting its positive role in assisting households cope with shocks. Fourth, the existence of the IDT program in a community was found to have a significant positive effect in moderating the impact of the shock for farm households, that is, 33.4%, 39.2%, and 35.9% higher total, nonfood, and food per capita expenditure respectively, relative to the comparison group.

34. The results above suggest that access to credit and public works projects in communities can help households cope with shocks and thereby play a strong protective role during times of crisis. On the other hand, technical irrigation and infrastructure improvement programs in communities are likely to help mitigate the impacts of the shocks. In light of these findings, these policy instruments should be given due consideration in the design and implementation of adaptation strategies.

2.5 Concluding Remarks

35. Very little empirical evidence exists on the welfare losses that households experience as a consequence of weather shocks. In principle, households at low levels of income are most vulnerable to the impacts of weather extremes given their geographical locations, limited assets and access to resources and services, low human capital and high dependence upon natural resources for income and consumption. While there is wide recognition of the impending threat of climate change upon the poor, limited attention is given to quantifying such effects of climate change and identifying household adaptation strategies and targeted measures that could mitigate the poverty impacts. This chapter analyzes the potential welfare impacts of rainfall shocks in rural Indonesia with a focus on households engaged in family farm businesses, in particular rice farming. It also attempts to identify community characteristics capable of dampening the adverse impact of climate change and extremes. The focus on rice farming is due to the fact that rice is a staple food in Indonesia.

36. The basic approach adopted here is to exploit cross-sectional variation in the data and link a welfare indicator (i.e. real consumption per capita) or some component thereof (i.e. food versus non-food expenditure) to a weather shock defined on the basis of available rainfall data focusing mainly on rural households. In particular, we consider two types of shocks: delayed onset of monsoon and rain shortfall in the 90 day period following monsoon onset. We find that delay in the monsoon onset does not have a significant impact on the welfare of rural households. However, rice farm households located in areas experiencing low rainfall following the monsoon onset are negatively affected by the low rainfall shock. Nonfood expenditure per capita is the most affected component. This suggests that rice farm households protect their food expenditure in the face of weather shocks. Further study is needed to better understand these choices and their implications for adaptation strategies.

37. We use propensity score matching to identify potential policy instruments that might moderate the welfare impact of climate change and extremes. Our results indicate that credit availability, the existence of safety nets and community-based programs offer the strongest cushion for these types of shocks. This is an important consideration for the design and implementation of adaptation strategies. Indeed, individual ability to cope with and recover from crises hinges critically on available social support. Taken together with other emerging evidence on the long lasting effects of rainfall shocks on human capital, our findings highlight the urgent need for effective adaptation strategies.

3. MEXICO

3.1 Introduction

1. While there is a great deal of uncertainty over the exact magnitudes of the global changes in temperature and precipitation, it is widely accepted that significant deviations of the variability of climate from its historical patterns are likely to occur (IPCC, 2007). Considering that millions of poor households in rural areas all over the world are dependent on agriculture, there are increasing concerns that the change in the patterns of climatic variability is likely to add to the already high vulnerability of households in rural areas of developing countries, thus posing a serious challenge to development efforts all over the world. In view of this impending threat of climate change upon the poor, it is critical to have a deeper understanding of the household adaptation strategies and targeted measures that could mitigate the poverty impacts of erratic weather. With these considerations in mind, in this study, an analysis of the welfare impacts of climatic variability in the rural areas of Mexico is carried out.

2. This study has three objectives; first, to quantify the extent to which unusual or erratic weather has any negative impacts on the welfare of households. Based on historical experience and the multiplicity of economic and institutional constraints faced, rural households in Mexico, as most rural households all over the world, have managed to develop traditional strategies for managing climatic risk. Eakin (2000), for example, documents how smallholder farmers have adapted to climatic risk in the Tlaxcala region of Mexico. Yet, quantitative evidence on how successful such risk management strategies are at protecting household welfare in Tlaxcala or elsewhere in Mexico is quite scarce.[15] To the extent that the current risk-coping mechanisms are not very effective in protecting welfare from erratic weather patterns one can be quite certain that the change in the patterns of climatic variability associated with climate change is likely to reduce the effectiveness of the current coping mechanisms even more and thus increase household vulnerability further. Two separate nationally representative household surveys—the first two waves of the Mexican Family Life Survey (MxFLS), carried out in 2002 and in 2005, and the 1999 National Survey on Nutrition (ENN) — are used to examine whether climatic variability, namely the incidence of rainfall and temperature more than one standard deviation from their respective long run means, have significant impacts on the wellbeing of rural households and vulnerable individuals. Well-being or welfare is defined by two (of many) important dimensions—household consumption expenditures per capita, and individual health outcomes.

3. Second, the study sheds light on the channels through which climatic variability can impact the two different dimensions of welfare examined. On the one hand, erratic weather may affect agricultural productivity which, depending on how effective was the portfolio of *ex ante* and *ex post* risk management strategies employed, may translate into reduced income and reduced food availability at the household level.[16] Such reductions in food availability may not affect all household members equally. On the other hand, both temperature and precipitation may affect the prevalence of vector borne diseases, water borne and water washed diseases, as well as determine heat or cold stress exposure (Confalonieri *et al.*, 2007). Many parasitic and infectious species have very specific environmental conditions in which they survive

[15] Other studies relying on the perceptions of respondents about the incidence of different types of shocks, such as floods, droughts, freeze, fires and hurricanes include Garcia Verdu (2002), Skoufias (2007) and de la Fuente (2010). None of these earlier studies, however, make use of actual meteorological data.

[16] For example, households may undertake ex-ante income-smoothing strategies and adopt low return-low risk crop and asset portfolios (Rosenzweig and Binswanger, 1993). Households may use their savings (Paxson, 1992), take loans from the formal financial sector to carry them through the difficult times (Udry, 1994), sell assets (Deaton, 1993), or send their children to work instead of school in order to supplement income (Jacoby and Skoufias, 1997). These actions enable households to spread the effects of income shocks through time. Additional strategies include the management of income risk through ex-post adjustments in labor supply such as multiple job holding, and engaging in other informal economic activities (Morduch, 1995; Kochar, 1988).

and reproduce, and a slight change in precipitation or temperature could render previously uninhabitable areas suitable for a particular parasitic and infectious species. Specifically in Mexico, several studies have shown positive correlations between temperature, and vector- and food-borne illnesses (Ministry of Environment and Natural Resources, 2007).

4. It is also the case, that changes in the environmental conditions do not uniformly affect the health of household members. Children are more likely to contract or die from vector borne diseases, more likely to suffer from diarrhea, more likely to suffer psychologically from extreme weather events, and more likely to suffer from maltreatment due to household economic stress (Bartlett, 2008). Early childhood health not only affects children's current wellbeing but may determine their adulthood quality of life including their productivity and cognitive development. Malnutrition, from having insufficient food intake or as a byproduct of repeated diarrheal infections, can cause structural damage to the brain and impair motor development in infants which in turn affect the cognitive development of a child (Victora et al., 2008; Guerrant et al., 2008). Furthermore, Eppig et al. (2010) find a correlation between infectious diseases and IQ. They explain their findings as the competition between energy needs for the development of the brain and energy needs needed to fight off disease. They single out diarrheal diseases as potentially being the most energy consuming ones. Overall, childhood health has been found to have an impact on adult health, and employment (Case et al., 2005), cognitive abilities (Case and Paxson, 2008; Grantham-McGregor et al., 2007; Maluccio et al., 2009), educational outcomes (Alderman et al., 2006; Glewwe and Miguel, 2008; Maluccio et al., 2009), and productivity (Hoddinott et al., 2008). These findings underline the importance of focusing on the health outcomes for young children.

5. Third, the study investigates the extent to which certain household or individual characteristics, such as gender, educational attainment, or participation in supplemental nutrition programs, or where the household lives, alter the welfare impacts of climatic variability in rural areas. It is quite possible that the resilience and the ability to adapt to changes in weather and environmental conditions differs significantly across the spectrum of socio-economic characteristics in the population and across geographical regions.

6. In view of these considerations, the study has two sets of analyses. First, the impact of weather shocks on household consumption controlling for a variety of socio-economic characteristics of the household and interact the weather shocks with key household characteristics is estimated. Then the effect of the climatic variability on child health, and again interact the weather shocks with different individual characteristics is examined. By analyzing two aspects of welfare and separating the impacts by key sub-populations, the study provides a deeper understanding of who and what aspects of welfare are most affected by weather shocks allowing for a more informed and more cost-effective policy design.

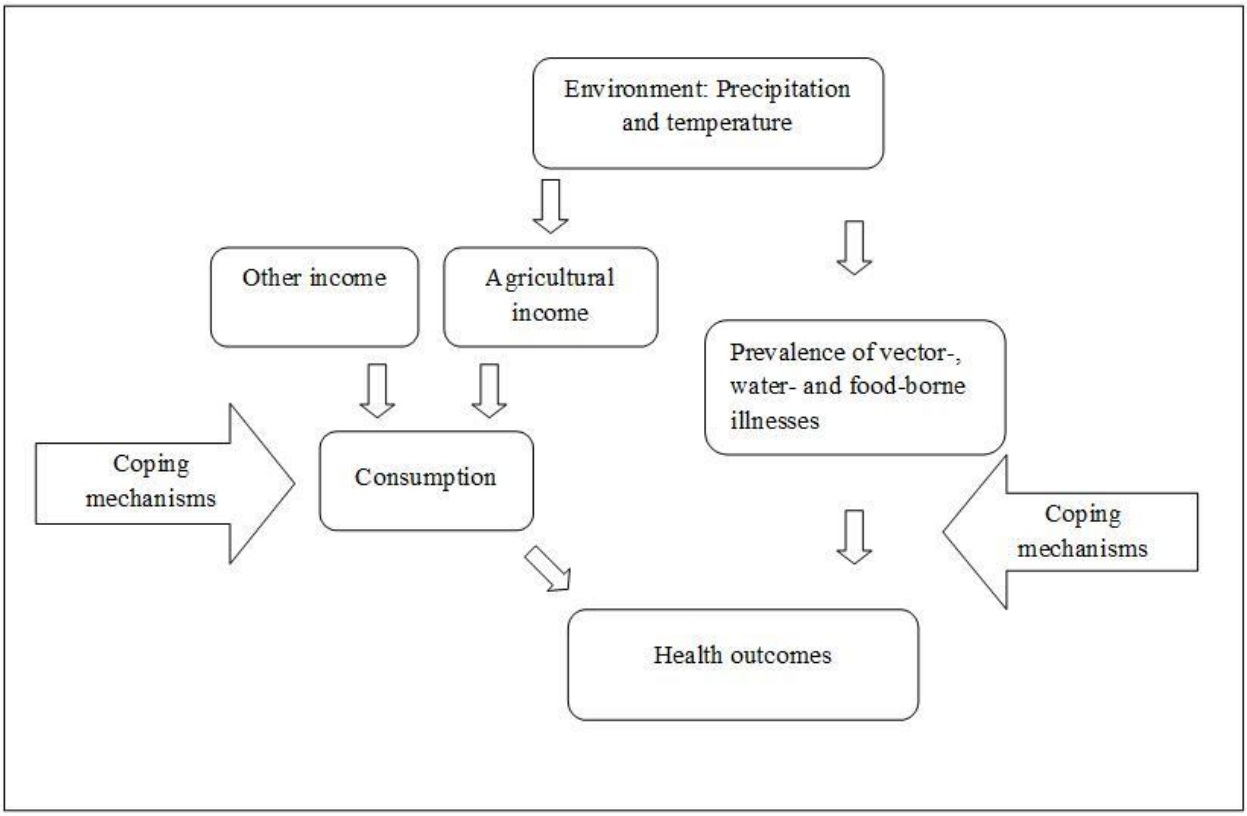
7. The rest of the chapter is organized as follows: The next section provides an overview of past research on the impact of weather on consumption and on health outcomes. Section 3.3 outlines the estimation strategy. Section 3.4 gives background on Mexican agriculture and describes the data sources. Section 3.5 presents the results and Section 3.6 concludes.

3.2 Past Research

8. One could think of the environment, health and consumption as being part of a simple system (Figure 3.1) where health and consumption are two important dimensions of welfare. Consumption, measured at the household level is influenced by the environment; and health, measured at the individual level, is influenced both by the environment and consumption.[17] To see the interaction among the three facets, it is instructive to think of each of the impacts in isolation from the other two.

[17] There may also be some feedback from the health status of an individual to his/wage earning capacity and ultimately to the consumption expenditures at the household level. For now, we do not explore this pathway. Also,

Figure 3.1 Environment, health and consumption relationships



9. The environment affects consumption mainly through its impacts on current agricultural production or income. This is especially true in rural areas where crop yields are a function of precipitation and temperature, but the environment could also affect non-agricultural income to the extent that it is connected to weather, such as providing outdoor activities, or vendors with open-air stalls. Depending on the household's ability to cope with income fluctuations, a negative income shock brought on by bad weather may translate into a reduction in consumption (e.g. Jacoby and Skoufias , 1998; Dercon and Krishnan, 2000). In general, households are better able to insure their consumption against idiosyncratic shocks, which are shocks that affect only a particular household, such as the death of a household member, than they are able to insure against covariant shocks, shocks that affect a large number of households in the same locality, such as weather related shocks (Harrower and Hoddinott, 2005). Furthermore, when consumption is affected by a shock, different types of consumption may be impacted differently. In general, food consumption is better insured than non-food consumption, including health (Skoufias and Quisumbing, 2005).[18]

10. Even if at the household level there does not appear to be a significant impact on total consumption, the intra-household allocation of resources may change after a weather shock possibly leading members to be differentially impacted. Differences in the health outcomes of individuals within a household would be brought about if the food resources to a particular individual were reduced sufficiently for them to

health affects the consumption bundle directly in two ways—ex post (e.g. being sick requires buying medicines) and ex ante (e.g. preventive health care).

[18] There is also some evidence that in some societies weather shocks affect household consumption differently depending on whose agricultural income (male or female) is impacted by the shock (Duflo and Udry, 2004).

experience malnutrition or if his share of other resources, such as preventive or curative health related goods, was lower than in a typical year. Such a reduction is likely in a household which in a typical year is only barely able to access sufficient nutrition for each household member. Furthermore, an environmental shock may also directly affect the health of an individual, for example, by changing the prevalence of diseases or the risk of exposure to heat or cold stress. Assuming no changes in consumption choices, a change in the prevalence of diseases itself has an impact on individual's health and again the impact depends on the individual's characteristics. Studies have shown negative impacts of weather events, such as droughts on health outcomes (both concurrent and persistent impacts), but in most cases the studies estimate aggregate impacts and it is not clear if the impacts stem from lower consumption levels or from the changes in environmental conditions.

11. Studies on the impacts of shocks on individual welfare generally use some health outcome as the preferred measure, with evidence from other countries suggests that both gender and age matter. For example, Rose (1999) finds that in rural India a positive rainfall shock increases the survival probabilities of girls more than the survival probabilities of boys. Similarly, Hoddinott (2006) finds that there is a small but transient effect of drought on the BMI of women, but not on men's. Also, the age of the individual at the time of the shock matters. For example, Hoddinott and Kinsey (2001) find that a drought experienced at 12 months to 24 months of age, had an impact on annual growth rate, and that the impact persisted for the four years of the study. No such impact was found for shocks experienced later in life. Maccini and Yang (2009) find a slightly different result where an individual is susceptible to weather. In their study on rural Indonesia weather shocks experienced in the first year of life have an impact on adult outcomes. Namely, women born in localities with a greater than average rainfall are taller as adults, have completed more years of education, and live in wealthier households. No impacts on men's outcomes are observed.

12. The final impact of a weather-related shock on health is an interplay among the indirect impact of weather on health through changes in income or production, the direct impact from changes in the environmental conditions, and the changes in the types of consumption that the household and individual is able to make. That is, weather conditions not only alter the budget constraint faced by a household, but may also alter the optimal consumption composition. The impact from an environmental shock on welfare depends on the household's and individual's abilities to cope against income fluctuations and changes in the environmental conditions. Such coping mechanisms may include availability of different assets, access to government sponsored programs, or access to healthcare.

13. A particular environmental shock may have a direct negative impact on health but a positive impact on health indirectly through consumption. Table 3.1 summarizes the expected direction of impacts from weather events on consumption and on health. The first column states the type of weather event, namely an extreme event or increase in rainfall or temperature within a normal range. The second column describes the impacts on agricultural production and income. Both extremes of rainfall (drought or flood) and temperature (extremely cold or extremely hot) will negatively impact yields and thus, potentially, income and consumption as well. In general within a normal range of rainfall and temperature, additional rainfall or warmer days should increase yields in temperate climates, but will most likely reduce yields in tropical climates. Specific to Mexico, Galindo (2009) identifies both states where higher temperatures lead to higher yields and states where they lead to lower yields. Given concave production functions, similar differences occur with precipitation. Malnutrition (and negative health outcomes) are possible, if food consumption is reduced as a result of a weather event especially if prior to the event the household or individual was barely consuming the required nutritional needs (column 3).

14. The impacts of changes in weather on health are even more complex (columns 4, 5, and 6).[19] The prevalence and range of a particular pathogen, disease vector, or animal reservoir are determined by

[19] The discussion on the impact of climate on health relies heavily on Patz et al. (2003).

specific ranges of temperature, precipitation and humidity (Patz et al., 2003). Whether an atypically rainy or dry period increases the prevalence of a disease depends on the specific climate of a region. In regions bordering a pathogen's habitat, even a small deviation from the normal climate, can make large areas susceptible to the infectious disease. That is, if a region is just too cold (or too hot) for a particular pathogen or vector then an unusually hot (or cold) year could make the region susceptible to the disease caused by the pathogen or carried by the vector. Evidence of the importance of climatic factors can be seen from the seasonality of many infectious diseases, such as influenza (to temperature), and malaria and dengue (to rainfall and humidity).

15. In general, extreme temperatures are lethal to vector-born disease pathogens. An increase in precipitation will in general improve breeding conditions. However, extremely high precipitation, i.e. floods, may, on one hand, reduce infectious diseases by eliminating breeding grounds but, on the other hand, may cause other vectors, such as rodents, to come in more frequent contact with humans. Extremely low precipitation, or droughts, may create stagnant pools of water from streams and rivers, which are good breeding grounds for pathogens and vectors, thus increasing the prevalence of the diseases associated with the pathogen or vector.

16. In addition, water- and food-borne pathogens (causing enteric infections) are also susceptible to precipitation and temperature, besides vector-borne pathogens. Unlike vector-borne illnesses, both heavy and low precipitation have been found to increase enteric infections. Furthermore, there is evidence of a positive relationship between temperature and diarrheal diseases.

Table 3.1 Impact of weather conditions on consumption and health outcomes in rural areas

Weather condition	Agricultural production / Income	Impact on consumption	Incidence of disease *	Impact on health**	
				From food consumption	Direct environmental
Extremely dry	Yields will be lower.	Negative if cannot smooth consumption.	Generally reduces the prevalence of vector-born diseases, but increases water/food-born diseases	Negative, possible malnutrition, if cannot smooth food consumption	Indeterminate, but most likely positive
An increase in rainfall (within normal range)	Yields will increase with additional rain.	Total consumption should not decrease.	Increases the prevalence of both vector and water/food-born diseases.	None or positive	Indeterminate, but most likely negative
Extremely wet	Yields will be lower.	Negative if cannot smooth consumption.	Increases the prevalence of both vector and water/food-born diseases.	Negative, possible malnutrition, if cannot smooth food consumption	Negative
Extremely cold	Yields will be lower.	Negative if cannot smooth consumption.	May reduce the prevalence both vector and water/food-born diseases. Increases cold stress related health problems.	Negative, possible malnutrition, if cannot smooth food consumption	Indeterminate, but most likely positive
An increase in temperature (within normal range)	Yields will increase with warmer temperatures.	Total consumption should not decrease.	Increases prevalence of both vector and water/born diseases.	None or positive	Indeterminate, but most likely negative
Extremely hot	Yields will be lower.	Negative if cannot smooth consumption.	Generally decreases prevalence of vector-born diseases. Potentially increases water/food –born diseases. Increases heat stress related health problems.	Negative, possible malnutrition, if cannot smooth food consumption	Indeterminate

* The impact on the incidence of disease depends on the general climatic conditions of the region. For example, if the average temperature is very high, then a decrease in the annual temperature may in fact increase the prevalence of vector born diseases.

** Also, there may be some impacts such as extremely cold weather inducing people to heat their homes using methods not apt for indoor use.

3.3 Estimation Strategy

17. Pooled panel data is used for the first set of analyses. To determine the impact of weather variability on consumption the following equation is estimated.

$$lnPCE_{h,l,t} = \alpha + \beta W_{l,t} + \gamma X_{h,l,t} + \mu_l + \rho_t + \sigma_s + \varepsilon_{h,l,t} \quad (3.1)$$

where $lnPCE_{h,l,t}$ is the logarithm of consumption expenditures per capita of household, h, located in locality l, in the year t. $W_{l,t}$ is a vector describing the weather shocks in locality l, at time t, $X_{h.l,t}$ is a vector of other factors explaining consumption levels, such as assets, and household characteristics. μ_l are locality fixed effects which control for all local, time invariant characteristics including the agro-climatic characteristics of each locality, ρ_t and σ_s control for survey year and season (wet or dry) differences, respectively, and ε_h is the error term. β measures the impact of weather shocks on consumption. In the absence of insurance against income shocks any weather shock that reduces income should also reduce consumption.

18. In order to determine if the impact of a weather shock differs among different populations, an interaction term is introduced into equation (3.1), such that it becomes,

$$lnPCE_{h,l,t} = \alpha + \beta_0 W_{l,t} + \beta_1 \left(W_{l,t} \cdot P_{h,l,t}\right) + \gamma_1 P_{h,l,t} + \gamma_2 X_{h,l,t} + \mu_l + \rho_t + \sigma_s + \varepsilon_{h,l,t} \quad (3.2)$$

19. Here $P_{h,l,t}$ identifies the type of household. It could indicate, for example, whether or not the household head is female or has completed at least primary school. In this case β_0 measures the impact of the weather shock on households without the particular characteristic and $(\beta_0 + \beta_1)$ measures the impact of weather on households with the particular characteristic, with β_1 denoting the difference in the impact between the two groups.

20. Cross sectional individual level data for the second set of analyses, relating weather shocks to health outcomes. The health outcome of an individual can be written as:

$$H_{i,l,t} = \alpha + \beta W_{l,t} + \gamma X_{i,l,t} + \mu_l + \rho_t + \sigma_s + \varepsilon_{i,l,t} \quad (3.3)$$

where $H_{i,l,t}$ is the health outcome of individual i in locality l at time t, $W_{l,t}$ is a vector describing the weather shocks in locality l, at time t, X_i is a vector of other factors influencing the health of an individual, such as household and housing characteristics, μ_l are location fixed-effects, ρ_t and σ_s control for survey year and season (wet or dry) differences, and $\varepsilon_{i,l,t}$ is the error term.

21. Similarly to the consumption equation, the health outcome equation can be expanded to include interaction terms to test for the relevance of specific policy measures. Equation (3.3) becomes,

$$H_{i,l,t} = \alpha + \beta_0 W_{l,t} + \beta_1 (W_{l,t} \cdot P_{i,l,t}) + \gamma_1 P_{i,l,t} + \gamma_2 X_{i,l,t} + \mu_l + \rho_t + \sigma_s + \varepsilon_{i,l,t} \quad (3.4)$$

where $P_{i,h,l}$ identifies the type of individual or household. It could indicate, for example, the gender of the individual or whether or not the individual participates in a supplemental nutrition program. In the case of gender, if $P = 1$ is set for girls, β_0 would measures the impact of the weather shock on boys and $(\beta_0 + \beta_1)$ the impact of weather on girls. Again, β_1 measures the difference in the impact between the two sexes.

3.4 Background and Data Sources

22. Rural households in Mexico are the focus of the empirical analyses. CONEVAL (2005) estimates that in 2005, 47% of the population lived in poverty, with 18% of the population living in extreme poverty. In 2006, 15.5% of 0 to 5 year-olds had a height-for-age z-score of less than -2 (stunted) and 3.4% of 0 to 5 year-olds had a weight-for-age z-score less than -2. In rural areas the rates were slightly higher with the height-for-age and weight-for-age z-scores below -2 for 4.9% and 24.1% of the 0 to 5 year olds, respectively (WHO). These statistics suggest that a relatively large population of the country could be at risk from even small decreases in their income.

23. In Mexico, about 82% of cultivated land is rainfed (INEGI, 2007), and thus being very susceptible to weather fluctuations. Corn is produced in 59% of cultivated land in the wet season and 31% of the land in the dry season. The total area cultivated is more than six times greater in the wet season than in the dry season (INEGI, 2007). More importantly, corn is used by many small-scale farmers not only as a source of income but also directly as a subsistence crop. Switching to other crops, such as wheat or barley, which have a shorter growth cycle but are not as useful for household consumption, is considered a last resort (Eakin, 2000).

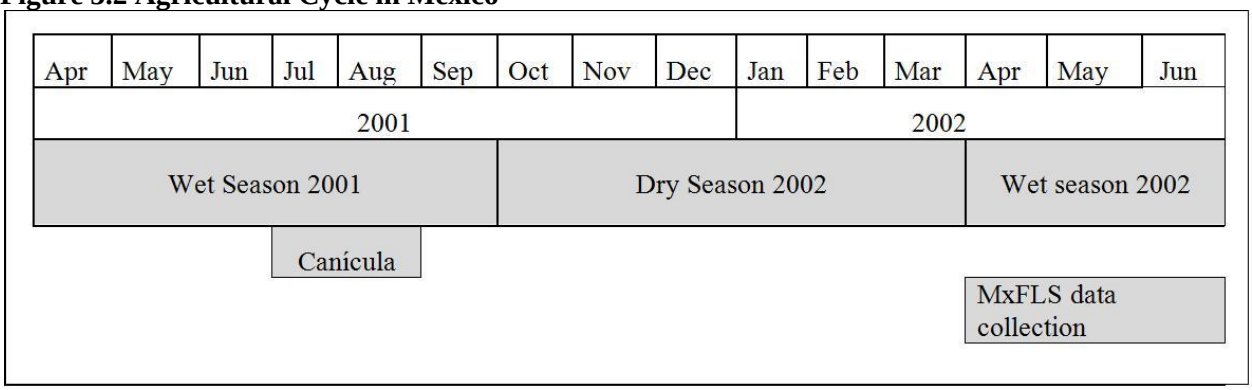
24. Both rainfall and temperature are important factors affecting crop yields and exhibit a concave relationship with agricultural productivity (Galindo, 2009). Whether increased precipitation or temperature is beneficial to the agricultural production process depends on the crop, region, and the season in which the change occurs. For example, corn production is found to benefit from additional temperature in Hidalgo, Estado de México, Puebla and Querétaro and decrease with additional temperature in Baja California de Sur, Campeche, Chiapas and Guerrero (Galindo, 2009). Similarly, he finds the optimal levels of rainfall below and above which yields fall depend on the class of crops considered. Alternatively, Conde et al. (1997) find that in the long run a climatic change with an increase of 2°C and a 20% decrease in rainfall would increase the amount of unsuitable land for corn production by 8% in a sample of seven corn producing municipalities (from the states of Mexico, Puebla, Veracruz and Jalisco). Similarly a 2°C increase in temperature but a 20% increase in rainfall would increase the amount of land unsuitable for corn production by 18%. Simulating a temperature increase of 4°C over the mean temperature, the amount of land unsuitable for production, with a 20% increase and a 20% decrease in rainfall, increased by 20% and 37%, respectively. Based on actual production estimates, Appendini and Liverman (1994) estimate that in Mexico droughts are responsible for more than 90% of all crop losses.

25. The agricultural year in Mexico runs from October to September: composed of a dry season, from October to the end of March, and a wet season, from April to the end of September. Given the water and temperature requirements of corn, most of the rainfed corn is planted and harvested during the wet season. The growing cycle for corn can be divided into three phases (Neild and Newman).[20] The first phase (vegetative phase) lasts between 60 to 40 days. The longer it takes for the seed to germinate (i.e. the colder it is after planting) the higher the probability that the seed is weak and subject to disease producing a lower yielding crop. For the first half of this time the growing point is usually below ground and the plant can withstand to some degree cold temperatures. After the growing point is above ground level then frost can cause significant damage to the plant. With the ear formation begins the reproductive phase with the ear forming stage lasting for about 20 days and an additional 20 to 30 days are required for the grain fill stage. Inadequate water availability during this phase greatly affects yields with the impacts being the greatest during the ear forming stage. Also extremely warm temperature (above 32˚C) during the second half of the vegetative phase and the reproductive phase reduce yields. The last phase (maturation phase) lasts between 20 to 35 days.

[20] The description of corn's growth cycle is adapted from Neild and Newman.

26. Planting later in the season ensures that the seed germinates quicker, however waiting too long does not allow the crop to complete the maturation stage before the growing season ends. Furthermore, specific to Mexico, in July and August there is a period of mid-summer drought called *canícula* (Figure 3.2) affecting farmer's planting decisions. In general, farmers want the corn to flower (for the ear formation stage to be complete) before the onset of the *canícula* in order to better the odds of the crop survival in case it is a drier than normal *canícula* (Eakin, 2000). This implies that the months leading up to the *canícula* are of special importance in Mexico.

Figure 3.2 Agricultural Cycle in Mexico



27. For the household data the first two waves of surveys from the Mexico Family Life Survey (MxFLS) (Rubalcava and Teruel, 2006) are used. The first wave of the survey in 2002 interviewed 3,353 rural households[21] in 75 different localities located in all regions of the country and was conducted between March 2002 and August 2002, with the majority of the information collected between April and June. The second wave of the survey was collected between 2005 and 2007 with the majority of the data collection occurring from May 2005 to September 2005. The follow-up survey interviewed 3,271 households in 112 rural localities.[22] Both waves collected detailed information on each household member including information on educational attainment, migration and anthropometric measures, and as well as on household expenditures.[23] Separate surveys were administered to the leaders of each locality on services and programs available at the locality.

28. For the health outcome analyses the *Encuesta Nacional de Nutricíon* (National Nutrition Survey) collected by the *Instituto Nacional de Estadística y Geografía* (INEGI) (National Institute of Statistics and Geography) and the *Secretaría de Salud of Mexico* (Secretary of Health) in the last quarter of 1999 are used.[24] The survey interviewed 7,180 rural households in 767 different localities. The survey collected general information on all members of the household and more detailed information, including anthropometric measures and illnesses in the past 2 weeks, for females between 12 and 49 years of age, and for all children 12 years or younger.

[21] Rural households are considered to be those that lived in localities with less than 2,500 inhabitants.
[22] In Wave 2 the households are spread out over a larger number of localities, because some households (or parts of households) had moved between the surveys.
[23] MxFLS collects information on the value spent purchasing various categories of goods—food, dining out, healthcare, transportation, personal items, education, recreation, cleaning services, communications, toys/baby articles/childcare, kitchen items and bedding, clothing, tobacco, gambling, appliances and furniture, and other expenses—as well as the value of goods consumed from own production or received as gifts. Unfortunately the value of goods consumed from own production versus the value of goods received from others cannot be separated.
[24] Although the MxFLS also collected anthropometric measures for the household members, we choose not to use them as we can only get accurate height-for-age information for the first wave observations and of the potential under 36 month olds we lose about 30% due to non-measurement and an additional 20% due to other missing information.

29. The climate data used in this paper come from the Mexican Water Technology Institute (*Instituto Mexicano de Tecnología del Agua*—IMTA). The IMTA has compiled daily weather data from more than 5,000 meteorological stations scattered throughout the country. The data span a very large period of time—from as far back as the 1920s to 2007—and contain information on precipitation, and maximum and minimum temperature.

30. The meteorological stations registered these variables on a daily basis and this information is used to interpolate daily values of these variables for a geographic centroid in each of the country's municipalities[25]. The centroid was determined as the simple average of the latitude and longitude coordinates of all the localities listed in INEGI's 2005 catalogue corresponding to each municipality, which resulted in a locality-based centroid. This method was chosen over a population-weighted average because that alternative would bias the interpolation towards urban rather than rural areas. The interpolation method used is taken from Shepard (1968), a commonly used method which takes into account relative distance and direction between the meteorological stations and the centroids (see Appendix A5).

31. Independent interpolation was carried out for every day between 1950 and 2007, for each municipality. Since not all meteorological stations existed throughout the entire period and given that during the time they were in operation they sometimes failed to report their records, each interpolation is based on a different number of data points—and indeed different weather stations. These problems as well as the accuracy of the data get worse as one looks at earlier years, which has a corresponding effect on the interpolations. Thus, interpolations for the year 1950 are less reliable than those for 2007.

32. From these weather data, total rainfall and growing degree days (GDD) were calculated for each agricultural year (October to September), for each wet season (April to September) and for each pre-*canícula* period (April, May, June), or the months leading to the *canícula*, from 1951 to 2002.[26] Instead of maximum of minimum temperatures the study uses GDD, a cumulative measure of temperature based on the minimum and maximum daily temperatures. GDD measures the contribution of each day to the maturation of the crop. Each crop, depending on the specific seed type and other environmental factors, has its own heat requirements for maturity. Different corn varieties, for example require between 2,450 and 3,000 GDDs to mature, whereas different wheat varieties only require between 1,800 and 2,000 GDDs.[27]

33. Each crop has specific base and ceiling temperatures, T_{base} and $T_{ceiling}$, respectively, which contribute to growth. The base bound sets the minimum temperature required for growth and the ceiling temperature sets the temperature above which the growth rate does not increase any further. Thus, the contribution of each day, j, to the cumulative GDD is given by

$$(T_{j,\overline{min}} + T_{j,\overline{max}})/2 - T_{base} = GDD_j \qquad (3.5)$$

[25] INEGI's 2005 catalogue of localities was taken, containing 2451 municipalities.
[26] Given that the agricultural year starts runs from October to September, the first agricultural year used is 1951, and we only use the last three months of the 1950 calendar year.
[27] For other important crops in Mexico the required GDDs are 2,400 for beans and 2,200 to 2,370 for sorghum. The GDD values are taken from The Institute of Agriculture and Natural Resources Cooperative Extension, University of Nebraska-Lincoln. Growing Degree Days & Crop Water Use. http://www.ianr.unl.edu/cropwatch/weather/gdd-et.html, Accessed July 22, 2010.

where $T_{j,\overline{min}}$ and$T_{j,\overline{max}}$ are the minimum and maximum daily temperature truncated at the base and ceiling values. In other words, any daily temperature (minimum or maximum) below the base temperature is assigned the base temperature value and any daily temperature above the ceiling temperature is assigned the ceiling temperature value.[28] To determine the cumulative GDD at any point in time for a specific cultivation the daily GDDs since planting are summed.

34. Given the mixture of different crops grown in the survey areas, the study uses the generalized bounds of 8° Celsius and 32° Celsius (for example, Schlenker and Roberts, 2008). Specifically, any daily minimum or maximum temperature below 8° Celsius is treated as being 8° Celsius and any daily minimum or maximum temperature above 32° Celsius is treated as being 32° Celsius. Thus a day with a minimum and maximum temperature of 8° Celsius or below will yield no GDDs, whereas a day with a maximum and a minimum temperature of 32° Celsius or above will yield 24 GDDs.

35. For the measures of weather shocks the municipal historic mean rainfall and GDD between 1951 and 1985 for the agricultural year, for the wet season and for the pre-*canícula* period were calculated. Given that there is incomplete information for some months for some of the municipalities (i.e. none of the 20 closest weather stations reported data for 5 or more consecutive days), in the sample of rural municipalities, the average climate is based on 15 to 35 years of information. 75% of the rural households in the samples live in municipalities with at least 30 years of complete weather information from 1951 to 1985.[29]

36. The chosen measures of weather shocks, W, are based on the degree of deviation from the 1951-1985 average weather. A shock is defined by an indicator variable identifying those observations where the weather variable is more than one standard deviation from its long-run mean. A municipality is defined to have experienced a negative rainfall shock if the prior period's rainfall was at least one standard deviation less than the average 1951-1985 rainfall; and a municipality is defined to have experienced a positive rainfall shock if the prior period's rainfall was at least one standard deviation more than the average 1951-1985 rainfall. Thus, there are in total four measures describing the prior year's (or wet season's or pre-*canícula* period's) weather. Table 3.2 shows the 1951 to 1985 average weather conditions by regions for Mexico. One standard deviation rainfall shock translates to an average of about 30% difference in annual or wet season rainfall and a 50% difference for the pre-*canícula* period. The GDD shocks are, on average, about 8% deviations from the mean. The climate in each of the regions is distinct and even within a region there is much variability. In general, however, the North is drier than the rest of the country and the Center is colder than the rest of the country.

[28] The Modified Growing Degree Days formula is used where the minimum and maximum temperatures are adjusted prior to taking the average.

[29] To balance the need to calculate the historic means with as many years of information as possible but excluding recent years which may have been affected by changing climate, we construct the historic means and standard deviations of the weather variables using data from 1951 to 1985.

Table 3.2 Prevalence of weather shocks in Mexican municipalities between 1986 and 2002 from mean 1951 to 1985 weather

St. dev. from mean	Rainfall						GDD					
	Annual		Wet season		Pre-canícula		Annual		Wet season		Pre-canícula	
	Freq.	Perc ent	Freq.	Perc ent	Freq.	Perc ent	Freq.	Perce nt	Freq.	Perc ent	Freq.	Perc ent
-2	3,487	4.27	3,122	3.69	1,476	1.74	6,102	7.47	7,312	8.63	7,598	8.93
-1	13,925	17.05	13,230	15.62	13,142	15.45	10,961	13.42	12,174	14.37	12,654	14.88
0	53,475	65.48	58,014	68.48	59,242	69.64	45,515	55.73	48,346	57.07	48,870	57.45
1	6,827	8.36	6,804	8.03	8,106	9.53	12,045	14.75	11,198	13.22	10,970	12.9
2	3,951	4.84	3,542	4.18	3,102	3.65	7,042	8.62	5,682	6.71	4,976	5.85

37. Comparing weather data from 1986 to 2002 with their historic means (from 1951 to 1985), there appears to be an increase in the number of *temperature* shocks (both negative and positive), but no similar increase in *rainfall* shocks (Table 3.3) in Mexico.[30] The survey date is used to match each household to the weather information. Each household is assigned the wet season and dry season prior to the survey. That is, if a household was surveyed in dry season of year *t*, the weather shocks would based on the weather in the dry season *t-1* and the wet season *t-1*. However, if the household was surveyed in the wet season of year *t*, the weather shocks would be based on weather in dry season *t* and wet season *t-1*. As an illustration, for the households in the 2002 wave of the MxFLS, the weather variables of interest are rainfall and GDD from the 2001 wet season and the 2002 dry season (Figure 3.2). The harvest from the 2002 wet season would not have been harvested prior to the surveys and thus the households' income and production would be based on the 2001 wet season and the 2002 dry season harvests.

Table 3.3 Deviations from 1951 to 1985 mean weather in rural MxFLS municipalities in 2001/2002

Standard deviations from mean	Rainfall						GDD					
	Annual		Wet season		Pre-canícula		Annual		Wet season		Pre-canícula	
	Freq.	Percent	Freq.	Percent	Freq.	Percent	Freq.	Percent	Freq.	Percent	Freq.	Percent
-2	2	3.13	1	1.56	0	0	5	7.81	6	9.38	6	9.38
-1	10	15.63	7	10.94	3	4.69	11	17.19	12	18.75	11	17.19
0	43	67.19	43	67.19	53	82.81	37	57.81	33	51.56	38	59.38
1	8	12.5	9	14.06	7	10.94	8	12.5	10	15.63	7	10.94
2	1	1.56	4	6.25	1	1.56	3	4.69	3	4.69	2	3.13

38. The distribution of rainfall and GDD shocks for the rural municipalities in the final samples from MxFLS and ENN, can be seen in Tables 3.4a and 3.4b respectively. Although the number of municipalities from which the household surveys are drawn is relatively small, there is still some

[30] The correlation of the 6 different weather shock variables for the MxFLS sample is given in Appendix A1. The rainfall deviations from mean for the various periods (annual, wet season and pre-*canícula* period) are positively correlated with annual rainfall and wet season rainfall being very highly correlated. The GDD deviations from mean are all very highly correlated. Given the high correlations among the different time periods, we only include weather variables from one time period in each regression.

variability in the weather variables. There are municipalities that experienced positive and negative rainfall as well as GDD events. As Table 3.4 shows, there are more GDD shocks than rainfall shocks in the sample.

Table 3.4a Weather shocks in MxFLS sample

Standard deviations from mean	Rainfall						GDD					
	Annual		Wet season		Pre-*canícula*		Annual		Wet season		Pre-*canícula*	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Freq.	%
-2	10	4.63	6	2.67	8	3.54	13	6.02	13	5.78	14	6.19
-1	36	16.67	39	17.33	26	11.5	35	16.2	35	15.56	35	15.49
0	142	65.74	147	65.33	167	73.89	126	58.33	135	60.00	142	62.83
1	20	9.26	22	9.78	23	10.18	33	15.28	35	15.56	29	12.83
2	8	3.70	11	4.89	2	0.88	9	4.17	7	3.11	6	2.65

Note: Deviations from 1951 to 1985 mean weather in rural MxFLS municipalities for agricultural years prior to household survey.

Table 3.4b Weather shocks in ENN sample

Standard deviations from mean	Rainfall						GDD					
	Annual		Wet season		Pre-*canícula*		Annual		Wet season		Pre-*canícula*	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Freq.	%
-2	3	1.67	6	3.33	14	7.78	9	5.00	8	4.44	7	3.89
-1	31	17.22	32	17.78	83	46.11	25	13.89	15	8.33	20	11.11
0	128	71.11	128	71.11	79	43.89	93	51.67	100	55.56	100	55.56
1	15	8.33	11	6.11	3	1.67	41	22.78	40	22.22	35	19.44
2	3	1.67	3	1.67	1	0.56	12	6.67	17	9.44	18	10.00

Note: Deviations from 1951 to 1985 mean weather in rural ENN municipalities for agricultural years prior to household survey.

Table 3.4 Correlations between weather shock variables and average (1951-1985) weather

	Deviation in annual rainfall from mean	Deviation in wet season rainfall from mean	Deviation in pre-canícula rainfall from mean	Deviation in annual GDD from mean	Deviation in wet season GDD from mean	Deviation in pre-canícula GDD from mean
Deviation in wet season rainfall from mean	0.953					
Deviation in pre-canícula rainfall from mean	0.517	0.397				
Deviation in annual GDD from mean	-0.027	0.044	-0.059			
Deviation in wet season GDD from mean	-0.016	0.061	-0.060	0.965		
Deviation in pre-canícula GDD from mean	-0.016	0.082	-0.116	0.907	0.959	
Average annual rainfall (1951-1985)	-0.101	-0.230	0.086	-0.083	-0.084	-0.139
Average wet season rainfall (1951-1985)	-0.087	-0.219	0.136	-0.106	-0.095	-0.157
Average pre-canicula rainfall (1951-1985)	0.004	-0.141	0.194	-0.103	-0.121	-0.194
Average annual GDD (1951-1985)	-0.014	0.064	-0.242	0.032	0.068	0.193
Average wet season GDD (1951-1985)	-0.053	0.046	-0.279	0.092	0.104	0.234
Average pre-canicula GDD (1951-1985)	-0.028	0.018	-0.187	0.025	0.041	0.158

39. The original MxFLS localities, those chosen for the 2002 survey, come from 16 different Mexican states and from all the different regions of the country. Although these states vary in the percentage of land cultivated under rainfed technologies, in most at least 75% of the land is rainfed (Table 3.5). Also, in most at least 50% of the land cultivated in the wet season is in corn and in all the area cultivated in the wet season is greater than the area cultivated in the dry season. These figures suggest that it can be expected that for an average rural household in the sample the income, as well as production for self consumption, to be relatively highly dependent on the weather and especially on the weather during the wet season. Also, given the relative importance of corn, the pre-*canícula* period is of interest.

Table 3.5 Agricultural production in Mexican states included in the MxFLS

Region	State	Hectares cultivated		% of land in corn		% of land in beans		% of land in sorghum		% of land in other		wet season/ dry season hectares	% land rainfed
		Dry season	Wet season	Dry season	Wet season	Dry season	Wet season	Dry season	Wet season	Dry season	Wet season		
National production		**2,167,069**	**13,758,639**	**31**	**59**	**11**	**12**	**13**	**13**	**45**	**15**	**6.35**	**82**
North	Baja California Sur	16,722	28,987	12	41	11	11	2	8	74	41	1.73	27
	Coahuila	44,874	281,365	3	27	1	6	9	47	87	20	6.27	66
	Durango	57,155	691,738	12	42	16	30	17	6	55	22	12.10	80
	Nuevo Leon	33,360	209,576	12	49	3	3	15	39	70	9	6.28	78
	Sinaloa	418,177	588,288	63	39	13	4	3	44	21	13	1.41	54
	Sonora	276,237	341,731	4	12	1	4	2	36	94	49	1.24	41
Center	Guanajuato	38,385	823,889	13	56	4	11	0	24	83	9	5.95	67
	Jalisco	52,172	732,411	26	87	5	2	3	7	66	4	14.04	85
	Estado de Mexico	42,074	544,033	25	81	7	2	7	0	61	17	12.93	89
	Michoacán	86,904	668,846	18	79	2	1	28	13	52	7	7.70	78
	Morelos	50,639	83,328	3	37	1	3	92	43	4	16	1.65	72
	Puebla	39,153	709,046	41	73	13	9	2	3	45	15	18.11	88
Mexico City	Distrito Federal	2,924	12,297	4	42	1	2	11	0	84	55	4.21	94
South Pacific	Oaxaca	54,170	611,187	64	84	22	7	2	4	12	5	11.28	96
Gulf and Caribbean	Veracruz	106,147	517,278	83	86	9	5	1	2	8	7	4.87	97
	Yucatan	8,370	220,175	46	79	33	11	0	0	20	10	26.31	92

Source: NEGI. Censo Agricola, Ganadero y Forestal (2007).
Note: Regional assignations are taken from Conroy (2009)

40. Besides differing in the types of crops cultivated, the localities also differ in the availability of services and programs. Table 3.6a summarizes some of the locality characteristics for the 2002 and 2005 MxFLS samples.[31] The information is only available for those localities in the original sample. In 2005 there were households from 85 different localities since some of the households had moved to non-MxFLS localities. In most of the original MxFLS localities there was access to primary education but access to higher education was only readily accessible in a few localities. In many localities there were health services available, as about 75% of the localities had a public health clinic, but not all had such services locally. In the majority (about 75% in the 2002 sample and 99% in the 2005 sample), but not in all, qualifying households were able to access Oportunidades.[32] Table 3.6b shows some characteristics of the ENN sample localities. Although on average 76% of the households in the localities have electricity, only 27% have access to a sewage system.

Table 3.6a Select characteristics of localities in MxFLS sample

Characteristic of locality	Localities with information in 2002	% of localities in 2002 with service / program	Localities with information in 2005	% of localities in 2005 with service / program
OPORTUNIDADES available	70	0.757	65	0.985
Primary school in locality	69	0.986	66	0.970
Secondary school in locality	70	0.343	66	0.364
Technical/trade school in locality	70	0.071	66	0.045
Public health clinic in locality	70	0.743	66	0.652

Note: Tabulated from MxFLS Community Survey Module. In the original survey households from 70 different localities were surveyed. For the 2005 survey information from official sources was used as the primary source. If there was no information from an official source, unofficial information was used. When two or more official sources reported information and the information was conflicting, the variable was treated as a missing value.

Table 3.6b Select characteristics of localities in ENN sample

Locality characteristic	Mean	Std. Dev.
Percentage of household with electricity	0.755	
Percentage of household with running water	0.585	
Percentage of household with a sewage system	0.265	
Average household size	5.19	0.89
Altitude from sea level (m)	1168	867

Note: Based on 547 rural localities where there are households with children under 3 years of age in the *Encuesta Nacional de Nutricion.*

[31] The information is more complete, although maybe more unreliable, for the 2002 sample. In 2005 information was sought from both official and unofficial sources. Information from official sources was used as the primary source of information and if no official information was available then the unofficial information was used instead. If more than one official source of information was used, and the information was conflicting, i.e. one source responding yes to the presence of a secondary school in the locality and the other responding no, the variable was coded as missing. Given this fact, in 2005 there are more observations with missing information than in 2002.

[32] Oportunidades, originally named PROGRESA, is a conditional cash transfer (CCT) program aimed to alleviate current poverty through monetary and in-kind benefits.

3.5 Results

41. The results from the analyses on the impacts of rainfall and GDD shocks on household consumption and on the health outcomes of children are presented next. To examine whether or not weather shocks impact household consumption, equation (3.1) is estimated. Consumption is measured by the logarithm of per capita expenditures on all non-health related items. Health spending is subtracted from the total expenditures since most health spending follows illness and thus is not welfare improving (Thomas et *al*., 2010). The impact of weather on food expenditures given that households may spend on different spending categories after weather shocks is also examined. The average share of food expenditures in the sample is 41% of total expenditures (without considering health expenditures). Included in the expenditures are the estimated value of goods consumed from own production and the value of goods received as gifts.[33] That is, the expenditure measure used reflects wellbeing after taking into account any self-production or any coping mechanisms used by households to smooth consumption (such as selling assets, help from friends and relatives, or benefits from government programs). The extent to which these impacts have long-run implications on the poverty status of the future welfare and poverty status of the household is beyond the scope of this study.

42. Besides the weather shock variables the variables include capture household composition (number of children in the household, number of adult males in the household, number of adult females in the household), characteristics of the household head (years of schooling of the household head, gender of the household head, and the age of the household head), an asset index,[34] and the characteristics of the housing unit (presence of a kitchen, access to tapped water indoors, presence of a toilet, access to piped sewage or septic tank, electricity, and flooring material). These variables are all thought to explain expenditures. To control for the agro-climatic conditions and other time invariant characteristics locality fixed effects are introduced. To account for any systematic change between the two survey periods, the analysis controls for the survey wave. Furthermore to account for the potentially different amount of resources available depending on the season in which the household responded to the survey, season indicator variable is introduced. Appendix A2 gives the descriptive statistics of the variables used in the analyses.

3.5.1 Impacts of climatic variability on expenditures

43. Six different specifications were run with different measures of welfare and different measures of weather shocks based on equation (3.1). Given differences in the average climatic conditions in the North, and the Centre and South regions of the country besides including all rural households, the sample is limited to only those households in the North and to only those households in the Centre and South. The first set of specifications uses the (ln) per capita expenditures on all non-health items and the second set uses the (ln) per capita expenditures on food as the dependent variable. For each welfare measure 3 different specifications are estimated. The first uses weather shocks in the prior agricultural year's annual rainfall and annual GDD. The second uses weather shocks in the prior wet season and the third in the prior pre-*canícula* period. Fixed effects are first introduced at the state level and then at the locality level.

[33] Given the way in which the expenditure survey was administered, it is not possible to separate the value of consumption from own production from the value of goods received as gifts. For about 7% of the rural households more than 50% of their food comes from non-purchased sources. On average for a rural household about 7% of all food comes from non-purchased sources.

[34] The asset index is based on the principal factor analysis of how many parcels of land the household owns, whether or not the household owns their residence, another house, bicycle, motor vehicle, an electric device, a washing machine or a stove, a domestic appliance, machinery or a tractor, bulls or cows, horses or mules, pigs or goats, or poultry.

44. The results were relatively insensitive to which geographic fixed effects are used and the coefficient estimates for the weather shock variables were reported with locality fixed effects.[35]

45. In terms of rainfall, on average a rural Mexican household spends more on non-health items after negative annual rainfall shocks and more on food after a positive annual rainfall shock (Table 3.7). Namely, if the prior agricultural year was at least one standard deviation drier than the 1951-1985 average, the per capita expenditures are 14 percent higher and per capita expenditures on food are 18 percent greater when the annual rainfall is at least one standard deviation more than the 1951 - 1985 average.

[35] Appendix A3 shows the complete set of coefficient estimates for all rural households using fixed effects at the state and at the locality level.

Table 3.7 Weather shocks and expenditures per capita

Variable	All rural households			Central and South			North		
	Annual	Wet season	Pre-*canícula*	Annual	Wet season	Pre-*canícula*	Annual	Wet season	Pre-*canícula*
Dependent variable: Per capita expenditures (ln) in non-health items									
Negative rainfall shock	**0.141***	0.065	-0.000	**0.246*****	0.110	-0.075	0.057	-0.030	0.121
	(0.082)	(0.096)	(0.080)	**(0.090)**	(0.112)	(0.103)	(0.143)	(0.154)	(0.189)
Positive rainfall shock	0.068	-0.008	-0.014	**0.247****	0.109	-0.026	-0.024	-0.086	0.026
	(0.087)	(0.072)	(0.086)	**(0.100)**	(0.095)	(0.104)	(0.109)	(0.094)	(0.133)
Negative GDD shock	-0.023	0.022	-0.013	-0.039	0.183	**0.205****	0.076	-0.057	**-0.328*****
	(0.093)	(0.131)	(0.129)	(0.127)	(0.111)	**(0.095)**	(0.132)	(0.209)	**(0.107)**
Positive GDD shock	0.027	**0.183****	0.081	-0.127	0.142	0.075	0.032	0.149	0.092
	(0.092)	**(0.082)**	(0.115)	(0.115)	(0.090)	(0.126)	(0.151)	(0.134)	(0.180)
Number of observations	4,929	4,950	4,951	2,624	2,641	2,642	2,305	2,309	2,309
Dependent variable: Per capita expenditures (ln) in food									
Negative rainfall shock	-0.085	0.057	-0.028	-0.070	0.126	-0.103	-0.111	-0.150	0.131
	(0.109)	(0.111)	(0.148)	(0.185)	(0.167)	(0.192)	(0.103)	(0.111)	(0.246)
Positive rainfall shock	**0.179***	0.131	0.036	**0.404****	0.322	0.030	0.085	0.019	0.062
	(0.107)	(0.119)	(0.119)	**(0.184)**	(0.209)	(0.163)	(0.102)	(0.099)	(0.155)
Negative GDD shock	-0.249	-0.041	0.221	-0.045	0.329	**0.396***	**-0.369*****	**-0.276****	0.032
	(0.162)	(0.184)	(0.159)	(0.300)	(0.231)	**(0.198)**	**(0.122)**	**(0.129)**	(0.157)
Positive GDD shock	0.150	-0.062	-0.110	0.022	-0.281	-0.020	**0.156***	0.010	-0.193
	(0.099)	(0.140)	(0.154)	(0.164)	(0.244)	(0.221)	**(0.090)**	(0.166)	(0.203)
Number of observations	4,929	4,950	4,951	2,624	2,641	2,642	2,305	2,309	2,309

Source: Skoufias et al. (2011b)

Note: Robust standard errors in parentheses, clustered by locality, and *** p<0.01, ** p<0.05, * p<0.1. Calculated using MxFLS rounds 1 and 2 with locality level fixed effects. A negative weather shock identifies those municipalities which in the previous agricultural year (or wet season or pre-*canícula* period) had at least 1 standard deviation less rain (or GDD) than in an average year. Similarly, a positive weather shock identifies those municipalities which in the previous agricultural year (or wet season or pre-*canícula* period) had at least 1 standard deviation more rain (or GDD) than in an average year. Other independent variables included are: household composition (number of children in the household, number of adult males in the household, number of adult females in the household), characteristics of the household head (sex, age and education), assets (index based on how many parcels of land the household owns, whether or not the household owns their residence, another house, bicycle, motor vehicle, an electric device, a washing machine or a stove, a domestic appliance, machinery or a tractor, bulls or cows, horses or mules, pigs or goats, or poultry), characteristics of the housing unit (presence of a kitchen, access to tapped water indoors, toilet, access to piped sewage or septic tank, electricity, floor type).

46. The results are quite different when equation (3.1) is estimated separately for each of the two regions—North and Center/South.[36] In the North, the more arid region of the country and with a higher percentage of irrigated land, a negative rainfall shock has no impacts on expenditures. However, for the Centre/South region both negative and positive rainfall shocks are associated with higher expenditures on non-health items (by 25%) and positive rainfall shocks are also associated with higher expenditures on food (Table 3.7). The results suggest that in the Centre/South regions both types of rainfall shocks are welfare improving. [37]

47. The results in terms of temperature indicate that the warmer than average wet seasons are associated with 18 percent higher expenditures per capita (Table 3.7). That is, on average, for the sample of Mexican households, warmer weather is in fact welfare improving. However, when the sample is separated in two—North and Center/South—positive wet season GDD shocks no longer are statistically significantly welfare improving.[38] In addition, negative GDD shocks during the pre-*canícula* period are associated with higher expenditures on all non-health items as well as higher expenditures on food in the Central/South sample and lower non-health expenditures in the North sample. In the North, food expenditures are also lower after a negative GDD shock during the prior agricultural year (37% lower) and during the prior wet season (28% lower). These results reflect Galindo's (2009) findings of variable impacts on agricultural production from changes in temperature by region and by the type of crop cultivated.

48. It is interesting to note that in the sample, on average, unusual weather (that is, weather that is at least one standard deviation from the mean) is never associated with lower welfare, with the exception of negative GDD shocks in the North. That is, even if the shocks do have a negative impact on agricultural production, the households do not see a reduction in their expenditures. This suggests that households are either able to protect themselves *ex-ante* by changing their agricultural practices in response to the weather shocks, or in the case of reduced agricultural revenue, that households are able *ex-post* to keep expenditures (and welfare) from deteriorating by drawing down on their assets, or receiving help from formal and informal safety networks, such as relatives or social programs, or accessing credit. While these types of responses used by the households are deserving of deeper analysis they are not within the scope of this study.

3.5.2 Heterogeneity of impacts

49. The average impacts may mask difference in response between types of households to weather shocks. The difference in welfare levels by the sex and by the educational attainment of the household head was examined by estimating equation (3.2). In general, a household headed by a female is never worse off because of a weather shock than a household headed by a male. In fact, if there is a positive annual or pre-*canícula* period rainfall shock female headed households have a higher per capita expenditure than male headed households by 16 percent and 25 percent, respectively (Table 3.8a). Furthermore, with positive annual rainfall shocks food expenditures per capita are 28 percent higher in

[36] The North includes the states of Baja California, Baja California Sur, Chihuahua, Coahuila, Durango, Nuevo Leon, Sinaloa, Sonora, Tamaulipas, and Zacatecas. All the other states are part of Center/South region.
[37] It is possible that the higher expenditure may be a consequence of the higher local prices faced by households rather than due to an increase in the quantity of goods consumed. We tried to shed some light on this issue, by regressing the average price (based on one to three stores) of a food item on the weather shocks controlling for state fixed effects. We found rather mixed results since for those municipalities in the Center/South of the country, the prices of five items are positively correlated with a positive rainfall shock (potato, lemon, chili, pork, and white bread) and four items are negatively correlated (tomato, apple, beef, and whole fish).
[38] The coefficient estimate is positive for both samples

female headed households than in male headed ones (Table 3.8b). Similarly a female headed household in a municipality with a positive pre-*canícula* GDD shock has, on average, 44 percent higher per capita expenditures on food than male headed households.

50. Examining the households by the two regions—North, Center/South—separately, differences between female and male headed households are found. Female headed households in the central and southern parts of the country have higher expenditures after a positive rainfall shock than the region's male headed households. Both non-health expenditures as well as food expenditures are between 28 percent and 42 percent higher, respectively. In contrast, female headed households in the North have 30 percent lower non-health expenditures than male headed households after a positive wet season rainfall shock. However, female headed households in the North are not statistically significantly different from male headed households in terms of food expenditures, suggesting that food expenditures are protected from the effects of the positive rainfall shock. Also, it is the northern female headed households who are positively affected by a positive pre-*canícula* GDD shock.

51. The education level of the household head also matters (Table 3.9a and 3.9b). On average, for some weather shocks, households where the head has not completed primary school have lower non-health and food expenditures per capita than households where the head has completed primary school. In terms of rainfall, on average households with less educated heads have 16% lower non-health expenditures after a positive pre-*canícula* rainfall shock, and 29% lower food expenditures after a negative pre-*canícula* rainfall shock. After separate analyses for the two regions, while statistically significant differences in the impacts of rainfall shocks on non-health expenditures are not found, regional differences on food expenditures are. In the northern states, households with less educated heads have 38 percent higher expenditures on food and 51 percent lower expenditures on food than households where the head has completed primary school after a negative rainfalls shock during the prior year and the prior pre-*canícula*, respectively.

52. Less educated households are more affected by GDD shocks than rainfall shocks and these differential effects are observed only in food expenditures. The less educated households have on average 14% lower food expenditures after a negative annual GDD shock and 34% lower food expenditures after a positive annual GDD shock than household where the household head has completed primary schooling. Separating the household regionally, no differential impacts either in the Center/South grouping or in the North after a negative GDD shock are observed.[39] However, large negative differentials in the North after positive GDD shocks are observed, regardless of the timing of the shock during the agricultural year (i.e., during the wet season or during the pre-*canícula* period). The negative differential suggests that households with less educated heads are less able to modify their agricultural practices to take advantage of more advantageous weather or to counter negative impacts of unfavorable weather. Another possibility is that households with less educated heads cannot access other mechanisms to offset negative effects of weather shocks on welfare. The only exception is a negative rainfall shock in the North when the less educated households do not have lower food expenditures whereas the more educated households do. This peculiar differential effect could be explained if crop choice is determined by education.

[39] The coefficient estimates for negative annual GDD shocks are negative in both regions, but not statistically significant.

Table 3.8a Per capita expenditures (ln) on non-health items

Variables	All rural households			Central and South			North		
	Annual	Wet season	Pre-*canícula*	Annual	Wet season	Pre-*canícula*	Annual	Wet season	Pre-*canícula*
HH head is female	0.007	0.011	-0.084	-0.095	-0.114	-0.158	0.106	0.151	-0.001
	(0.070)	(0.083)	(0.083)	(0.113)	(0.111)	(0.122)	(0.079)	(0.109)	(0.108)
Negative rainfall shock	**0.153***	0.066	-0.010	**0.269****	0.130	-0.107	0.043	-0.051	0.118
	(0.084)	(0.101)	(0.080)	**(0.103)**	(0.130)	(0.104)	(0.140)	(0.153)	(0.191)
... X female HH head	-0.089	-0.018	0.049	-0.123	-0.091	0.153	0.211	0.209	0.000
	(0.207)	(0.236)	(0.232)	(0.258)	(0.329)	(0.243)	(0.191)	(0.176)	(0.000)
Positive rainfall shock	0.032	-0.007	-0.065	0.170	0.042	-0.118	-0.013	-0.021	0.043
	(0.088)	(0.067)	(0.086)	(0.104)	(0.089)	(0.099)	(0.107)	(0.087)	(0.150)
... X female HH head	**0.163***	-0.004	**0.250***	**0.351****	**0.284****	**0.423****	-0.042	**-0.303***	-0.083
	(0.095)	(0.120)	**(0.128)**	**(0.135)**	**(0.127)**	**(0.160)**	(0.117)	**(0.167)**	(0.159)
Negative GDD shock	0.016	0.043	-0.016	-0.016	**0.180***	**0.199***	0.103	-0.064	**-0.346*****
	(0.096)	(0.132)	(0.126)	(0.123)	**(0.106)**	**(0.099)**	(0.146)	(0.217)	**(0.112)**
... X female HH head	-0.153	-0.092	-0.020	-0.093	-0.051	-0.076	-0.108	0.014	0.102
	(0.112)	(0.115)	(0.123)	(0.166)	(0.163)	(0.169)	(0.135)	(0.123)	(0.161)
Positive GDD shock	0.043	**0.197****	0.057	-0.134	0.126	0.053	0.064	0.179	0.068
	(0.095)	**(0.090)**	(0.115)	(0.123)	(0.117)	(0.131)	(0.156)	(0.144)	(0.180)
... X female HH head	-0.078	-0.077	0.132	0.061	0.056	0.062	-0.189	-0.166	0.148
	(0.140)	(0.163)	(0.138)	(0.169)	(0.238)	(0.281)	(0.208)	(0.212)	(0.114)

Source: Skoufias et al. (2011b)

Note: Robust standard errors in parentheses, clustered by locality, and *** p<0.01, ** p<0.05, * p<0.1. Calculated using MxFLS rounds 1 and 2 with locality level fixed effects. A negative weather shock identifies those municipalities which in the previous agricultural year (or wet season or pre-*canícula* period) had at least 1 standard deviation less rain (or GDD) than in an average year. Similarly, a positive weather shock identifies those municipalities which in the previous agricultural year (or wet season or pre-*canícula* period) had at least 1 standard deviation more rain (or GDD) than in an average year. Other independent variables included are: household composition (number of children in the household, number of adult males in the household, number of adult females in the household), characteristics of the household head (sex, age and education), assets (index based on how many parcels of land the household owns, whether or not the household owns their residence, another house, bicycle, motor vehicle, an electric device, a washing machine or a stove, a domestic appliance, machinery or a tractor, bulls or cows, horses or mules, pigs or goats, or poultry), characteristics of the housing unit (presence of a kitchen, access to tapped water indoors, toilet, access to piped sewage or septic tank, electricity, floor type).

Table 3.8b Per capita expenditures (ln) on food

Variables	All rural households			Central and South			North		
	Annual	Wet season	Pre-*canícula*	Annual	Wet season	Pre-*canícula*	Annual	Wet season	Pre-*canícula*
HH head is female	-0.042	-0.080	-0.082	-0.060	-0.067	-0.063	-0.019	-0.098	-0.105
	(0.129)	(0.126)	(0.109)	(0.199)	(0.172)	(0.153)	(0.165)	(0.170)	(0.147)
Negative rainfall shock	-0.080	0.032	-0.024	-0.081	0.102	-0.102	-0.066	-0.174	0.120
	(0.106)	(0.117)	(0.148)	(0.183)	(0.175)	(0.195)	(0.111)	(0.117)	(0.246)
... X female HH head	-0.059	0.190	-0.061	0.060	0.136	-0.015	-0.540	0.290	0.000
	(0.190)	(0.187)	(0.223)	(0.218)	(0.240)	(0.248)	(0.603)	(0.191)	(0.000)
Positive rainfall shock	0.122	0.087	-0.015	0.320	0.235	-0.036	0.055	0.019	0.055
	(0.115)	(0.130)	(0.119)	(0.206)	(0.232)	(0.163)	(0.097)	(0.120)	(0.157)
... X female HH head	**0.279****	0.208	0.238	**0.395***	**0.384***	0.288	0.123	0.012	0.079
	(0.121)	(0.141)	(0.161)	**(0.231)**	**(0.195)**	(0.215)	(0.121)	(0.204)	(0.170)
Negative GDD shock	-0.218	-0.021	0.218	0.005	0.352	**0.400****	**-0.378*****	**-0.276***	0.017
	(0.153)	(0.174)	(0.151)	(0.288)	(0.213)	**(0.194)**	**(0.134)**	**(0.143)**	(0.166)
... X female HH head	-0.121	-0.083	-0.006	-0.166	-0.154	-0.085	-0.003	0.079	0.110
	(0.154)	(0.134)	(0.154)	(0.232)	(0.179)	(0.222)	(0.175)	(0.159)	(0.157)
Positive GDD shock	0.103	-0.107	-0.189	-0.018	-0.303	-0.080	0.118	-0.056	-0.277
	(0.116)	(0.149)	(0.168)	(0.211)	(0.254)	(0.237)	(0.092)	(0.187)	(0.220)
... X female HH head	0.244	0.244	**0.438****	0.238	0.128	0.248	0.243	0.371	**0.567****
	(0.178)	(0.185)	**(0.171)**	(0.271)	(0.198)	(0.217)	(0.249)	(0.257)	**(0.225)**
Number of observations	4,929	4,950	4,951	2,624	2,641	2,642	2,305	2,309	2,309

Source: Skoufias et al. (2011b)

Note: Robust standard errors in parentheses, clustered by locality, and *** p<0.01, ** p<0.05, * p<0.1. Calculated using MxFLS rounds 1 and 2 with locality level fixed effects. A negative weather shock identifies those municipalities which in the previous agricultural year (or wet season or pre-*canícula* period) had at least 1 standard deviation less rain (or GDD) than in an average year. Similarly, a positive weather shock identifies those municipalities which in the previous agricultural year (or wet season or pre-*canícula* period) had at least 1 standard deviation more rain (or GDD) than in an average year. Other independent variables included are: household composition (number of children in the household, number of adult males in the household, number of adult females in the household), characteristics of the household head (sex, age and education), assets (index based on how many parcels of land the household owns, whether or not the household owns their residence, another house, bicycle, motor vehicle, an electric device, a washing machine or a stove, a domestic appliance, machinery or a tractor, bulls or cows, horses or mules, pigs or goats, or poultry), characteristics of the housing unit (presence of a kitchen, access to tapped water indoors, toilet, access to piped sewage or septic tank, electricity, floor type).

Table 3.9a Per capita (ln) expenditure on non-health items

Variables	All rural households			Central and South			North		
	Annual	Wet season	Pre-*canícula*	Annual	Wet season	Pre-*canícula*	Annual	Wet season	Pre-*canícula*
HH head has not completed primary school	-0.154**	-0.180***	-0.168**	-0.264***	-0.348***	-0.303***	-0.089	-0.037	-0.087
	(0.064)	(0.067)	(0.066)	(0.078)	(0.083)	(0.088)	(0.107)	(0.108)	(0.093)
Negative rainfall shock	**0.184***	0.061	0.079	**0.233***	0.023	-0.107	0.085	0.023	0.277
	(0.100)	(0.123)	(0.097)	**(0.137)**	(0.176)	(0.108)	(0.160)	(0.157)	(0.194)
... X no primary school	-0.075	0.006	-0.127	0.017	0.131	0.050	-0.051	-0.099	-0.365
	(0.136)	(0.149)	(0.119)	(0.196)	(0.256)	(0.122)	(0.140)	(0.116)	(0.221)
Positive rainfall shock	0.090	0.012	0.090	**0.282*** **	0.096	0.020	-0.011	-0.026	0.117
	(0.091)	(0.075)	(0.086)	**(0.099)**	(0.101)	(0.098)	(0.118)	(0.095)	(0.138)
... X no primary school	-0.038	-0.036	**-0.159** **	-0.050	0.030	-0.062	-0.025	-0.107	-0.154
	(0.075)	(0.074)	**(0.079)**	(0.081)	(0.086)	(0.096)	(0.108)	(0.118)	(0.122)
Negative GDD shock	0.001	0.021	-0.041	-0.074	0.095	0.114	0.106	-0.004	**-0.316** **
	(0.100)	(0.135)	(0.124)	(0.124)	(0.122)	(0.106)	(0.155)	(0.216)	**(0.129)**
... X no primary school	-0.042	0.001	0.039	0.055	0.160	0.128	-0.054	-0.106	-0.006
	(0.072)	(0.076)	(0.072)	(0.084)	(0.095)	(0.091)	(0.126)	(0.141)	(0.142)
Positive GDD shock	0.032	**0.175***	0.078	-0.074	0.102	0.041	0.061	0.209	0.139
	(0.094)	**(0.092)**	(0.109)	(0.129)	(0.125)	(0.190)	(0.153)	(0.144)	(0.150)
... X no primary school	-0.007	0.016	0.007	-0.076	0.053	0.062	-0.054	-0.119	-0.096
	(0.086)	(0.104)	(0.094)	(0.102)	(0.200)	(0.202)	(0.124)	(0.114)	(0.113)

Source: Skoufias et al. (2011b)

Note: Robust standard errors in parentheses, clustered by locality, and *** p<0.01, ** p<0.05, * p<0.1. Calculated using MxFLS rounds 1 and 2 with locality level fixed effects. A negative weather shock identifies those municipalities which in the previous agricultural year (or wet season or pre-*canícula* period) had at least 1 standard deviation less rain (or GDD) than in an average year. Similarly, a positive weather shock identifies those municipalities which in the previous agricultural year (or wet season or pre-*canícula* period) had at least 1 standard deviation more rain (or GDD) than in an average year. Other independent variables included are: household composition (number of children in the household, number of adult males in the household, number of adult females in the household), characteristics of the household head (sex, age and education), assets (index based on how many parcels of land the household owns, whether or not the household owns their residence, another house, bicycle, motor vehicle, an electric device, a washing machine or a stove, a domestic appliance, machinery or a tractor, bulls or cows, horses or mules, pigs or goats, or poultry), characteristics of the housing unit (presence of a kitchen, access to tapped water indoors, toilet, access to piped sewage or septic tank, electricity, floor type).

Table 3.9b Per capita (ln) expenditure on food

Variables	All rural households			Central and South			North		
	Annual	Wet season	Pre-*canícula*	Annual	Wet season	Pre-*canícula*	Annual	Wet season	Pre-*canícula*
HH has not completed primary school	0.080	0.052	0.069	-0.025	-0.103	-0.039	0.159*	0.182	0.119
	(0.064)	(0.081)	(0.071)	(0.089)	(0.098)	(0.100)	(0.081)	(0.117)	(0.097)
Negative rainfall shock	-0.153	-0.002	0.151	-0.111	0.005	0.000	**-0.317****	-0.161	**0.362***
	(0.127)	(0.147)	(0.136)	(0.185)	(0.198)	(0.197)	**(0.151)**	(0.150)	**(0.192)**
... X no primary school	0.118	0.100	**-0.285***	0.063	0.174	-0.146	**0.376***	0.012	**-0.509****
	(0.180)	(0.185)	**(0.157)**	(0.226)	(0.259)	(0.196)	**(0.194)**	(0.171)	**(0.199)**
Positive rainfall shock	**0.210***	0.156	0.132	**0.406***	0.295	0.097	0.160	0.103	0.099
	(0.119)	(0.136)	(0.149)	**(0.240)**	(0.243)	(0.210)	(0.117)	(0.115)	(0.155)
... X no primary school	-0.035	-0.046	-0.151	-0.002	0.046	-0.089	-0.120	-0.159	-0.057
	(0.101)	(0.111)	(0.120)	(0.184)	(0.175)	(0.166)	(0.092)	(0.123)	(0.103)
Negative GDD shock	-0.169	0.021	**0.272***	-0.023	0.342	**0.398***	**-0.273****	**-0.227***	0.089
	(0.173)	(0.191)	**(0.157)**	(0.311)	(0.246)	**(0.206)**	**(0.125)**	**(0.126)**	(0.167)
... X no primary school	**-0.135***	-0.100	-0.083	-0.036	0.008	-0.013	-0.142	-0.085	-0.068
	(0.080)	(0.086)	(0.085)	(0.097)	(0.117)	(0.117)	(0.106)	(0.116)	(0.125)
Positive GDD shock	**0.356*****	0.041	-0.033	0.137	-0.396	-0.220	**0.427*****	0.259	0.020
	(0.092)	(0.144)	(0.162)	(0.153)	(0.316)	(0.384)	**(0.103)**	(0.157)	(0.167)
... X no primary school	**-0.344*****	-0.196	-0.152	-0.168	0.189	0.338	**-0.531*****	**-0.469****	**-0.452***
	(0.103)	(0.155)	(0.192)	(0.170)	(0.247)	(0.325)	**(0.135)**	**(0.172)**	**(0.235)**
Number of observations	4,929	4,950	4,951	2,624	2,641	2,642	2,305	2,309	2,309

Source: Skoufias et al. (2011b)

Note: Robust standard errors in parentheses, clustered by locality, and *** p<0.01, ** p<0.05, * p<0.1. Calculated using MxFLS rounds 1 and 2 with locality level fixed effects. A negative weather shock identifies those municipalities which in the previous agricultural year (or wet season or pre-*canícula* period) had at least 1 standard deviation less rain (or GDD) than in an average year. Similarly, a positive weather shock identifies those municipalities which in the previous agricultural year (or wet season or pre-*canícula* period) had at least 1 standard deviation more rain (or GDD) than in an average year. Other independent variables included are: household composition (number of children in the household, number of adult males in the household, number of adult females in the household), characteristics of the household head (sex, age and education), assets (index based on how many parcels of land the household owns, whether or not the household owns their residence, another house, bicycle, motor vehicle, an electric device, a washing machine or a stove, a domestic appliance, machinery or a tractor, bulls or cows, horses or mules, pigs or goats, or poultry), characteristics of the housing unit (presence of a kitchen, access to tapped water indoors, toilet, access to piped sewage or septic tank, electricity, floor type).

3.5.3 Impacts of climatic variability on child health

53. To analyze the impacts of weather on health outcomes the study focuses on children 36 months or younger living in rural areas. This is the age group most likely to suffer negative health outcomes and any impacts potentially have long term consequences. Between the ages of zero and three the growth rates are faster than at any other point and thus any delays have a greater probability of affecting overall growth (Martorell, 1999). Shrimpton et al. (2001) find that in developing countries although the children when born are on average at the mean of standardized height-for-age there is a sharp decline in the height-for-age from ages 0 months to 24 months and no subsequent catching up in the first 5 year of life.

54. Furthermore, Martorell et al. (2010) find evidence that weight gain the first 2 years of life had a strong impact on schooling outcomes whereas weight gain between 2 years and 4 years of life had a weaker impact. Alderman (2010) emphasizes the fact that weather caused nutritional shocks experienced in the first years of life have lasting impacts on productivity even if the household is able to later on overcome poverty. Victora et al. (2008) find in their meta-analysis that height-for-age and weight-for-age are strong predictors of school achievement and that stunting between 12 and 36 months of age is associated with poorer cognitive development.

55. The impacts of weather on child outcomes was also estimated. The standardized height-for-age z-score for children 36-months or younger were used as the measure of health.[40] Unlike weight-for-age, height-for-age is not as sensitive to very short-term and immediate scarcities or illness, but would capture more chronic conditions.[41] Given that all the data were collected during the 1999 dry season, the year and season terms drop out. Given that the weather data are at the municipal level, state level fixed effects were used to control for the time invariant characteristics, such as the agro-climatic conditions at the state level.

56. Besides the measures of weather shocks, other information was included on:

- household composition (the number of children, the number of adult males, and the number of adult females);
- on mother's characteristics (mother's education, height, and whether she speaks an indigenous language);
- information about the child (gender, if the child has an older sibling who was born alive within 2 years of the child's birth, multiple birth, the birth order of the child, whether the child was characterized as very small at birth, and the age of the child at the time anthropometric measurement was taken);
- an asset index;[42]
- housing characteristics (presence of indoor toilet, tap water, type of floor);
- and information about the child's locality (altitude) as regressors in the analyses.[43]

[40] The study used, WHO Anthro for personal computers, version 3, 2009: Software for assessing growth and development of the world's children. Geneva: WHO, 2009 (http://www.who.int/childgrowth/software/en/) for calculating the standardized height-for-age scores.

[41] The measure does not capture any differences in mortality from unusual weather.

[42] The asset index is based on the principal factor analysis of the household's ownership of a radio, a television, a VCR, a telephone, a computer, a refrigerator, a washing machine, a stove, a heater, and motor vehicle.

[43] Only when analyzing the effects by participation in a nutritional program, we also include nutritional program participation as a regressor.

57. The variables used in the analyses are described in Table 3.10. Given the differences in the average climate in the North and in the Centre/South regions, the children in each region are analyzed separately.

58. There are 1,995 rural children less than 36 months in the ENN dataset. The sample consisted of only 1,540 children.[44] The study only included those children whose mother has not moved in the past year to ensure that the weather shocks match what the child experienced. Of the excluded children, there are 138 children with missing height information and 91 children with improbable z-scores,[45] suggesting data entry errors. The other excluded children have incomplete information on the covariates. The children measured (and with probable z-scores) are statistically significantly older than those who are not measured. This poses a problem given that those children who were not measured are different, and they may be systematically different in other characteristics besides age as well.[46] Furthermore, since only a few children (less than 2 percent of the sample) experienced a positive pre-*canícula* rainfall shock, the coefficient estimates for positive pre-*canícula* rainfall should be interpreted with caution (Table 3.11).

59. Bearing these caveats in mind, Table 3.12 summarizes the average relationship between weather shocks and height-for-age. The full results for the specification are included in Appendix A4. A positive rainfall shock is associated with lower height-for-age scores. This is true for both a positive annual and a positive wet season rainfall shocks. The coefficient estimate of around 0.5 points is non-trivial given that a z-score of -2 is indicative of stunting and the average height-for-age z-score for the children in the sample is -1.09.[47] The earlier results based on the MxFLS consumption data suggest that there is no correlation between a positive rainfall shock and non-health expenditures, and that households spend more on food. Yet, the height of children under three years of age is negatively affected after such a shock. Together, these results suggest that direct environmental effects are important and that an analysis of the impacts of weather shocks at the household level has serious limitations in terms of capturing the impacts of these shocks on certain individuals in the household.

60. The negative impacts of a positive rainfall shock during the prior agricultural year or wet season are consistent in both of the regional subsamples (Table 3.12). The biggest impact is from a positive rainfall shock during the wet season in the North. Children who experienced such a shock are 0.7 points shorter than children who experienced an average amount of rain. Negative rainfall shocks appear to have different impacts in the Centre/South regions than in the North. Children living in the Center/South region are taller if the prior agricultural year or wet season was at least one standard deviation drier than average. In the North, however, children are shorter after such a shock.

61. Not all children experience the same kind of health outcomes from weather shocks. Tables 3.13, 3.14, and 3.15 present the results between weather shocks and sex of the child, the mother's educational level, and the household's participation in a supplemental nutrition program, respectively.

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[44] This is the pre-*canícula* sample without nutritional supplement program variables and access to health care included as explanatory variables.

[45] That is, their height-for-age z-scores are less than -6 or more than 6.

[46] If those who are not measured are more likely to be sick (and some of these illness are due to the weather), then the coefficient estimates of the weather shock variables is likely to provide a lower bound of the impact of the weather shock.

[47] The average does include the 144 children who lived in a locality where the rainfall was at least one standard deviation more than on average. However, excluding these children the average z-score does not change significantly and is -1.08.

Table 3.10 Characteristics of rural children

Variable	All		Center/South		North	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Number of adult males in hh	1.375	0.942	1.349	0.857	1.434	1.114
Number of adult females in hh	1.502	0.912	1.475	0.799	1.566	1.132
Number of children (16 yrs or younger) in hh	3.449	1.893	3.693	2.000	2.876	1.464
Mother's height	148	23	146	22	152	24
Mother speaks an indigenous language	0.164		0.198		0.085	
Education mother: has not completed primary	0.456		0.526		0.293	
Sex	0.517		0.518		0.514	
Birth order	3.372	2.480	3.651	2.679	2.720	1.775
Multiple birth	0.017		0.017		0.017	
Categorized as very small at birth	0.071		0.071		0.069	
Has an older sibling less than 2 years apart	0.184		0.195		0.158	
Age: 6 months to 12 months	0.180		0.174		0.193	
Age: 12 months to 24 months	0.333		0.332		0.336	
Age: 24 months to 36 months	0.329		0.338		0.306	
Altitude of locality (in km)	1.192	0.892	1.305	0.870	0.929	0.888
Household asset score	-0.305	0.719	-0.487	0.652	0.120	0.688
Floor of dirt	0.338		0.383		0.234	
No tap water to kitchen or bath	0.866		0.908		0.766	
No proper indoor toilet	0.745		0.758		0.716	
Observations	1540		1079		461	

Source: Data come from the *Encuesta Nacional de Salud*.

Table 3.11 Number of observations for different sub-populations and types of weather shocks

Sub population	Rainfall						GDD					
	Negative shock			Positive shock			Negative shock			Positive shock		
	Annual	Wet season	Pre-*canícu-la*	Annual	Wet season	Pre-*canícu-la*	Annual	Wet season	Pre-*canícu-la*	Annual	Wet season	Pre-*canícu-la*
Boys	117	128	417	59	50	7	102	57	75	238	241	227
Girls	106	127	444	85	73	14	104	73	81	238	274	249
Mother has completed primary school	112	124	443	79	77	9	100	62	75	267	301	262
Mother hasn't completed primary school	111	131	418	65	46	12	106	68	81	209	214	214
Not in a nutritional program	107	145	463	90	79	19	85	54	68	254	270	272
In a nutritional program	116	110	398	54	44	2	121	76	88	220	245	204
Total number of observations	1,536	1,536	1,540	1,536	1,536	1,540	1,536	1,536	1,540	1,536	1,536	1,540

Note: Based on ENN and includes all children under 36 months and with non-missing information on all covariates.

Table 3.12 Impact of weather on child's height-for-age

Variables	All			Centre/South			North		
	Annual	Wet season	Pre-*canícula*	Annual	Wet season	Pre-*canícula*	Annual	Wet season	Pre-*canícula*
Negative rainfall shock	0.185	0.246	-0.025	**0.384***	**0.479****	0.127	-0.265	**-0.294****	**-0.371***
	(0.150)	(0.166)	(0.128)	**(0.204)**	**(0.228)**	(0.149)	(0.174)	**(0.142)**	**(0.199)**
Positive rainfall shock	**-0.526*****	**-0.513*****	0.960^	**-0.518*****	**-0.478*****	**5.143***^**	**-0.524*****	**-0.701***	-0.401^
	(0.111)	**(0.132)**	(1.040)	**(0.134)**	**(0.142)**	**(1.023)**	**(0.143)**	**(0.367)**	(0.257)
Negative GDD shock	0.004	0.032	0.008	0.045	-0.081	-0.062	-0.075	0.113	-0.034
	(0.152)	(0.167)	(0.178)	(0.177)	(0.189)	(0.217)	(0.256)	(0.369)	(0.211)
Positive GDD shock	-0.100	-0.084	-0.152	-0.062	-0.048	-0.121	**-0.343***	-0.251	-0.313
	(0.090)	(0.092)	(0.105)	(0.105)	(0.110)	(0.127)	**(0.176)**	(0.157)	(0.189)
Observations	1,536	1,536	1,540	1,079	1,079	1,079	457	457	461

Source: Skoufias et al. (2011b)

Note: Robust standard errors in parentheses, clustered by locality, and *** p<0.01, ** p<0.05, * p<0.1.

^ Less than 2% of the sample experienced a positive rainfall shock in the pre-*canícula* period.

Calculated using ENN with state fixed effects. A negative weather shock identifies those municipalities which in the previous agricultural year (or wet season or pre-*canícula* period) had at least 1 standard deviation less rain (or GDD) than in an average year. A positive weather shock identifies those municipalities which in the previous agricultural year (or wet season or pre-*canícula* period (had at least 1 standard deviation more rain (or GDD) than in an average year. Other independent variables included are: household composition (number of children in the household, number of adult males in the household, number of adult females in the household), characteristics of the mother (height, speaks an indigenous language and education), characteristics of the child (age, sex, birth order, multiple birth, small at birth, older sibling less than 2 years older, household assets and housing characteristics (asset index, presence of a kitchen, access to tapped water indoors, toilet, floor type), and altitude of locality.

Table 3.13 Impact of weather shocks on height-for-age, by sex

Variables	All			Center/South			North		
	Annual	Wet season	Pre-*canícula*	Annual	Wet season	Pre-*canícula*	Annual	Wet season	Pre-*canícula*
Girl	-0.155	-0.178	-0.091	-0.186	-0.288**	-0.228	0.010	0.146	0.160
	(0.114)	(0.116)	(0.119)	(0.142)	(0.144)	(0.167)	(0.194)	(0.179)	(0.197)
Negative rainfall shock	0.139	0.216	0.006	0.253	0.287	0.051	-0.140	-0.181	-0.080
	(0.192)	(0.190)	(0.148)	(0.258)	(0.279)	(0.179)	(0.285)	(0.203)	(0.258)
... X girl	0.110	0.082	-0.065	0.272	0.410	0.139	-0.274	-0.275	**-0.506****
	(0.279)	(0.250)	(0.159)	(0.352)	(0.353)	(0.203)	(0.439)	(0.321)	**(0.251)**
Positive rainfall shock	**-0.518*****	**-0.519****	0.562^	**-0.651*****	**-0.670*****	**5.331***^**	-0.153	-0.213	-0.245^
	(0.188)	**(0.213)**	(0.902)	**(0.226)**	**(0.232)**	**(1.105)**	(0.225)	(0.458)	(0.299)
... X girl	-0.013	0.001	0.549^	0.266	0.326		**-0.699****	**-1.103*****	-0.285^
	(0.226)	(0.282)	(0.553)	(0.252)	(0.298)		**(0.316)**	**(0.263)**	(0.248)
Negative GDD shock	0.072	0.131	0.139	0.273	0.101	0.180	-0.257	-0.012	0.005
	(0.195)	(0.267)	(0.220)	(0.226)	(0.328)	(0.280)	(0.331)	(0.573)	(0.300)
... X girl	-0.142	-0.167	-0.276	-0.464	-0.310	-0.471	0.335	0.171	-0.093
	(0.212)	(0.302)	(0.272)	(0.287)	(0.368)	(0.304)	(0.300)	(0.548)	(0.533)
Positive GDD shock	**-0.297****	**-0.300****	**-0.294****	**-0.291***	**-0.357****	**-0.282***	-0.285	-0.127	-0.251
	(0.126)	**(0.121)**	**(0.131)**	**(0.149)**	**(0.144)**	**(0.158)**	(0.267)	(0.230)	(0.250)
... X girl	**0.382****	**0.412****	0.270	**0.448****	**0.602*****	0.302	-0.092	-0.239	-0.112
	(0.178)	**(0.169)**	(0.179)	**(0.214)**	**(0.206)**	(0.221)	(0.327)	(0.273)	(0.294)
Number of observations	1,536	1,536	1,540	1,079	1,079	1,079	457	457	461

Source: Skoufias et al. (2011b)

Note: Robust standard errors in parentheses, clustered by locality, and *** p<0.01, ** p<0.05, * p<0.1.

^ Less than 2% of the sample experienced a positive rainfall shock in the pre-*canícula* period.

Calculated using ENN with state fixed effects. A negative weather shock identifies those municipalities which in the previous agricultural year (or wet season or pre-*canícula* period) had at least 1 standard deviation less rain (or GDD) than in an average year. Other independent variables included are: household composition (number of children in the household, number of adult males in the household, number of adult females in the household), characteristics of the mother (height, speaks an indigenous language and education), characteristics of the child (age, sex, birth order, multiple birth, small at birth, older sibling less than 2 years older, household assets and housing characteristics (asset index, presence of a kitchen, access to tapped water indoors, toilet, floor type), and altitude of locality.

Table 3.14 Impact of weather shocks on height-for-age, by mother's education

Variables	All			Center/South			North		
	Annual	Wet season	Pre-*canícula*	Annual	Wet season	Pre-*canícula*	Annual	Wet season	Pre-*canícula*
Mother has not completed primary school	-0.213**	-0.207**	-0.162	-0.120	-0.138	-0.068	-0.222	-0.172	-0.146
	(0.106)	(0.104)	(0.109)	(0.121)	(0.127)	(0.146)	(0.240)	(0.218)	(0.186)
Negative rainfall shock	0.140	0.159	-0.042	**0.421***	0.426	0.166	-0.252	-0.305	**-0.433***
	(0.190)	(0.212)	(0.141)	**(0.246)**	(0.339)	(0.157)	(0.239)	(0.196)	**(0.233)**
... X mother has not completed primary school	0.068	0.148	0.028	-0.046	0.102	-0.087	-0.004	0.050	0.074
	(0.321)	(0.265)	(0.161)	(0.393)	(0.410)	(0.189)	(0.424)	(0.329)	(0.306)
Positive rainfall shock	**-0.447****	**-0.457****	**1.807*^**	**-0.462***	**-0.399***	**5.183***^**	**-0.349***	-0.522	0.010^
	(0.181)	**(0.196)**	**(1.038)**	**(0.246)**	**(0.233)**	**(1.011)**	**(0.196)**	(0.532)	(0.406)
... X mother has not completed primary school	-0.155	-0.143	**-1.674**^**	-0.088	-0.157		-0.313	-0.360	**-0.604*^**
	(0.241)	(0.282)	**(0.722)**	(0.326)	(0.332)		(0.399)	(0.728)	**(0.341)**
Negative GDD shock	-0.105	-0.091	0.111	0.057	-0.147	-0.034	-0.225	-0.077	-0.040
	(0.192)	(0.201)	(0.226)	(0.247)	(0.186)	(0.211)	(0.295)	(0.592)	(0.369)
... X mother has not completed primary school	0.206	0.218	-0.222	-0.017	0.105	-0.060	0.414	0.398	-0.043
	(0.241)	(0.276)	(0.297)	(0.299)	(0.289)	(0.280)	(0.402)	(0.680)	(0.650)
Positive GDD shock	-0.125	-0.072	-0.161	0.025	0.066	-0.070	**-0.452****	-0.289	**-0.469****
	(0.117)	(0.119)	(0.131)	(0.139)	(0.155)	(0.161)	**(0.217)**	(0.189)	**(0.232)**
... X mother has not completed primary school	0.054	-0.040	0.023	-0.175	-0.232	-0.104	0.504	0.141	0.533
	(0.175)	(0.174)	(0.181)	(0.205)	(0.214)	(0.209)	(0.345)	(0.286)	(0.405)
Number of observations	1,536	1,536	1,540	1,079	1,079	1,079	457	457	461

Source: Skoufias et al. (2011b)

Note: Robust standard errors in parentheses, clustered by locality, and *** p<0.01, ** p<0.05, * p<0.1.

^ Less than 2% of the sample experienced a positive rainfall shock in the pre-*canícula* period.

Calculated using ENN with state fixed effects. A negative weather shock identifies those municipalities which in the previous agricultural year (or wet season or pre-*canícula* period) had at least 1 standard deviation less rain (or GDD) than in an average year. Other independent variables included are: household composition (number of children in the household, number of adult males in the household, number of adult females in the household), characteristics of the mother (height, speaks an indigenous language and education), characteristics of the child (age, sex, birth order, multiple birth, small at birth, older sibling less than 2 years older, household assets and housing characteristics (asset index, presence of a kitchen, access to tapped water indoors, toilet, floor type), and altitude of locality.

Table 3.15 Impact of weather shocks on height-for-age, by participation in a nutritional supplement program

Variables	All			Center/South			North		
	Annual	Wet season	Pre-*canícula*	Annual	Wet season	Pre-*canícula*	Annual	Wet season	Pre-*canícula*
HH receives any nutritional supplement	0.195 (0.126)	0.092 (0.119)	0.154 (0.140)	0.222 (0.143)	0.107 (0.134)	0.243 (0.179)	0.253 (0.243)	0.090 (0.251)	0.065 (0.228)
Negative rainfall shock	0.173 (0.162)	0.181 (0.184)	-0.009 (0.135)	**0.428**** **(0.214)**	0.468 (0.293)	0.197 (0.152)	-0.217 (0.223)	**-0.351*** **(0.181)**	-0.348 (0.247)
... X nutritional supplement	0.001 (0.259)	0.091 (0.254)	-0.061 (0.168)	-0.090 (0.327)	-0.012 (0.395)	-0.184 (0.200)	-0.173 (0.409)	0.112 (0.347)	-0.045 (0.318)
Positive rainfall shock	**-0.377***** **(0.143)**	**-0.329**** **(0.166)**	0.708^ (1.090)	**-0.408**** **(0.161)**	**-0.352**** **(0.167)**	**6.541*****^ **(0.383)**	-0.256 (0.266)	0.157 (0.456)	-0.508^ (0.321)
... X nutritional supplement	**-0.370*** **(0.207)**	**-0.611**** **(0.265)**	1.627^ (1.101)	-0.255 (0.190)	**-0.421*** **(0.252)**	**-2.860*****^ **(0.389)**	-0.711 (0.537)	**-1.418***** **(0.474)**	0.617^ (0.386)
Negative GDD shock	0.039 (0.179)	-0.156 (0.163)	0.062 (0.249)	0.162 (0.288)	-0.249 (0.182)	-0.109 (0.235)	-0.024 (0.251)	-0.130 (0.340)	-0.092 (0.238)
... X nutritional supplement	-0.088 (0.242)	0.378 (0.277)	-0.136 (0.318)	-0.225 (0.373)	0.304 (0.354)	-0.028 (0.355)	-0.133 (0.318)	0.545 (0.445)	0.102 (0.380)
Positive GDD shock	-0.059 (0.115)	-0.098 (0.117)	-0.170 (0.121)	-0.016 (0.125)	-0.076 (0.137)	-0.181 (0.144)	-0.183 (0.278)	-0.182 (0.225)	-0.196 (0.262)
... X nutritional supplement	-0.123 (0.176)	-0.005 (0.173)	0.047 (0.170)	-0.133 (0.197)	0.021 (0.199)	0.100 (0.198)	-0.449 (0.419)	-0.168 (0.357)	-0.439 (0.420)
Number of observations	1,536	1,536	1,540	1,079	1,079	1,079	457	457	461

Source: Skoufias et al. (2011b)

Note: Robust standard errors in parentheses, clustered by locality, and *** p<0.01, ** p<0.05, * p<0.1.

^ Less than 2% of the sample experienced a positive rainfall shock in the pre-*canícula* period.

Calculated using ENN with state fixed effects. A negative weather shock identifies those municipalities which in the previous agricultural year (or wet season or pre-*canícula* period) had at least 1 standard deviation less rain (or GDD) than in an average year. Other independent variables included are: household composition (number of children in the household, number of adult males in the household, number of adult females in the household), characteristics of the mother (height, speaks an indigenous language and education), characteristics of the child (age, sex, birth order, multiple birth, small at birth, older sibling less than 2 years older, household assets and housing characteristics (asset index, presence of a kitchen, access to tapped water indoors, toilet, floor type), and altitude of locality. Also, the household's participation in a supplemental nutrition program is included.

62. Although, on average in this sample, the girls' and boys' average height-for age measures are not statistically significantly different, they are significantly different when the child experiences a positive GDD shock in the prior agricultural year (Table 3.13). Boys are shorter when the prior year, wet season or pre-*canícula* period was at least one standard deviation warmer than on average. Girls are statistically significantly different from the boys and in girls there are no differences between those who experienced an unusually warm year and those who did not. The result may reflect the differences in disease morbidity rates by gender. In general, infant boys, especially those with even slight malnutrition, have higher mortality and morbidity rates from early childhood infections and diseases (Wells, 2000). It is also possible that there are differences in the types of activities that the children engage in (for example boys may play more outside and be more exposed to the new set of diseases) or that there are differences in the care. The average results are driven by children in the central and southern regions of the country. In the North boys are not any worse off from a positive GDD shock than girls are. The regional result may reflect the regional differences in the climate. It may be that on average in the North positive GDD shock does not alter the environment in a way to change the prevalence of diseases or households are better apt at dealing with such changes. However, in the North, it is observed that girls are worse off than boys from rainfall shocks—from a negative pre-*canícula* rainfall shock and from positive annual and wet season rainfall shocks. Again, the result may reflect differences in the type of activities that the children engage in or indicate differences in care.

63. When faced with a weather shock, the mother's educational attainment is not associated with a child's height-for-age (Table 3.14). That is, even though children of less educated mothers—those mothers who have not completed primary school—are on average shorter than children of more educated mothers, there are no differences in the height-for-age measure associated with weather shocks.[48] These results suggest that mothers have similar resources available to adjust their caretaking practices to weather shocks regardless of their educational attainment. Furthermore, there are no regional differences in the result.

64. Another household characteristic that may differentiate the results between heath outcomes and weather is the household's participation in some type of social protection or assistance program. Supplemental nutrition programs (such as PROGRESA and LICONSA in Mexico) attempt to improve childhood nutrition in the poorest households. Households participating in such targeted programs are from the poorest households in the country and they may have fewer resources to cope with weather shocks. For the sample of children, when faced with a positive rainfall shock the health of children living in households receiving supplemental nutrition is statistically significantly worse than the health of children not in such programs (Table 3.15). Since program participation is not random (that is, the participants come from the most impoverished households), the results do not suggest that participation in such programs is disadvantageous to children. The results do suggest that participation in a supplemental nutrition program does not fully level the playing field in terms of child health outcomes after a positive rainfall shock. In order to determine the causal impact of the program (and the interaction of weather shocks with program participation) the counterfactual would need to determined, that is, the health outcomes for children who participated in such programs had they not benefitted from the programs.

3.6 Discussion and Conclusions

65. Weather-related events can have an impact on the welfare of individuals either through changes in agricultural production and therefore on consumption, and/or through changes in the prevalence of certain types of diseases and ailments associated with different weather conditions. The study analyzed the impacts of rainfall and temperature deviations from their long-run means on rural households and young

[48] The observed difference in the two groups from a positive rainfall shock in the prior pre-*canícula* period needs to be interpreted with caution given the low number of children who experienced such a shock.

children in Mexico. On average, the analysis did not find any consistently strong effects from weather shocks on welfare as measured by expenditures. However, it did find regional differences as well as differential impacts based on household and individual characteristics.

66. Regarding rainfall shocks, the study found that dry years are associated with increased per capita expenditures. The result is driven by higher expenditures in the central and southern parts of the county and not observed in the semi-arid North. In the North, rainfall shocks do not have an impact on expenditures which may partly be explained by the higher percentage of irrigated land in the North than in the rest of Mexico.

67. For an average rural household, food expenditures are higher after a positive annual rainfall shock. Again the result is driven by the states in the central and southern parts of the country, where per capita non-health spending is also higher after a positive rainfall shock.

68. Regarding temperature shocks, no evidence that warmer weather leads to lower expenditures is found, at least for the sample of rural households in Mexico. In fact, the study found that warmer weather during the wet season is associated with higher expenditures (and thus of income if expenditures track income). Also, the analysis did not observe any negative impacts on welfare (as measured by expenditures) from weather shocks. These results suggest that, on average, the risk management strategies adopted by rural households ex-ante combined with their coping strategies ex-post are successful at keeping expenditures decreasing after unusual weather. In fact, households may benefit from some types of weather shocks with the average expenditures being higher than when such shocks did not occur.

69. However, there are significant regional differences. Households in the North have lower non-health expenditures after a cold pre-*canícula* period, and lower food expenditures after a cold agricultural year or wet season, whereas expenditures are higher after a cold pre-*canícula* period elsewhere in Mexico. That is, colder weather appears to be welfare decreasing in the North, but welfare increasing elsewhere, at least immediate after the shock.

70. Climatic variability also appears to have heterogenous impacts depending on the socioeconomic characteristics of the household head. Positive rainfall shocks appear to affect only female headed households as do positive GDD shocks. Some shocks (positive annual, wet season and pre-*canícula* rainfall, and positive pre-*canícula* GDD) impact female and male headed households statistically significantly differently; other shocks do not have a statistically significant impact in male headed households but do so in female headed households (positive annual rainfall, positive wet season rainfall, and positive annual GDD). In the central and southern states, all the differences are positive such that, after a weather shock, female headed households are never worse off than male headed households. In the North, female headed households have lower non-health expenditures after a positive rainfall shock during the wet season, but higher food expenditures after a positive GDD shock in the prior pre-*canícula* period. The differences depending on the gender of the household head may reflect differences in occupation and types of crops grown.

71. Another factor that differentiates the impact of climatic variability on household welfare is the educational attainment by the head of the household. Households headed by less educated heads (those who have not completed primary school) tend to have lower expenditures after weather shocks than households headed by more educated heads. On average after a weather shock, households with less educated heads are never better off than households with more educated heads and, in fact, households with less educated heads have, on average, lower food expenditures after a negative annual GDD shock than similar households not experiencing such a shock. The only exceptions are households with less educated heads in the North after a negative rainfall shock. The results could signal the inability of households with less educated heads to adjust their agricultural production as easily as those headed by a

more educated head or their inability to draw on external resources when weather shocks affect their agricultural production to keep expenditures constant.

72. Exploring the impacts of weather on the health of a group of vulnerable individuals (rural children under the age of three), the study found some evidence of both unusual rainfall and unusual temperature having an impact on a child's height-for-age. Precipitation has a more marked impact on height-for-age than temperature, such that an unusually rainy year or wet season is associated with lower average height-for-age everywhere in the country. That is, even though rainier than usual weather does not decrease per capita non-health or food expenditures, young children have worse health outcomes after such shocks. In the North a dry wet season and pre-*canícula* period as well as a warm prior agricultural year are all also associated with shorter children. Considering the available evidence to date linking childhood health to various aspects of adult wellbeing,[49] these results warrant further research on the policy options that might be effective at reducing the negative impact of unusually rainy weather anywhere in Mexico and dry and hot weather in the North.

73. The impacts of weather shocks on height-for-age are different for boys and girls, and for those children in households benefitting from supplemental nutrition programs. Although girls are not affected by positive GDD shocks, boys are negatively impacted by unusually warm years, wet seasons and pre-*canícula* periods. This is in spite of the fact that after an unusually warm wet season, households' expenditures on non-health items are higher and after an unusually warm year or pre-*canícula* period are similar to a normal year's expenditures. One possible explanation for a negative impact on boys is the difference in morbidity rates between girls and boys especially when marginally malnourished (Wells, 2000). The results suggest that, in order to mitigate any negative impact on boys, some counteractive measures need to be taken during a warmer than usual year. Furthermore, in the North, during a rainy year, especial attention needs to be given to girls who are on average, much shorter, than boys after a positive rainfall shock.

74. Additionally, it is found that children who benefit from supplemental nutrition programs are shorter than non-beneficiaries when the prior agricultural year or wet season was unusually rainy. That is, even though all children are affected by unusually rainy weather, those who participate in supplemental nutrition programs are affected even more. Given that the households who participate in these programs are in general the poorest ones, the results suggest the additional nutrition provided does not (fully) protect the children from the impacts of a positive rainfall shock. The results also suggest that poorer families are less able to draw on other resources to counter negative health impacts associated with higher levels of precipitation.

75. All, in all, the results reveal that the current risk-coping mechanisms are not very effective in protecting the two dimensions of welfare examined here from erratic weather patterns. These findings imply that the change in the patterns of climatic variability associated with climate change is likely to reduce the effectiveness of the current coping mechanisms even more and thus increase household vulnerability further. Moreover, the heterogeneous impacts of climatic variability documented in this study suggest that a "one size fits all" approach to designing programs aimed at decreasing the sensitivity and increasing the capacity of rural households to adapt to the changes in climatic variability in Mexico is not likely to be effective.

[49] Childhood health has been shown to have an impact on employment (Case, Fertig and Paxson, 2005), cognitive abilities (Case and Paxson, 2008; Grantham-McGregor et al., 2007), educational outcomes (Glewwe and Miguel, 2008), and productivity (Hoddinott et al., 2008).

4. VIETNAM

4.1 Natural Disasters and Welfare

1. As the world prepares for a changing climate and natural disasters hit with increasing frequency (UNISDR, 2009), especially in coastal areas (Costanza and Farley, 2007), it is imperative to better understand how natural disasters affect economies and their people. While disasters are known to cause substantial human and economic suffering (Okuyama, 2009), there remain important uncertainties about the magnitudes of the welfare loss and its persistence over time, the heterogeneity in their effects across socio-economic groups, the conditions under which they are more or less harmful, and the effectiveness of different interventions in dealing with them. When it comes to economic or GDP growth (as opposed to welfare/GDP levels), there is neither an empirical nor a theoretical consensus about whether natural disasters are actually damaging for growth (not levels) (Cavallo and Noy, 2009; Loyaza, et al., 2009).

2. Careful examination of the welfare effects of natural disasters requires in the first place a disaggregated mapping of the natural disasters themselves. While the (economics) literature typically glances over this, this is anything but straightforward. For example, micro-studies nowadays often use subjective measures of shocks and disasters.[50] When available, these are useful, but also suffer from important methodological and practical shortcomings. In particular, whether a household considers a meteorological event a natural disaster is likely to depend both on its ex ante exposure to it and its ex post capacity to cope with it. Yet, to reduce its exposure it may have adopted less risky portfolio strategies over time, which could come at the expense of lower average returns. The household may also be able to fall back on (formal or informal) support systems to cope with it ex post, leading it to consider the event less of a shock or disaster, as it is not bearing its full costs. Such considerations, which remain largely unknown to the researcher, may lead to an underestimation of the full welfare cost of the event. Besides methodological concerns, it is typically also hard to extrapolate the findings across space and time, as subjective shock measures are usually not available outside the sample. Neither are their probability distributions, which are necessary to predict in the future.[51] When objective measures of natural disasters have been used instead, for example directly derived from the weather data, these measures have often been constructed only at rather aggregated levels (Christiaensen and Subbarao, 2005).

3. To overcome these methodological and practical concerns, this study derives measures of natural disasters and hazards at disaggregated geographical levels from primary meteorological weather station data, storm tracks and satellite observations. Second, in understanding the economic impact from disasters both direct and indirect effects need to be considered. Their most direct (and visible) impact relates to the destruction of capital (for example productive assets, property and infrastructure in case of floods and hurricanes; livestock and crop loss, but also hunger and reduced work capacity in case of droughts and famines) (Loyaza, et al., 2009). But they also have important indirect effects (Okuyama, 2009), as the effects of the initial destruction of private and public capital works its way through the economy via the product and factor markets. Ruptures in infrastructure or the electricity supply for example reduce the flow of goods and services and interrupt manufacturing processes thereby diminishing the returns to capital. Droughts cause food prices to rise and livestock prices to tumble (the latter in the face of collapsing demand for meat, Barrett (2001)). The effects of disasters may also be felt in the labor markets, with wages often substantially lower several years after the event (Jayachandran, 2006; Mueller and Osgood, 2009). Quisumbing and Mueller (2010) estimated for example that for each one foot deviation from the normal flood level agricultural and non-agricultural wages were 4 to 7 percent lower five years after the 1998 flood of the century in Bangladesh.

[50] These are typically derived from answers to a shock module incorporated in household questionnaires asking respondents whether they experienced different types of shocks over a certain period (e.g. a drought, a flood, a storm).
[51] The latter could in theory be obtained (Delavande et al., 2010).

4. Whether a household also sees its income and consumption reduced, and the extent of this reduction, depends further on its exposure to the disaster and its capacity to cope with it ex post (Dercon, 2002; Hasegawa, 2010). For example, those with irrigated fields or those earning their living outside agriculture are less likely to suffer from droughts, while domestic and foreign remittances and well targeted disaster relief can make up for a substantial part of the income loss. The better credit and insurance markets work, the better households are usually also able to cope with disasters and the less they see their consumption decline (Lopez, 2009). Furthermore, in the aftermath of the disaster, there may also be a temporary boost in certain sectors such as construction (building-back), opening up opportunities for certain groups. The Keynesian type construction boom may even accelerate the overall growth rate if it results in an accelerated upgrading of the existing capital stock (building-back-better; Hallegatte and Dumas, 2009).

5. To capture both direct and indirect effects and illuminate the implicit costs associated with some of the coping strategies, this study pursues a fully reduced form analysis at the household level (very much in the spirit of Dercon, 2004). In particular, it examines the effect of natural disasters on household consumption, using disaggregated (objective) disaster measures derived from geo-referenced meteorological data and controlling for some of the coping strategies. The overall objective of the study is thus twofold: 1) to develop and illustrate a methodology to construct more objective and disaggregated natural hazard and disaster maps from primary meteorological data; and 2) to illustrate a methodology to estimate the expected welfare loss associated with natural disasters based on such natural hazard and disaster maps.

6. By deriving natural disaster measures from historical weather data several of the methodological and practical challenges associated with subjective measures can be mitigated. Furthermore, though not pursued in this study, the hazard and disaster maps thus obtained can also be used for planning and targeting purposes. In estimating the welfare loss, an estimator which simultaneously accounts for heteroskedasticity, survey design (cluster effects), and spatial correlation is also developed. Though oft ignored, as the effects of natural disasters permeate through the economy, spatial correlation in consumption following a disasters is likely. Ignoring this may cause bias and reduce the efficiency of the estimation procedures. To be clear, an in depth examination of the channels through which the different disasters affect welfare is not aspired. Nonetheless, a limited exploration of the effects of disasters on intermediary outcomes is presented to facilitate an intuitive interpretation of the reduced form findings. Potential persistence of the effects and heterogeneity across key socio-economic groups is also explored.

7. The empirical application is to Vietnam, which UNISDR (2009) ranked fourth in the world in terms of the absolute number of people exposed to floods; tenth in terms of the absolute number of people exposed to high winds from tropical cyclones, and sixteenth in terms of the absolute number of people exposed to drought. The regular occurrence of natural disasters together with the availability of three highly comparable nationally representative household living standard surveys (2002-2004-2006) render Vietnam particularly suitable to illustrate the approach advanced in this paper. The study constructs in particular disaggregated maps of the annual occurrence of droughts, (local and riverine) floods and storms during 2001-2006 as well as the likelihood of their occurrence using meteorological data from rainfall stations, storm tracks, and satellite images. The occurrence of these geo-referenced disasters, further augmented with the likelihood of their occurrence derived from the historical weather records, is subsequently linked with household consumption and other household and location characteristics from the repeated nationally representative household surveys and secondary data sources to estimate the effect of extreme weather events on household welfare.

8. The results suggest that the immediate losses from floods and hurricanes can be substantial, with hurricanes causing most havoc (up to 52 percent consumption loss among households close to large urban centers). Households tend to cope well with droughts, largely through irrigation. Frequent exposure to disasters erodes the standard of living, but reduces the immediate effects of shocks as households become less exposed and better prepared. Households in frequently inundated areas have even been able to turn the floods into an advantage, as long as the flooding is not too severe. There is however no adaptation to hurricanes. Rather the contrary, high frequency hurricanes exacerbate the

losses from particular events. Finally, those further away from the large urban centers are not only poorer, but also tend to suffer less from disasters, likely due to the adoption of less risky (but less remunerative) portfolios and a higher likelihood of receiving disaster relief.

9. The next section outlines the approach used to obtain geographically disaggregated estimates of droughts, heavy rainfall, river floods and storms with hurricane force. Section 4.3 reviews the empirical methodology to estimate the welfare effects. Section 4.4 reviews the data used and section 4.5 presents the empirical findings regarding the welfare effects of different natural disasters. Section 4.6 concludes.

4.2 Mapping Natural Hazards

10. Vietnam's 2007 "National Strategy for Natural Disaster Prevention, Response and Mitigation to 2020" identifies droughts, floods, and cyclones as its most important natural hazards. Landslides, which often happen following flash floods or cyclones, are mentioned as well. One common approach to determine whether a household has been affected by an extreme weather event is to ask the household directly. In contrast to external measures of extreme weather events derived from spatially scattered weather stations or satellite data, self-reported shock measures have the advantage of being locally more accurate – households know whether they experienced an extreme weather event or not. They also circumvent the challenge of identifying the cut-off beyond which a particular meteorological variable or combination of meteorological variables constitutes an extreme weather event. Indeed, deciding when rainfall is too much or too little, when winds are too strong, flood levels too high, or temperatures too high or too low across a series of settings and groups is demanding.

11. Yet not only are subjectively reported shock modules often not included in standard household surveys, they also raises issues of endogeneity, especially when incorporated in consumption regressions. These can typically only be overcome through the use of panel data, which are rarely available at the national level. The location, time, and household specificity of the subjective shock data also limits generalizations across time and space. In contrast, knowledge of the historical distribution of weather patterns allows the construction of probability distributions of weather events, which is useful to explore patterns of adaptation over time. It also helps in controlling for potential endogeneity of the extreme weather event measures in the absence of panel data. Interpolation of the extreme weather event data across space further permits the construction of disaggregated natural hazard maps, a useful tool in the spatial allocation of interventions and the simulation of the welfare effects of changing climate patterns.

12. Several global meteorological databases are available. But with the exception of the cyclone databases (UNEP/GRID-Europe, 2007a, 2007b) they do not have a high resolution typically. This paper exploits access to Vietnam's detailed historical daily weather station data from 166 stations across the country to generate geographically disaggregated rainfall maps at the 0.1-degree resolution (corresponding nominally to 11 km at the equator).[52] These data form the basis to derive geo-referenced local measures of drought and localized floods/heavy rainfall. To also capture riverine floods, which may occur downstream following heavy rainfall in the mountains or as a result of storm surges in coastal areas, riverine flood indicators will be constructed based on the satellite based flood data from the Dartmouth Flood Observatory (DFO) (2008). The 1980-2006 geo-referenced UNEP/GRID-Europe storm track dataset is used to separately explore the effects from high winds and gusts from cyclones. As the damage from heavy rainfall associated with cyclones will already be captured by the localized and riverine flood indicators, these measures will capture the wind damage associated with cyclones.[53]

[52] The frequently used CRU TS2.1 monthly rainfall database (Mitchell and Jones, 2005) only has a half degree resolution, which is around 55 kilometres at the equator.
[53] See Thomas (2009) for a detailed description of the different data sources and a more elaborate description of the construction of the different natural hazard maps.

Rainfall maps

13. To construct spatially disaggregated indicators of drought and excess rainfall, the weather station data must first be spatially interpolated and cut-offs must be determined beyond which precipitation is considered too little or too much. Spatial interpolation of weather data is a discipline in itself which has developed an array of techniques that go from the most crude and obvious (such as the nearest neighbor techniques[54]) to the more precise and resource intensive (such as the radial basis functions).[55] Nonetheless, as the complexity of the techniques increase, they also display rapidly decreasing returns in terms of precision given resources spent.[56] As the focus of the paper is not on constructing highly accurate rainfall maps as such, necessary for example for the design of weather index insurance programs, but rather on the household welfare effects of weather related events, a pragmatic approach has been pursued here, aimed at minimizing measurement error of the disaggregated rainfall measures at a reasonable cost, while maintaining maximum replicability of the approach in other settings.

14. In particular, using the historical daily rainfall records over 1980-2006 in 166 geo-referenced weather stations from across Vietnam (see Figure 4.2)[57], monthly rainfall grids of 0.1 degree resolution are constructed[58] using both inverse distance weighting (IDW) and inverse elevation difference weighting (IEW). In IDW, one of the most widely used spatial interpolation techniques in practice (Tomczak, 2003), the rainfall value in a particular grid cell is obtained as the weighted average of the rainfall data from a predetermined set of neighboring weather stations (e.g. the 5 closest or all the neighboring stations within a certain distance) using the inverse distance between the station and the center of the grid cell (raised to a power) as weight and normalized by the sum of the weights.[59] The squared inverse distance to the five nearest stations for which data were available was chosen in the empirical application below. IDW exploits the intuition that the further away the station is, the less its rainfall pattern will resemble this at the point of interest. However, even over short distances rainfall patterns can still diverge widely, especially among locations at different altitudes (Hutchinson, 2003). Given its mountainous range, high slope gradients are frequently observed in Vietnam, with some grids displaying within grid elevation differences of more than 1,000 meters. To exploit this largely neglected insight (Dubois and Shilbi, 2003), an elevation difference weighted rainfall index based on the ten nearest stations is also constructed.[60]

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[54] The nearest neighbour method assigns the value of the weather station nearest to the grid cell centre.

[55] Radial basis functions are functions of distance used for exact interpolation of point data. They attempt to overlay a smooth surface on the point data, allowing for various degrees of bending in that surface through a smoothing parameter that is specified by the researcher. Common radial basis functions are thin-plate spline and multiquadratic functions. See De Smith et al. (2007) for a comprehensive textbook that is reasonably accessible.

[56] In a comparison of the performance of different interpolation techniques on rainfall data from May 8 1986 in Switzerland, the latter was found to be the most precise (Dubois, 2003). Yet, as highlighted by Dubois and Shilbi (2003), at 5.93 mm, the root mean square error (RMSE) for the multiquadratic function was only slightly better than this for IDW (6.3 mm), which is negligible compared to the average rainfall of 18.51 mm among the 367 omitted data points for which rainfall was interpolated from the remaining 100 rainfall stations.

[57] The average distance between rainfall stations is 32 km.

[58] While the satellite based rainfall maps produced by CPC/NOAA could also be used in principle, they only dated back to 2001, preventing us from constructing disaggregated historical rainfall patterns, necessary to explore patterns of adaptation. There is an additional concern as the satellite based CPC / NOAA data for Vietnam appear calibrated on a rather small number of rainfall stations (10 or so) from within Vietnam.

[59] To be precise, $IDW = r(x) = \sum_{k=0}^{N} \frac{w_k(x)}{\sum_k^N w_k(x)} r_k$ with r(x) the inverse distance weighted rainfall at interpolated point x, based on observed rainfall values r_k at k=0,1, …, N known interpolating (known) points x_k, with $w_k(x) = \frac{1}{d(x,x_k)^p}$ as weight, x_k an interpolating (known) point, d a given (Euclidean) distance from the known point x_k to the unknown point x and p a positive real number, the power parameter.

[60] Further corrections for anisotropy can be taken. This is important if nearness in one direction is more important than nearness in the perpendicular direction in determining the distance weights. This may be the case

15. The relative importance of both the IDW and IEW indices in determining rainfall in a grid is subsequently estimated through an ordinary least square regression of the log of the observed monthly rainfall patterns in the 166 stations during 1980-2006 on the log of their IDW and the log of their IEW index, monthly dummies and their interactions to allow for monthly variations in the relative importance of both indices.[61] The regression explained 76.8 percent of the observed variation in the monthly rainfall records from these stations (R-squared = 0.768), which provides some confidence in the predictive power of the method.[62] The IEW index carries substantially more weight in predicting rainfall during the wetter months (April-November), while the IDW index is also important in predicting rainfall during the dry months (December-March). An estimate of monthly rainfall for each grid cell was obtained by applying the estimated coefficients in Table C1 to their respective IEW and IDW indices. By way of illustration, Figure 4.2 presents the interpolated rainfall map for June 2006, both based on the regression prediction method and the IDW and IEW indices separately.

Drought maps

16. While Vietnam does receive large amounts of rainfall on average, moderate and severe droughts occur across the country, albeit with diverging frequency. They are more common and more severe in the Northeastern part of the country and the Red River Delta, but have also been reported in the Mekong Delta in the South, despite widespread irrigation.[63] In keeping with the study's focus on exogenous measures of a natural hazard, the focus here is on meteorological drought, defined as rainfall deficits over extended periods of time.[64] Unlike agricultural drought indices, meteorological ones also allow exploration of the (indirect) effects of droughts on urban households for example through water shortages and electricity outages.

17. A multitude of meteorological drought indices has been proposed in the literature (see Keyantash and Dracup (2002) for a review). Following Dilley et al (2005), the cumulative precipitation anomaly index is taken. This is the deviation in precipitation from a long-term mean or median for a specific period of time, usually expressed as the proportion of the long term mean or median. It is straightforward to calculate and does not require other meteorological input (such as temperature data) and thus also no additional spatial interpolation. It is also flexible. It does not impose a distributional structure on the rainfall data, like the widely used Standardized Precipitation Index (SPI) (McKee et al., 1993). Furthermore, unlike the rainfall decile index, which ranks the historically observed rainfall in each location and considers rainfall episodes in the lowest decile(s) as droughts, the cumulative precipitation anomaly index also allows the likelihood of a drought in a particular area to vary across space. The latter is important to explore potential adaptation to frequent drought exposure, as will be seen later on.

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when mountain ranges are oriented at particular angles, or when prevailing winds are from a specific direction. This has not been pursued here, given the inclusion of the elevation difference in the final predictions and the reasonable prediction precision obtained when using both inverse distance squared and inverse elevation weighted indicators (see below).

[61] By taking log transformations, negative predictions are avoided and estimation issues related to the skewness of the rainfall data are mitigated.

[62] A similar degree of precision was registered in a series of modified specifications. Using a polynomial regression of the IEW and IDW indices reduces the root mean square error by 0.01 (from 0.764 in the current specification). Similarly, application of the interpolation on the log or squared root transformed values reduces the RMSE only by 0.03. Inclusion of time varying month dummies yields virtually no improvement, while inclusion of regional dummies reduces the RMSE by 0.05.

[63] The administrative regions of Vietnam are presented in Figure 4.0.

[64] Other disciplinary conceptualizations of drought include hydrological, agricultural and socio-economic drought, each accounting for the effect of rainfall deficits on their respective domain of interest. Hydrological droughts relate to shortages of water in river systems which can be due to meteorological droughts in subsets of the river basins but also to land use changes. Agricultural droughts consider the amount of water available in relation to crop growth. Socio-economic droughts occur when meteorological, hydrological, or agricultural droughts cause economic distress.

18. In particular, the monthly rainfall estimates for each grid cell were accumulated into annual measures[65]. The annual shortfall from the long term median (for the 1975 to 2006 period) was calculated for each year and each grid cell, and expressed as a proportion of the long term median. Figure 4.3 shows the proportional deviations from the long run median for the 2001-2006, i.e. the current (2002, 2004, 2006) and preceding VLSS survey years.

19. Vietnam enjoyed above average rainfall in most of the country in 2001, with only small patches of 20-30 percent below median rainfall in the Mekong River Delta and the Central Highlands. In 2002, however, serious rainfall shortages were observed in large patches of the Mekong River Delta. The Northcentral Coast had a serious drought in 2003, along with less substantial shortages in the Northeastern and Northwestern Uplands. In 2004, the entire nation appeared to suffer from rainfall shortages, with severe deficiencies along the Southcentral Coast and the Central Highlands. This is followed by a year of abundant rainfall in 2005 with only very small patches of shortfalls. Finally, 2006 shows moderate and severe drought along the Northcentral and Southcentral Coastal regions, as well as the Northwestern Uplands and the Red River Delta. The wide variation in rainfall within and across localities over the different survey years provides the necessary variation to identify the effects of rainfall deficiency.

20. Different cut-offs below which a certain shortfall is considered a drought can be identified. Shortfalls of 10, 20 and 30 percent or more were considered. Figure 4.4 presents the proportion of episodes during 1975-2006 that rainfall was 20 percent or more below the median. Based on this definition areas along the coast and in the Red River Delta appear more drought prone, and to a lesser extent also those in the Mekong Delta.

Localized excess rain maps

21. Systematic and accurate information about floods at geographically disaggregated levels is notoriously hard to come by or to construct. One of the reasons is that satellite imagery relies on visibility, and during floods there is usually much cloud cover. Radars can see through clouds, but have not been set aside for this purpose. Yet, floods are part and parcel of livelihoods in many parts of Vietnam and it is thus key to explore their welfare effects.[66] This study distinguishes between localized and regional events. Localized events are based on large amounts of rainfall in short periods of time. They may also induce landslides. Regional events arise when rivers exceed their banks, potentially due to heavy rainfall upstream or snowmelt, or in coastal areas following storm surge.

22. Inspired by Zubair et al. (2006), who use rainfall intensity in a short period to proxy localized flooding, daily rainfall maps were generated, obtained through spatial extrapolation of the daily rainfall records in the rainfall stations (as opposed to the monthly rainfall data used before) using the inverse distance squared weighting technique.[67] In particular, rainfall was considered excessive in a particular year if it exceeded either 300 millimeters, 450 millimeters, or 600 millimeters in any rolling five-day period throughout that year. By using 5-day periods as opposed to monthly data, a more refined picture of localized flooding could be constructed.

23. The annual occurrence of excess rain across the grid during 2001-2006 is presented in Figure 4.5. Figure 4.6 presents the proportion of years the 0.1 degree grid cells experienced at least one episode

[65] Using 4-months rainfall deficits instead, excluding the 4 driest months of the year, yielded very similar maps. Given the existence of multiple cropping seasons in Vietnam, an alternative approach would be to focus on rainfall shortages during particular periods of the year. This was not pursued here, as it would greatly increase the need for location specific information, and thereby reduce the practical applicability of the approach in other settings. Nonetheless, the approach is sufficiently flexible to accommodate such considerations.

[66] Vietnam has 2,360 rivers and streams that are more than 10 km long. Severe floods were recorded in 1945, 1961, 1964, 1966, 1969, 1971, 1996, 1998, 1999, 2000, and 2001. As a result, the government of Vietnam has actively applied a number of flood control methods, including reforestation, watershed protection; dykes; reservoirs for flood regulation; flood diversion, detention and drainage systems.

[67] Because the construction of interpolated daily rainfall maps was very data and time intensive, interpolation was limited to the IDW technique only.

with more than 300 mm rain in a consecutive five-day period. The North-central and South-central Coastal regions appear especially prone to excess rain. Localized flooding occurred also in the Red River Delta Region in 2003. More generally, localized flooding appears especially concentrated along the coast. Excess rainfall is however rather rare in the northern uplands and the south (Southeast and Mekong River Delta regions), suggesting that excess rain is closely related to tropical cyclones, and less to riverine floods. Nonetheless, there are also small inland patches with excess rain, spread across the country.

Riverine floods

24. Given the historical importance of riverine floods in Vietnam and the limited correlation between the geographical distribution of localized floods and the location of the rivers, the localized flood maps were complemented with riverine (and coastal) flood maps constructed from the Dartmouth Flood Dataset (Dartmouth Flood Observatory, 2008). The latter is an historical worldwide flood database spanning 1985-2007 and showing locations of floods and their major causes (monsoonal rain, heavy rain, tropical cyclones). The information is derived from a wide variety of sources including news and governmental reports based on locally gauged and remote sensing observations.[68] Unfortunately, the maps are not very disaggregated (ten by ten degrees in latitude and longitude). In principle, the flooding caused by any of the types of rainfall might have been picked up already by the localized flooding dataset. What would not be picked up is when rainfall in one place is transported by rivers or terrain to another place or when high tides push ocean water inland.

25. Given the focus here on riverine and coastal floods and to better pinpoint the locations that actually experienced riverine or coastal floods, the DFO flood maps were overlaid with the location of the rivers taken from the Hydroshed project (Lehner et al., 2008). Only the major rivers were mapped as these will have sufficiently large catchment areas exposing the downstream areas they traverse to (non-localized) flooding. Riverine and coastal flood bands were then derived by considering DFO flooded areas within 2, 5 and 8 meters elevation difference from the closest point on the major river or the coast using a Digital Elevation Model from GLOBE (GloBe Task team, 1999).

26. The recorded riverine and coastal floods using bands of 2 m elevation difference for each year from 2001 to 2006 are in Figure 4.7. First, there is little overlap over the years between the localized and riverine flood maps, confirming the complementary nature of both flood indicators. Second, there appears extensive flooding in the Mekong River Delta region almost every year. Third, 2005 was likely the worst year for riverine and coastal flooding. Fourth, riverine flooding was further observed on and off in the other regions, in 2002 and 2005 in the northern uplands, in 2003 and 2005 in the Red River Delta region, and in all years, but scattered around the region in the Southcentral Coastal. Consistent with the events during 2001-2006, the historical record shows that riverine floods happen most frequently in the Mekong and Red River Delta (Figure 4.8).

Cyclone maps

27. Tropical storms approach Vietnam from the east. They typically arrive during the Southeast and Northeast monsoon (Christiaensen et al., 2009), with 90 percent of them occurring between June and November, and almost half of them coming ashore in the northern part of the country. To generate annual cyclone maps, a GIS dataset of areas affected by hurricane force winds was developed from the UNEP/GRID-Europe (2007a, 2007b) tropical cyclones databases. In particular, the storm track and wind speed data were used to create symmetric polygons about each path, based on the algorithm by Klotzbach and Gray (no date).[69]

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[68] Many floods have now also been imaged by satellite or airborne sensors, and many of them have been translated by DFO into maps of inundation events. Yet, as these satellite based maps did not cover all floods, partly because at times the images were obscured by cloud cover and partly because not all floods have been imaged, it was decided not to use this data source to ensure consistency.

[69] The storm track dataset (UNEP/GRID-Europe 2007) had some missing wind speeds. These were filled in using values obtained by regressing known winds speeds on pressure, pressure squared, and dummy variables

28. The areas exposed to hurricane force wind (of 120 km/hour) in Vietnam between 2001 and 2006 are in Figure 4.9, and the frequency with which they have been exposed between 1980 and 2006 is depicted in Figure 4.10. During the first three years, the tropical cyclones did not affect the land much, though the impact was larger in 2004 to 2006, with two separate cyclones with hurricane force winds hitting the country in 2006. The coastal areas in the Northcentral coast and the Northeastern Uplands appear most exposed to cyclones, with hurricane force winds occurring once every five years. Visual comparison of Figures 4.4 and 4.8 suggests that heavy rainfall was caused by the cyclones in some cases, though not in all. There appears less correlation between coastal and riverine flooding and cyclones. Not only do the localized and riverine flood variables not capture the wind damage associated with cyclones, they also overlap only partially with the cyclone paths, underscoring the need to use an additional measure to reflect damages associated with cyclones.

4.3 Identifying Welfare Effects from Natural Disasters

29. The effects of natural disasters and other shocks on household welfare are commonly assessed by augmenting a standard reduced form consumption regression with explicit measures of the disasters themselves:

$$\ln c_{ict} = X_{ict}\beta \quad + ND_{kct}\gamma_k + (X_{it} \otimes ND_{kct})\phi + \varepsilon_{ict} \qquad (4.1)$$

where c_{ict} is a measure of consumption for a household *i* in cluster *c* at time t, *X* represent a series of household, cluster and regional characteristics that determine the level of consumption, *ND* are (stochastic) measures of (covariate) natural disaster k in cluster c at time t, and ε is a residual term.

30. Estimation of γ_k yields an estimate of the average effect of natural disaster k on household consumption. Yet different socio-economic groups are likely to be affected differently either because they are less/more exposed to the disaster ex ante or because they are better/worse able to cope with it ex post. For example, farm households with irrigated fields are less likely affected by droughts than those without, and the more educated may be better able to cope with natural disasters ex post. Similarly, the reception of disaster relief or food aid may lead one to (erroneously) conclude that there were no welfare losses associated with the disaster, even though they induced substantial budgetary outlays elsewhere (by the local or national government) (Yamano et al., 2005). To explore such heterogeneity in damage or the existence of indirect/hidden welfare losses, natural disasters are interacted with different household and community characteristics and assets ($X_{ict} \otimes ND_{kct}$).

31. Much of the empirical literature has so far assumed natural disaster measures to be exogenous. Not only does this depend on how they have been measured (objective versus subjective, as discussed above), even when objective measures are used, they may still yield biased estimates. The occurrence of a natural disaster in a locality is likely correlated with the likelihood of it occurring in the first place, which may in turn affect the level of consumption, e.g. through accumulated asset loss at the household and/or community level. Moreover, households in localities that are frequently plagued by natural disasters have likely adapted to these circumstances (for example by adopting more disaster resistant, but less remunerative portfolios (Dercon, 1996), or at times even by building successful livelihood systems around it—"living with floods"). The use of panel data provides the cleanest way to protect welfare estimates of natural disasters from (time invariant) unobserved heterogeneity across communities. However, sufficiently long panels of communities are usually not available for large geographical areas, let alone countries. Within community estimators are usually also less efficient given the lower signal-to-noise ratio, especially when panels are short. This in turn may lead to the disproportionate acceptance of the null-hypothesis of no welfare effect.

32. Here, repeated cross sections are used instead. To mitigate potential bias from unobserved community heterogeneity, a comprehensive set of socio-economic and agro-ecological characteristics of the locality is included. Most importantly the likelihood of the occurrence of different disaster

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for hurricane monitoring centres. The R-squared was above 0.91, giving confidence in the predictive power of the data and the regression.

types is controlled for, omission of which is identified as the major cause for biased estimation of the coefficients on natural disasters. Explicit inclusion of disaster exposure further permits exploration of the occurrence of adaptation. In particular, disaster incidence is hypothesized to mitigate the immediate effect of a particular disaster if households have reverted to low-risk, low-return activities. They are likely to suffer less when disasters hit, and benefit less if there is a rebound, for example due to accelerated replacement of the capital base with more productive equipment.

33. Empirical analysis of the effects of shocks on household welfare is often predicated on the assumption that the observations are independent from each other, thereby also abstracting from spatial correlation. But in many cases, it seems more likely that observations that are "near" in a geographic sense either influence each other more so than an observation that is far, or that they are more influenced by the same unmeasured force than an observation that is far. This seems especially relevant in a study of natural disasters, where their effects on welfare may permeate across locations especially when product (e.g. food) and/or factor (e.g. labor) markets are integrated.[70] Ignoring such interactions may lead to inefficient and sometimes even inconsistent estimates. [71]

34. Two types of spatial models are considered: 1) a spatial lag and 2) a spatial error. In the spatial lag model, the dependent variable (consumption in this case) is correlated among neighbors. In the spatial error model, it is the unknown residual that is correlated. Ignorance of spatial lags yields biased estimates, while ignorance of spatial errors reduces efficiency. The full spatial model (also denoted SAC), which combines both forms of spatial correlation, is given by

$$\ln c_{ict} = \rho_1 W_1 lnc_{ict} + Z_{ict}\zeta + \varepsilon_{ict} \text{ with } \varepsilon_{ict} = \rho_2 W_2 \varepsilon_{ict} + u_{ict} \qquad (4.2)$$

where u_{ict} is iid normal, with mean of 0 and variance of $\sigma^2 V$, when allowing for heteroskedasticity, or $\sigma^2 I$ otherwise) and Z capturing X, ND and its interaction terms. This can be rewritten as $lnc_{ict} = (I - \rho_1 W_1)^{-1} Z_{ict}\zeta + (I - \rho_1 W_1)^{-1}(I - \rho_2 W_2)^{-1} u_{ict}$. Sometimes $W_1 = W_2$; that is, the spatial relations for the lag and error are assumed to be the same. For shorthand notation, define $A = (I - \rho_1 W_1)$ and $B = (I - \rho_2 W_2)$. Equation (4.2) can then be written as $BAc_{ict} = B\, Z_{ict}\zeta + u_{ict.}$ The parameters can be estimated by maximizing the log likelihood function:

$$lnL = -(n/2)ln(2\pi) - (n/2)ln(\sigma^2) - (1/2)ln|V| + ln|A| + ln|B| \qquad (4.3)$$

$$-(1/2\sigma^2)(Alnc - Z\zeta)'B'V^{-1}B(Alnc - Z\zeta)$$

35. The key difference with the standard log likelihood function[72] is that it also requires calculation of the log determinants of A and B, since these are part of the Jacobian.

36. One kind of spatial error that has attracted a lot of attention in household survey analysis is the spatial error related to the clustering in the survey design (Deaton, 1997). To accommodate this within the maximum likelihood framework considered here[73], a different weight matrices W_c is

[70] Trung et al. (2007) find little spatial integration of paddy markets between North and South Vietnam, but a substantial degree of spatial price transmission within the North (Red River Delta) and South (Mekong Delta). See (Mueller and Osgood, 2009) for the transmission of the effects of natural disasters through the labor market.

[71] The contemporaneous spatial relationship between observations is typically specified using (row standardized) weights matrices. The weights matrix tells how observation *i*, represented by values in row *i*, relate to another observation *j*, given in column *j*. By convention, the weights matrix assumes that the weight of observation *i* on observation *i* is 0 for all *i*. Most analyses assume many zeroes in the weights matrix. In part, this is because the direct interaction between distant observations is expected to negligible. Row normalization means that each row is normalized so that it sums to 1. The spatial parameters can then be interpreted as correlation measures, which in analogy to time series, could range from -1 to 1 (an in most spatial analyses, would be expected to range from 0 to 1).

[72] The log-likelihood function associated with (2) can be written as $lnL = -(n/2)ln(2\pi) - (n/2)ln(\sigma^2) - (1/2)ln|V| - (1/2\sigma^2)(lnc - Z\zeta)'V^{-1}B(lnc - Z\zeta)$

[73] Fortunately, Stata allows for weighting and clustering in most of its regressions, and the study will take advantage of that capability whenever it is available.

introduced, with two different multipliers ρ_{c1} and ρ_{c2}, which together define the spatial error *and* spatial lag of the within cluster observations.[74] As a result, A and B in (4.3) are replaced by $A^* = (I - \rho_1 W_1 - \rho_{c1} W_c)$ and $B^* = (I - \rho_2 W_2 - \rho_{c2} W_c)$, with W_c the weights matrix for clustering, with zero on its diagonal, just like the other weight matrices. In doing so, the method also improves upon most statistical packages like Stata. They typically use a modified Huber-White estimator for the variance estimator in the case of clustering rather than trying a maximum likelihood solution. In doing so, they do not allow for a direct impact of intra-cluster neighbors' dependent variables. It is assumed that there is no spatial lag from the cluster variables. This assumption can be tested, but it is not necessarily a good assumption to make *a priori*, as the existence of spatial lag can introduce omitted variable bias.

37. Finally, to increase precision in estimating the welfare effects of natural disasters, the multiplicative heteroskedastic specification advanced by Just and Pope (1978, 1979), is adopted: $u_{ict} \sim N(0, \sigma_{ic}^2)$ with $\sigma_{ic}^2 = \sigma^2 \exp(Z_{ict}\alpha)$. Explicit specification of the heteroskedastic nature can be accommodated in the likelihood framework and also helps shed some light on the correlates of the conditional (idiosyncratic) variance of consumption. These can be of interest in themselves (see Christiaensen and Subbarao, 2005) for an application in the context of estimating household vulnerability).[75] The log likelihood estimation function applied to the data thus becomes:

$$lnL = -(n/2)ln(2\pi) - (n/2)ln(\sigma^2) - (1/2)ln|V| + ln|A^*| + ln|B^*|$$

$$- (1/2\sigma^2)(A^* lnc - Z\zeta)' B^{*\prime} V^{-1} B^* (A^* lnc - Z\zeta) \qquad (4.4)$$

with V a diagonal matrix with $\exp(Z_{ict}\alpha)$ on the diagonal.[76] Thomas (2010) provides a detailed discussion of the optimization routines developed in Matlab to estimate (4.4).[77]

4.4 Towards an Empirical Application

38. The socio-economic data to estimate equation (4.4) were obtained from the Vietnam Household Living Standard Surveys (VHLSS) of 2002, 2004, and 2006. In each round, households were selected

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[74] To see this, note that the variance matrix for a single cluster consisting of 3 surveyed households might be given by $\begin{matrix} \sigma_\varepsilon^2 + \sigma_c^2 & \sigma_c^2 & \sigma_c^2 \\ \sigma_c^2 & \sigma_\varepsilon^2 + \sigma_c^2 & \sigma_c^2 \\ \sigma_c^2 & \sigma_c^2 & \sigma_\varepsilon^2 + \sigma_c^2 \end{matrix}$ where σ_ε^2 is the variance of each individual element and σ_c^2 is the covariance within each element of the cluster. The practical difficulty in solving this in a maximum likelihood framework is that this block diagonal matrix needs to be inverted at each phase of the optimization routine. With small household surveys of a few hundred households this might be possible, but for large surveys, this is extremely slow and in many cases it becomes too numerically intensive to run successfully. This is why statistical packages like Stata use a modified Huber-White estimator for the variance estimator in the case of clustering rather than trying a maximum likelihood solution. Yet, using an insight from the spatial approach, the off-diagonal, non-zero elements (i.e., the σ_c^2) can be considered as a type of W matrix specifying that the neighbors are those elements within the same cluster. This avoids having to invert the matrix at each iteration of the maximum likelihood routine. Just to be clear, to follow the convention that W matrices have diagonal elements of 0 (this is okay, because in the spatial approach the study also differences a multiple of the W matrix from the identity matrix, thus restoring the diagonal elements), the previous block of the cluster matrix would be given as a W matrix as $\begin{matrix} 0.0 & 0.5 & 0.5 \\ 0.5 & 0.0 & 0.5 \\ 0.5 & 0.5 & 0.0 \end{matrix}$ with standardized row weights summing to 1.

[75] The multiplicative specification proposed here has some particular advantages in this regard as it does not constrain the parameters to affect the conditional mean and variance of consumption in the same direction (Just and Pope, 1979).

[76] Note that the usual Jacobian term of $\frac{1}{2} ln\sigma_{ic}^2$ would be $\frac{1}{2}\ln\,[\exp(Z_{ic}\alpha)]^2 = Z_{ic}\alpha$

[77] The optimization routines were written in Matlab and are available from the authors upon request.

using a 3-stage sampling process.[78] These three survey waves provide high quality and nationally representative household information on household consumption and income, their demographic characteristics, health status, educational achievements, asset holdings and the availability of public services in the community. The latter is obtained from the community survey which was fielded in parallel to the household surveys. The questions in the VHLSS were similar throughout the different surveys rendering them highly comparable. The surveys were conducted each year between May and November of the survey year, with expenditures referring to the past 12 months.

39. Real total per capita expenditure less per capita expenses on health care is taken as dependent variable. Health expenditures are subtracted as the study also controls for the effect of idiosyncratic health shocks, proxied by the number of days spent ill in bed over the past year by senior adults, adults and children respectively. Inclusion of health expenditures in the overall expenditure measure, which are highly correlated with illness and not routine or maintenance health outlays, might perversely suggest an increase in welfare following sickness. The expenditure data are expressed in January 2002 prices using the CPI provided by the Government Statistical Office. They are also corrected each year for regional and rural/urban differences across the eight regions.

40. A series of standard household demographics (household size, the dependency ratio, the age, gender, educational status of the household head[79]) are included to control for household characteristics in determining a household's consumption level. In this context, controlling for ethnicity is especially important as poverty is increasingly concentrated among ethnic minorities, often located in Vietnam's mountainous areas. While productive assets affect the capacity of a household to generate income and thus its consumption level, current asset levels may be simultaneously determined with consumption, as the disposal of assets (e.g. livestock) may be relied upon to cope with disasters, or they may reflect destruction by the disasters, leading to an underestimate of the welfare effects of the latter. In the absence of information of asset ownership prior to the survey, only those assets that display limited variation over time were included such as the amount of land owned and an indicator variable indicating whether the household owns a house or not.

41. To reflect access to public services, indicator variables are included that take the value of one if clean water[80], sanitary latrines,[81] or electricity are present in the community, and zero otherwise. To proxy a household's integration in the overall economy, the community data were further augmented with the distance of the centroid of the community (in meters) to the nearest part of the nearest primary or secondary road, as designated in the VMAP0 dataset (NIMA, 1997). These measures were computed that using Arc View 3.2. In addition, the estimated travel time to the nearest town or city of at least 25,000 people, the nearest city of at least 100,000 people, and the nearest city of at least 500,000 people were included. The travel times were computed in Arc View from a friction grid that

[78] Communes (the primary sampling units) were selected in the first stage with a probability proportionate to population size based on the 1999 Population census. On average, a commune contains 1,600 households. Subsequently, three enumeration areas (EAs), containing about 100 households each, were randomly selected within each commune. One of these EAs would be used to draw a sample of households in each VHLSS during the final (third) stage. In, 2002, this resulted in a sample of 29,530 households across 2,910 communes (EAs) (25 households per EA in 75% of the EAs and 5 in the remaining 25%). In 2004 and 2006, three households were selected per EA, resulting in 9,189 households each year in 3,061 communes. Phung and Nguyen (2008) provide a detailed description of the questionnaire and survey design.

[79] 0 refers to no degree, 1 to primary school, 2 to lower secondary school, 3 to higher secondary school, 4 to short-term technical worker, 5 to long-term technical worker, 6 to professional secondary school, and 7 to college diploma and above.

[80] Two sources of water are typically distinguished in Vietnam: water for direct human consumption (drinking, cooking), and water for sanitation and maintenance purposes (washing clothes and bathing). Water is considered clean if it comes from (1) private tap water inside the house, (2) private tap water outside the house, (3) public tab water, (4) water pumped from deep drill wells, (5) water from hand-dug and reinforced wells, (6) rain water, (7) purchased water, or (8) water from a water tank.

[81] Sanitary latrines include flush toilets with septic tank/sewage pipes, suilabh toilets, and double vault compost.

assigned differing travel times to various classes of roads, urban areas, water bodies, off-road, and crossing international boundaries.[82]

42. To further control for geological and agro-ecological characteristics at the community level, elevation figures were included, taken from the GLOBE 1 kilometer elevation database (GLOBE Task Team et al. 1999). Elevation differences were also incorporated as a measure of terrain roughness. These were computed using the SRTM3 data (Jarvis et al., 2006) by subtracting the minimum elevation in a 1 kilometer grid from the maximum elevation in the 1 kilometer grid. Finally, urban/rural and regional indicator variables help capture unobserved (time invariant) location specific characteristics related to the urban and rural livelihood systems as well as those related to regional variation in the agro-ecological, economic and political environment. Year dummies were included to control for the survey year.

43. The disaster data were mapped into the household survey data at the commune level, which are on average only 30,3 kilometer squared.[83] More precisely, the centroid for each commune was identified and given the highly covariate character of the different disasters, the state of nature observed at that point in the disaster maps was assumed to be the state of nature experienced by all the VHLSS households in that commune. It emerges that while most households have some limited drought risk, twenty percent of the population has at least 30 percent chance of being flooded each year (Figure 4.11). At the same time, about two fifths of the population will never be affected by a flood and storms pass by about half the population.

44. Given the concentration of flood events, it does not come as a surprise that there is a strong intertemporal correlation in the occurrence of floods (0.44 for flash floods and 0.55 for riverine floods), i.e. households experiencing a flood his year also have a high chance of experiencing one the following year (Table C2). As expected, there is also a correlation between the statistical frequency with which extreme weather events happen (their incidence) and their actual occurrence during the current or previous survey years, a correlation which is most pronounced for floods. Finally, some bunching of events is also observed, with households subjected to a hurricane, often also hit by flash floods, as indicated by the correlation coefficient of 0.55 between the incidence of flash floods and the incidence of hurricanes. Hurricanes thus manifest themselves partly through localized flooding. Riverine floods on the other hand appear negatively correlated with flash floods and hurricanes. Finally, note that a higher incidence of drought does not exclude the occurrence of floods within the same year as indicated by the positive correlation between the incidence of droughts and floods (and hurricanes).

45. The bunching of the disasters underscores the importance of considering their effect separately, but jointly in the regression analysis. Potential persistence in the effect is examined through consideration of both the current and one year lagged events. Finally, to separate out the potential effects of adaptation from the immediate welfare effects from current events, the regressions also control for the frequency with which the different events occurred.

[82] The VMAP0 (NIMA, 1997) was used to obtain data on three classes of roads: 1) divided highways; 2) primary/secondary roads; 3) paths or trails. For rivers and lakes, the CIA World Data Bank II (CIA, 1972) was used. The population centers are from the GRUMP settlement points dataset (CIESIN et al., 2004a) and the World Gazetteer database (Helders, 2005). Urban boundaries are from the GRUMP urban extents database (CIESIN et al., 2004b). The international boundaries are from the World Bank mapping office.

[83] To maintain confidentiality, the geographic coordinates of each household in the VHLSS are not made publicly available, only the shapefiles for the different communes surveyed.

4.5 Welfare Effects of Natural Disasters in Vietnam

46. To benchmark the results, Table 4.1 (column 1) presents the estimated OLS coefficients[84] of a standard consumption model augmented with information on the present and lagged occurrence of the different extreme weather events (droughts, localized and riverine floods, hurricane force winds). These are subsequently augmented with data on the frequency of their occurrence (column 2) and interaction terms between the extreme events and the distance to cities with more than 500,000 inhabitants to capture geographical diversity in the effects (column 3). The Maximum Likelihood estimates which also correct for spatial correlation (in addition to heteroskedasticity and cluster design) are in column 4. The following cut-offs were settled on to identify an event as extreme: rainfall 20 percent below the long run median for drought; at least one episode of more than 300 mm rainfall in 5 consecutive days for excess rain/localized flooding; DFO recorded floods within 2 m elevation difference from the major rivers or coast line; and areas affected by 65 knot (or 118 km/hour) hurricane wind force.

47. The regressions display high explanatory power (R-squared between 55 and 60 percent) and the estimated coefficients on the different household and community characteristics are consistent with those reported in the literature. This provides confidence in the base results.[85] Larger households with more dependents and belonging to ethnic minorities are poorer, while the more experienced and more educated households with more land and in possession of a house enjoy higher living standards. Illness of adult household members (not for children or elderly) tends to be negatively associated with consumption levels, though it is only statistically significant for the spatially corrected ML estimates. Households in communities with better sanitary conditions (sanitary living water and sanitary latrines) and better road access are also richer, while households located on steeply sloped areas tend to be poorer. Households in urban areas are on average about 30 percent richer, with levels of consumption declining the further away from the urban center and the gradients steepening the larger the urban center. Consistent with the steep GDP growth observed in Vietnam during the survey period, household consumption levels (in real terms) increase substantially between the survey years, as reflected in the large and statistically significant coefficients on the year dummy variables.

The more exposed to natural disasters, the poorer households tend to be

48. Turning to the welfare effects of weather events, household welfare is substantially affected by natural disasters, but at first sight, not always in the direction expected. When included without controls for exposure (Table 4.1, column 1), current droughts, localized and riverine floods appear positively correlated with household welfare, with the occurrence of a localized flood last year also increasing welfare, with the lagged effects of riverine floods exercising a dampening effect on household welfare. However, when the frequency of extreme events in each locality is included together with their interaction with the current and lagged occurrence of the event (column 2), a different picture emerges.

49. Welfare is lower in areas frequently exposed to droughts and hurricanes, while (surprisingly) it appears to increase welfare in areas frequently exposed to excess rain, with no discernable effect in frequently inundated riverine areas. Second, the direction of the immediate welfare effects of current and lagged events also changes when interacted with the frequency of their occurrence. Current droughts, localized and riverine floods no longer increase welfare and excess rainfall in the current year is now negatively related with consumption, at least when excess rain is not a regular phenomenon. The signs and statistical significance of past weather events, reflecting the lagged welfare effects, also change when they are interacted with their frequency.

[84] These were obtained from the pooled 2002, 2004, and 2006 VHLSS data with standard corrections for heteroskedasticity and clustered survey design using the Hubert-White estimator provided in STATA.

[85] The comprehensive controls for community (and household) characteristics help protect the natural disaster variables from omitted variable bias. As the survey comprises more than 3000 communities, each surveyed at least two times, overfitting is not considered a concern. Note also that the number of controls is in effect still substantially less than when estimating a household or community fixed effect regression.

50. Frequent exposure may induce the adoption of low risk, low return portfolios (Eswaran and Kotwal, 1990; Rosenzweig and Binswanger, 1993), but the associated welfare loss could also reflect accumulated asset loss (Carter and Barrett, 2006), issues further discussed below. Poor people may also concentrate in areas considered too risky to live in. Given the myriad of household and environmental controls that already capture household wealth, such as education, ownership of land and housing, access to public infrastructure and amenities, proximity to urban centers as well as agro-ecological conditions (elevation and slope), the latter interpretation of the results is less likely. The results in columns (1) and (2) underscore especially the importance of controlling for the frequency of exposure in studying the immediate and lagged welfare effects of natural disasters.

Those further away from large urban centers are poorer, but also tend to suffer less from being regularly confronted with natural disasters

51. The welfare effects likely also differ depending on the proximity to large urban centers (Table 4.1, column 3). In particular, interaction of the different events with the distance (in tenths of hours) to cities with more than 500,000 inhabitants suggests that the welfare effects gradually change away from these large urban centers. Locations further away are typically less affected. For example, while areas frequently hit by drought are less wealthy, frequent exposure to droughts appears less damaging in terms of welfare loss further away from the large cities, that is, after controlling for the welfare reducing effect of living far away from urban centers. Similarly, areas located in storm prone areas further away from the urban centers are less affected than those in storm prone areas close to the city. A similar phenomenon is observed when it comes to localized flooding –with frequent exposure less damaging among those further out.

52. Economies and livelihoods become more rural and agriculturally oriented further away from the metropolitan areas. Asset holdings and the share of agricultural land irrigated typically declines (Table C3) and the support systems weaken. In particular, households further away tend to be less likely to receive remittances from abroad and the amounts received tend to be smaller. And while they are as likely to receive domestic remittances and even more likely to receive disaster relief, the latter is still rare (only 12 % of the households received disaster relief during the 2002-2004-2006 surveys) and it usually comes in much smaller amounts than the relief received by those close to the metropolitan centers. Taken together these descriptive suggests that households further away are not only more exposed ex ante (at least to drought) but also have lower capacity to cope with natural disaster ex post (less assets/savings and less effective support systems). This may have induced them to adopt portfolios that are more resilient to damage from natural disasters, though portfolios that are also less remunerative , as indicated by the steep declining gradient in household welfare as one moves away from the metropolitan centers.

53. From this perspective, the reverse finding on riverine flooding comes as a surprise. Out of the 4 disasters considered, only frequent exposure to riverine flooding is associated with an increase (as opposed to a decline) in living standards, with its benefits declining as one moves away from the major metropolitan centers. In this case, regular flooding seems to have induced a superior livelihood system, at least among those closer to the metropolitan area. This is mostly in regard to households in the Mekong River Delta, that have their livelihood systems built around floods ("living with flood", very much as in Bangladesh, Beck, 2005). Comparison of self-reported flood measures with the riverine flood measure used here (taken from the DFO) supports this interpretation. The flood incidence based on the latter measure is much larger than the flood incidence based on the former, indicating that not all floods recorded in DFO are actually also experienced as negative events by the households themselves. It is not so much the flooding as such which is detrimental, but rather its duration and level, rendering only a subset of the DFO observed floods really damaging.

Immediate, lagged and persistent welfare effects by event

54. For a more detailed shock by shock comparison of the welfare effects, the study turns to the Maximum Likelihood welfare estimates, which also correct for spatial correlation (Table 4.1, column 4). While they qualitatively correspond to the OLS estimates in column 3, the size of the effects

changes at times substantially and the coefficients are also more precisely estimated, yielding additional insights. This is expected given that both the tests for spatial lags and errors (not reported here) point to the existence of spatial correlation (within and beyond the cluster). To provide some further intuition to the findings, it is simultaneously explored how households cope with each of the shocks. In particular, the immediate, lagged and persistent effects of the different natural disasters on a household's asset holdings, its reception of official disaster relief and domestic and foreign remittances, and its degree of income diversification as captured in the Herfindahl index,[86] are given in Table 4.2. The effects of natural disasters on asset holdings and income diversification are estimated using OLS with suitable corrections for heteroskedasticity and cluster design, while left censored tobits are used for the household assistance regressions, as many households did not receive any assistance/remittances. To control for household, community and environmental characteristics, the same controls are used as in the household welfare regressions above. The ML results are repeated in the first column (Table 4.2, column 1) to facilitate the discussion.

Droughts reduce welfare, though mainly among those with few irrigated plots

55. As before, there are no statistically significant signs of immediate or lagged effects of droughts. Further investigation using the 2004 and 2006 survey years for which information on irrigation is also available, shows that irrigation provides effective protection against droughts. In particular, households with no irrigated plots see their per capita consumption decline by 16 percent on average the year of the drought, while those with all their plots irrigated (the majority of the sample) experiencing only a 3 percent loss in welfare. In other words, irrigation proves quite effective in protecting households from drought. No lagged effect of droughts is observed. Self insurance through asset disposal (which shows up with a lag,Table 4.2, column 2) and income diversification (lower Herfindahl index), especially in drought prone areas, enables households to further soften the blow of immediate drought shocks. Yet, this also erodes their asset base over time, consistent with the lower welfare observed in drought prone areas. The loss can be substantial — households in areas with a 10 percentage point higher frequency of drought are on average 12 percent poorer — though the majority of households only experience a drought once a decade, with only two percent facing a drought every three to five years.

56. Interestingly, the welfare loss associated with frequent drought occurrences declines as one moves away from the metropolitan areas. This is likely related to the somewhat larger responsiveness of official relief efforts to current drought events in those more remote areas (albeit with lower amounts disbursed on average),[87] which appears to mitigate the need for self insurance through asset disposal, as suggested by the lower asset loss experienced in less urbanized areas (positive coefficient on the interaction term of lagged drought and distance to large city—column 2). Over time this yields lower accumulated asset loss in the more remote areas (column 2) and less severe welfare loss (column 1) than in the areas closer to the metropolitan areas. The disaster relief systems appears to enable these households to remain more specialized (higher Herfindahl index), i.e. more agriculture focused, than those in other drought prone areas closer to the metropoles, suggesting that the relief efforts also help in mitigating the effects of droughts, even though the amounts disbursed tend to be smaller than among those closer to the metropoles.

Localized floods cause an immediate welfare loss, which households largely recuperate thereafter

57. Heavy rainfall has an immediate welfare reducing effect, by 7.7 percent on average (Table 4.2, column 1), likely through the destruction of assets (Table 4.2, column 2), though less in areas, which are frequently exposed, and thus better adapted, or those further away from the metropoles. There is

[86] The Herfindahl index is a measure of income diversification, defined as the sum of the squares of the different income shares. It ranges between one and zero, with 1 indicating full specialization and lower values pointing to increasingly diversified income portfolios.

[87] Indicated by the jointly positive and statistically significant coefficients on current drought events and their interaction term with distance away from the metropolitan areas when 2 hours or more away from the metropolitan area.

also a lagged welfare increasing effect of heavy rainfall. Heavy rainfall often goes hand in hand with landslides which can cause substantial damage to infrastructure, property and capital. When not too severe or not too frequent, households can take advantage of such asset loss to accelerate replacement of their assets by better, more productive ones, accelerating their return to their normal growth path, as postulated in the vintage capital growth models (Hallegate and Dumas, 2009). Households in areas more frequently affected by localized floods tend to experience lower levels of consumption, though again, less severe so among those in flood prone areas further away.

58. Overall the welfare losses from frequent exposure to excess rain are only one fourth to one fifth (-0.28/-1.26) those brought about by regular exposure to rainfall shortages. Lower net asset loss (the immediate negative effects largely compensated by technically better replacements in the next period helps understand the difference in the welfare effects of rainfall shortages and rainfall excesses (Table 4.2). While the destruction of assets associated with excess rain does not lead to higher welfare levels altogether, their replacement with better more productive alternatives, especially in areas that are not frequently confronted with excess rain (see the negative coefficient on interaction term of lagged localized flood and excess rain frequency in column 2) can mitigate their negative effects. Droughts on the other hand, do not induce an immediate asset loss as such (beyond livestock loss). Assets are disposed off to cope with the shocks, smoothing consumption in the current period, but eroding the household's coping capacity over time, consistent with the larger negative effect of the frequent occurrence of droughts on asset holdings (coefficient equals -3.4, the largest among all disasters considered), and by extension on consumption. Larger official relief efforts in frequently flooded areas closer to the larger cities may further attenuate the welfare loss compared with those related to water shortages. Households do not appear to change their income portfolios in response to heavy rainfall—none of the coefficients on the localized flood variables and their interaction terms are statistically significant, with the exception of one, whose coefficient is very small.

While households learned to live with riverine floods, severe floods can cause substantial damage

59. The occurrence of a riverine flood reduces household welfare on average with a combined 23 percent, by 5.8 percent immediately and by 17.2 percent in the subsequent year, indicating that it takes some time for the full effect to be felt. But as indicated above, not all riverine floods recorded in DFO make for a negative experience, and households in areas prone to riverine floods appear on average even slightly better off. They experience less immediate welfare loss (positive coefficient on interaction term between flood frequency and current flood event—column 1, Table 4.2) and dispose less of their assets to cope with the effects (positive coefficient on interaction term with lagged riverine flood – column 2, Table 4.2), likely linked to the much better provision of disaster relief in regularly flooded areas. While the disaster relief in the flood prone areas prevents the erosion of the asset base (no loss of assets in frequently affected areas—column 2), it is nonetheless not sufficient to prevent a substantial 17 percent temporary reduction in their consumption welfare loss based on the floods recorded in this sample. This loss manifests itself with a lag, together with lagged reduction in the asset base.

60. Households in flood prone areas away from the urban centers on the other hand appear more negatively affected by riverine floods. They receive much less disaster assistance, find themselves over time with a lower asset base (negative coefficient on interaction distance to city and flood frequency), resulting in a long term welfare loss (negative coefficient interaction term distance to city and flood frequency—column 1). Households also cope with the lagged effects of shocks through income diversification, especially closer to the cities.

Hurricane force winds inflict immediate and lasting damage to household welfare.

61. The occurrence of a hurricane is associated with a 52 percent immediate welfare loss inside cities with more than 500,000 inhabitants, a potential 16 percent loss in the subsequent year, and a 20 percent reduction in welfare in areas with a 10 percentage point higher chance of being hit by hurricane wind forces. Furthermore, unlike with (localized and riverine) floods the immediate effects are not mitigated in areas that are more frequently hit, i.e. there is no adaptation. Rather the opposite,

the immediate and lagged effects are, if anything, even more detrimental, indicating that households have not been able to adapt to and that the official disaster relief system has not been effective in dealing with hurricane forces winds in Vietnam. Second, the damage is less severe the further away from the urban centers. This can be expected given the larger concentration and reliance of the economy and livelihoods on infrastructure in the more urban economies. Official and private transfers have largely been unresponsive to storm related disasters (columns 3-5, Table 4.2). Similarly portfolio choice remains largely unaffected in the face of storms, with the exception of some lagged portfolio diversification in areas frequently affected.

62. Summarizing the key insights regarding the allocation of disaster relief, one of the key ex post policy responses to disasters, households further away from the larger urban centers (more than 500,000 inhabitants) are on average more likely to receive disaster aid (see positive coefficient on log hours to 500k city). While the amounts received tend to be smaller, it does help in coping with the welfare loss. Furthermore, relief efforts appear not to be sustained much beyond the first year. The disaster relief systems appear especially well developed in frequently flooded areas (both localized and riverine or coastal) close to the major urban centers. Official disaster assistance is not given following hurricane force winds. There are no clear systematic patterns with respect to the reception of domestic or foreign remittances. Sectoral income diversification does not emerge as a major coping strategy, with the exception of the larger income diversification observed in drought prone areas closer to the urban centers. Asset losses, which can result from direct damage or through asset disposal to self insure, often show up with a delay and tend to be less severe further away from the urban centers.

63. In conclusion, while households largely manage to cope with drought events, often through asset disposal, but especially through irrigation, the frequent occurrence of droughts erodes their capacity to cope with them over time. These result in substantial welfare loss among households in drought prone areas closer to the urban centers. Households in drought prone areas further away from the urban capitals also suffer, but less as they manage to hang on to their assets better because of drought responsive relief efforts. Localized flooding exerts an immediate 7 percent toll on welfare though much of that loss appears to be recuperated the next year potentially through replacement of the lost asset base by better more productive ones, at least among those that are not frequently hit. The latter tend to suffer less immediately, partly through the reception of disaster aid, but they also benefit less from the faster adoption of more productive assets, likely resulting in some asset erosion over time and lower consumption levels (though to a lesser extent than in the case of regular rainfall failure). The damage from frequent exposure to localized floods is again less severe among those further away from the urban centers, as they experience less asset loss, while receiving more immediate disaster relief. Riverine floods can cause substantial welfare damage (23 percent), especially among those not frequently exposed, who tend to be better served by disaster relief, at least when living close to the urban centers. Finally, the largest damage is inflicted by hurricane force winds, with both regular exposure and proximity to the urban centers exacerbating the welfare losses substantially.

4.6 Concluding Remarks

64. Understanding how natural disasters affect human welfare is an increasingly pressing concern, not least in Vietnam, which ranks among the most disaster prone countries in the world. This study illustrates a methodology to study the welfare effects of such events in a country specific setting using spatially disaggregated disaster maps derived from primary meteorological data combined with nationally representative geo-referenced household survey data. By deriving the spatially disaggregated event and hazard maps directly from the meteorological data, issues of endogeneity in estimating the effect of such events on consumption are mitigated. The event and hazard maps provide also useful tools for policy and project planning. In addition, in estimating the welfare effects, spatial correlation was accounted for. While the latter is routinely ignored, this is less suitable in empirical examinations of the household welfare effects of spatially disaggregated disasters whose effects regularly permeate the economy through product (food prices) and factor (labor) markets.

65. The econometric results suggest that households in Vietnam largely manage to cope with the immediate effects of drought events, through irrigation. However, the frequent occurrence of droughts erodes their capacity to cope with them, resulting in substantial welfare loss especially among households in drought prone areas closer to the urban centers, where disaster relief is less pronounced. Localized floods exert important welfare losses, on average an estimated at 7 percent, though much of that loss appears to be recuperated through capital replacement in the subsequent year, at least among those who are only occasionally affected by such floods. Those who are frequently affected suffer more, though the long run effects from frequent exposure to localized floods are substantially less than those from frequent exposure to droughts, partly due to a responsive relief system in the more urban areas that are frequently affected. Riverine floods cause substantial welfare damage (23 percent) in the short run, though less so among households who are frequently exposed. Not only do they tend to be much better served by disaster relief, especially when close to the metropolitan centers, it is important to note that not all riverine floods recorded in DFO are experienced as negative events, as households built their livelihood systems around them, especially close to the metropolitan areas. They learned to live with floods. Finally, the largest damage is inflicted by hurricane force winds, with regular exposure and proximity to the urban centers, both of which exacerbate the welfare losses substantially.

66. Overall, the study shows that there is promise in using meteorological data to construct spatially disaggregated weather event and weather hazard maps, the first objective of the study. Such data are becoming increasingly available and natural event and hazard maps have also important direct applications for policymakers beyond their use in estimating the welfare effects of disasters. The fine-tuning and validation of such maps is an important area for further research. Second, there are important long run negative effects of being regularly confronted with natural disasters. Third, short run losses can be substantial, with hurricanes causing most havoc. Fourth, there are signs of adaptation, with frequent exposure to localized and riverine floods reducing the welfare losses associated with these events, partly through the development of effective disaster relief systems. There is however no adaptation to hurricanes, rather the contrary, with high frequency of hurricanes exacerbating the losses from particular events. Fifth, those further away from the large urban centers often enjoy more immediate disaster relief which appears to mitigate the current effects of natural hazards, underscoring the importance of effective disaster relief systems. In the absence of further support systems, they likely also adopted less risky, but also less remunerative portfolios. Sixth, the disaster relief systems have largely eluded areas affected by hurricane force winds so far, an important area of attention for Vietnamese policymakers.

Figure 4.1 Regions of Vietnam

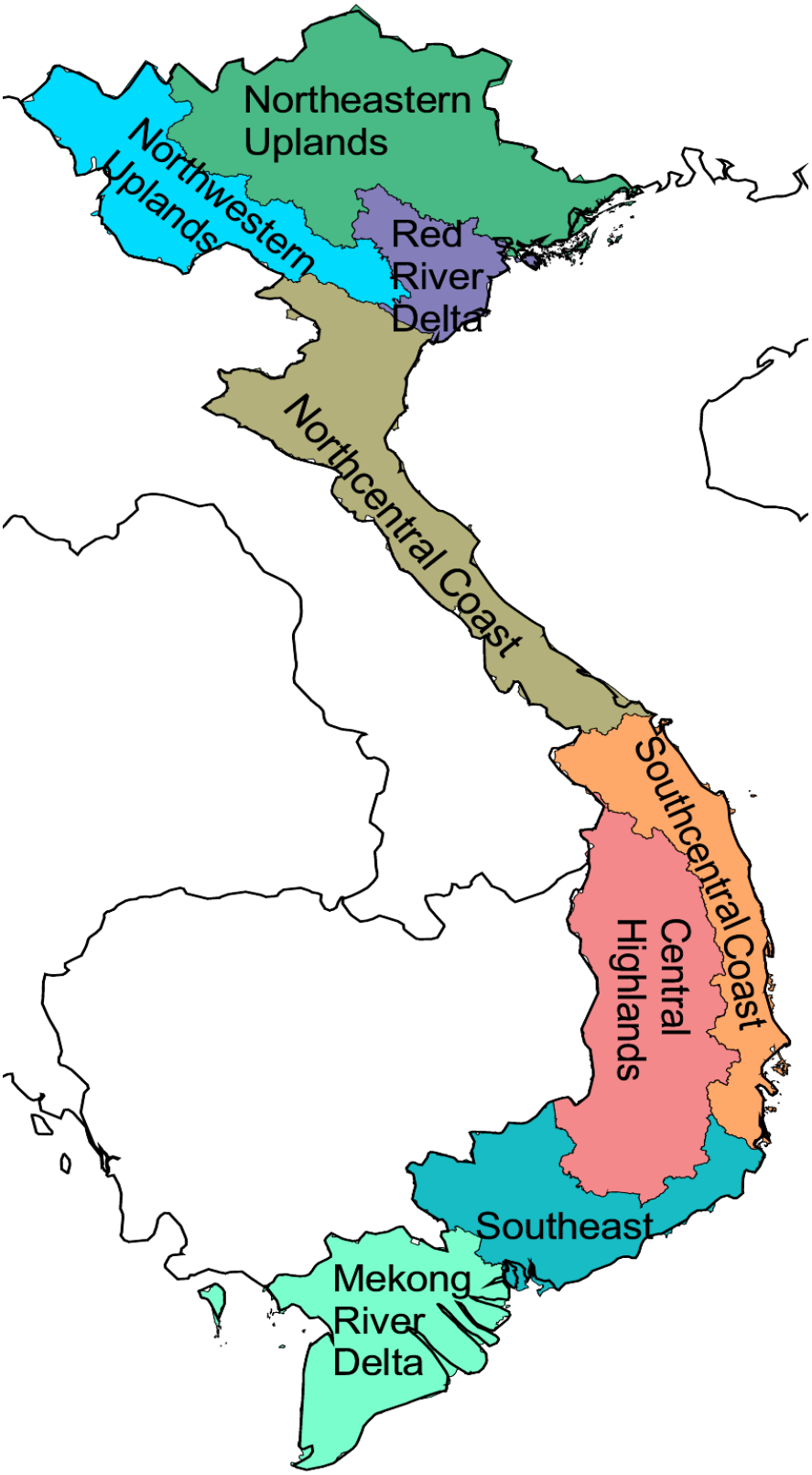


Figure 4. 2 Rainfall maps using inverse distance weighing and inverse elevation difference weighting display close resemblance

Figure 4.2a: Rainfall prediction using inverse distance squared from 5 nearest station data only, June 2006

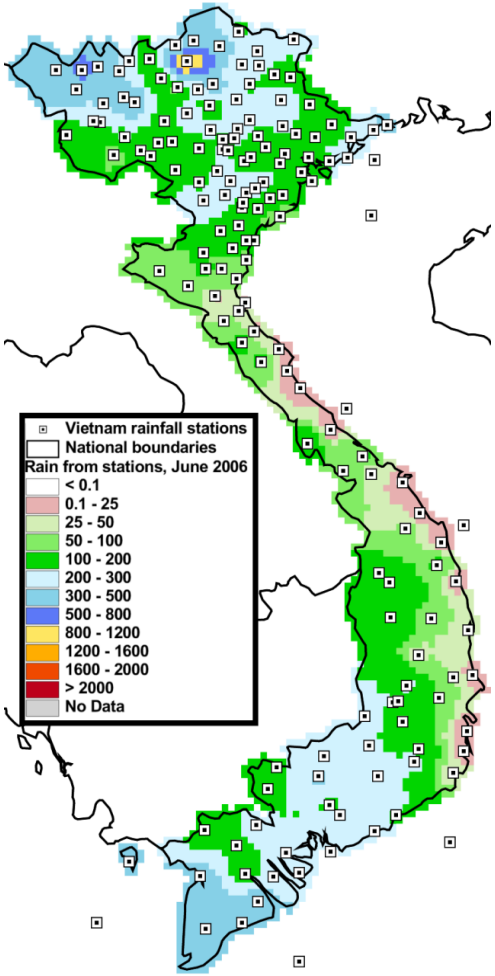


Figure 4.2b: Rainfall prediction using elevation difference weighting for 10 nearest stations only, June 2006

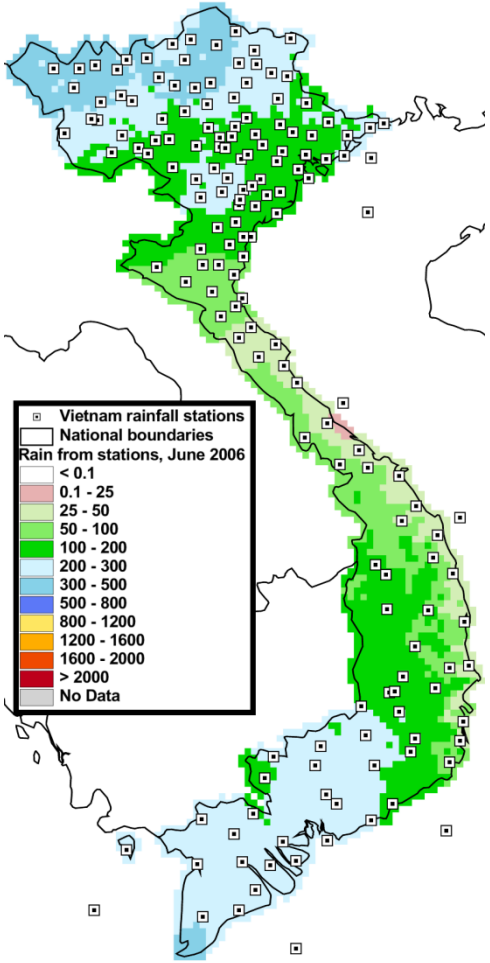
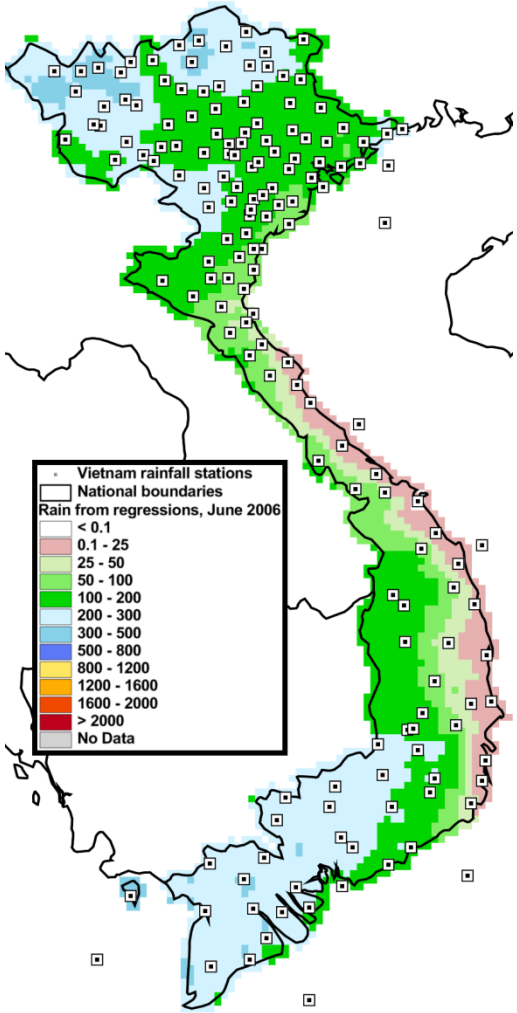
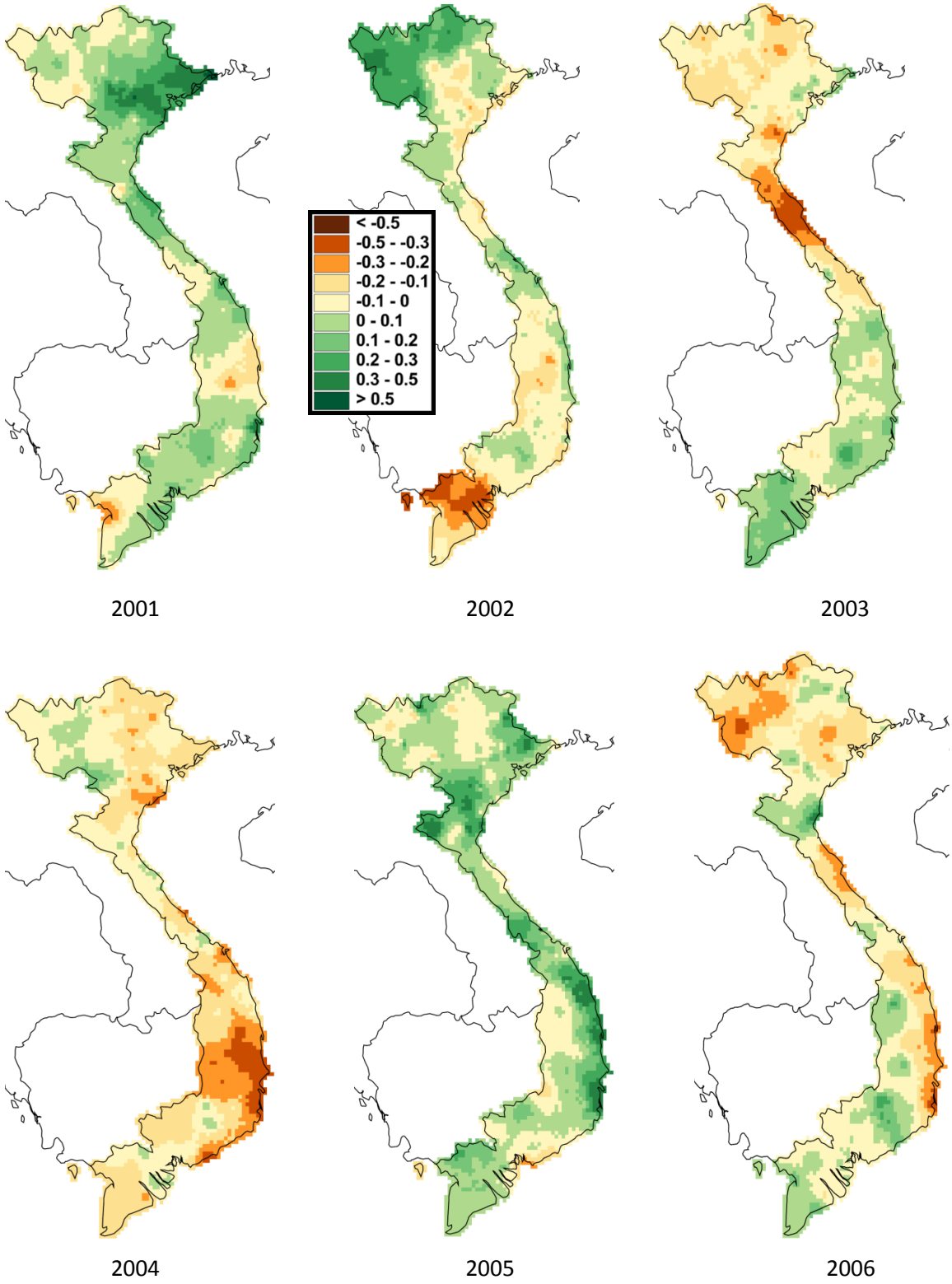


Figure 4.2c: Rainfall prediction from regression analysis, June 2006



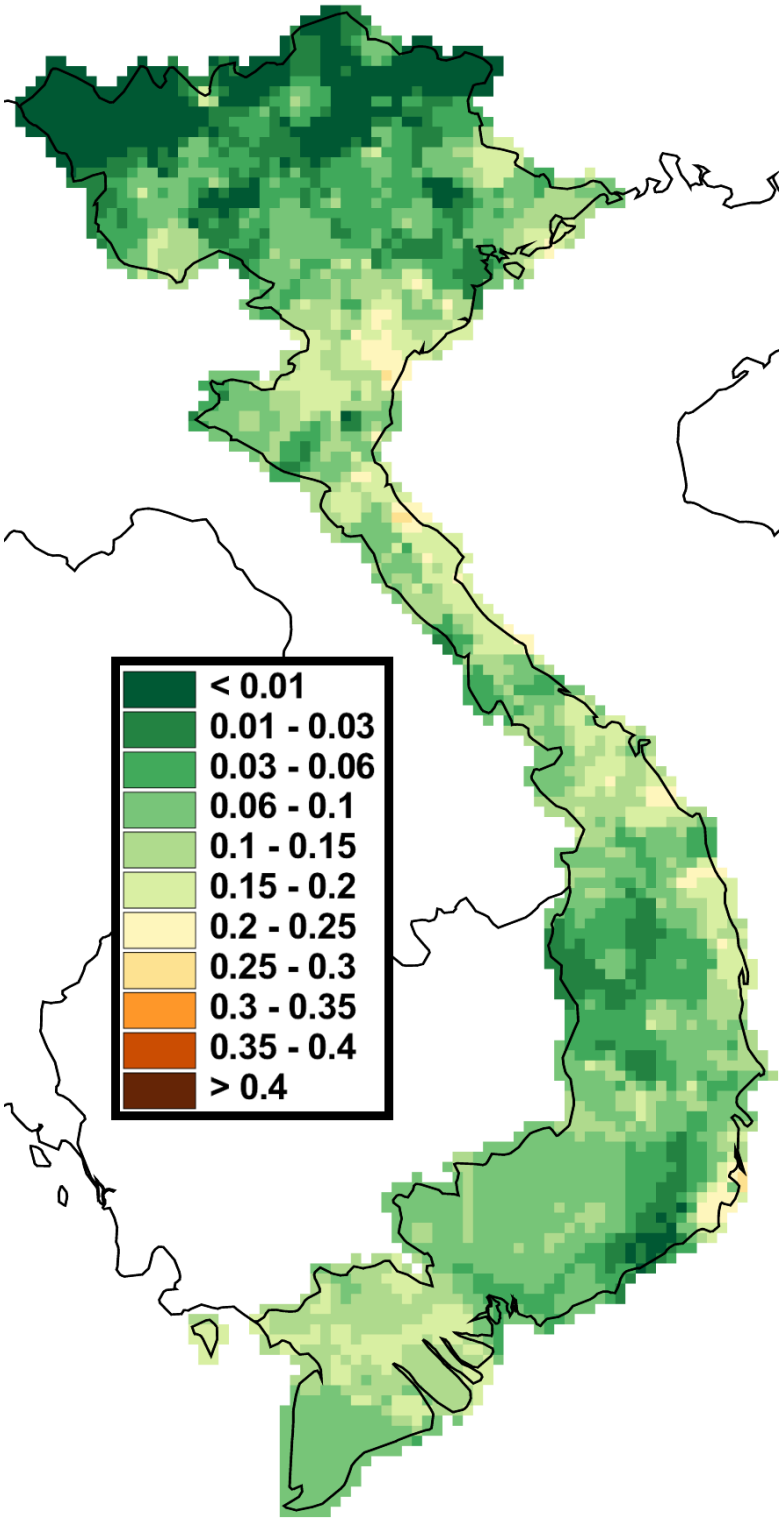
Source: Thomas et al. (2010)

Figure 4. 3 Deviations from median annual rainfall for each year 2001 to 2006.



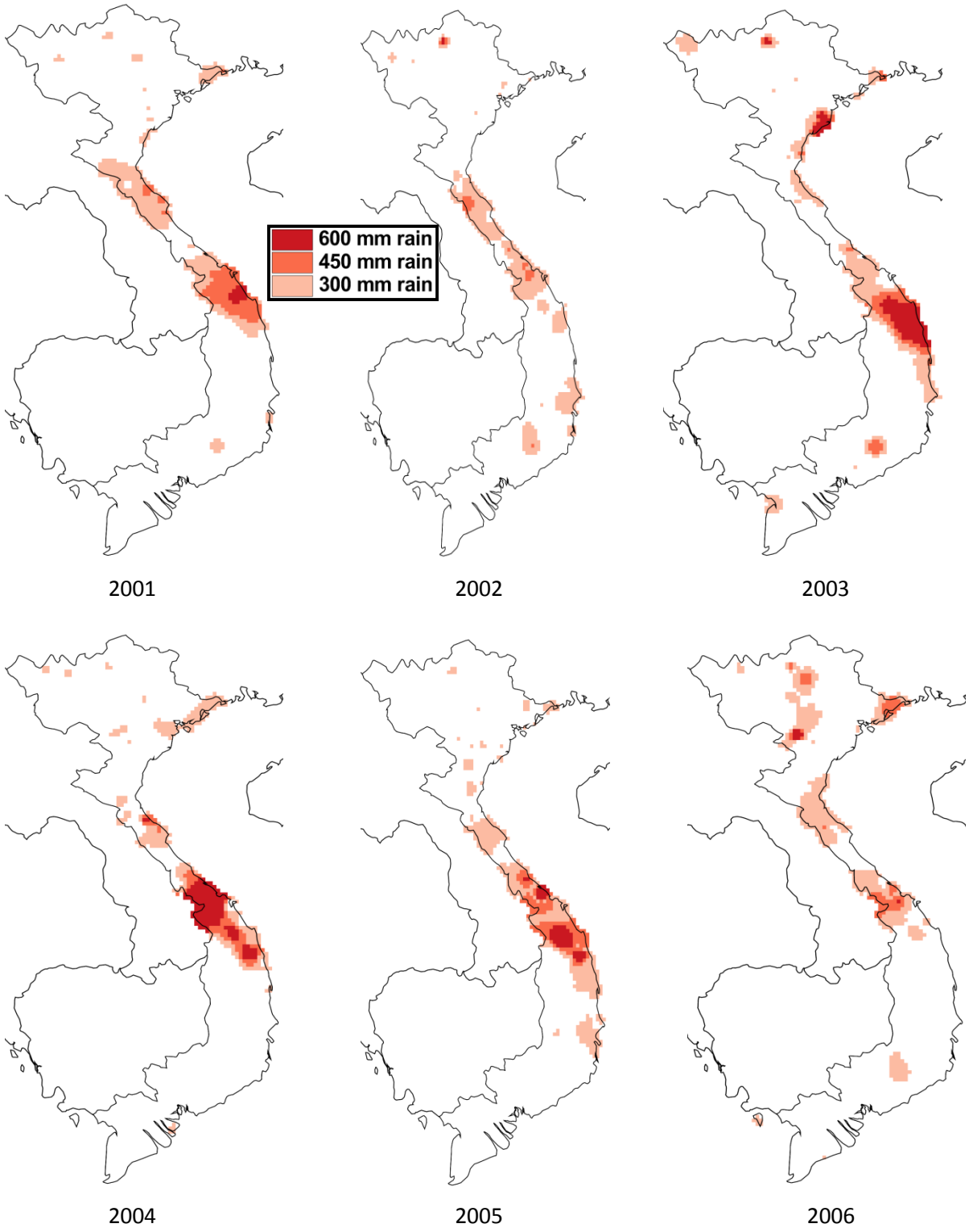
Source: Thomas et al. (2010).

Figure 4.4 Proportion of years with 20 percent shortfall in median annual rainfall



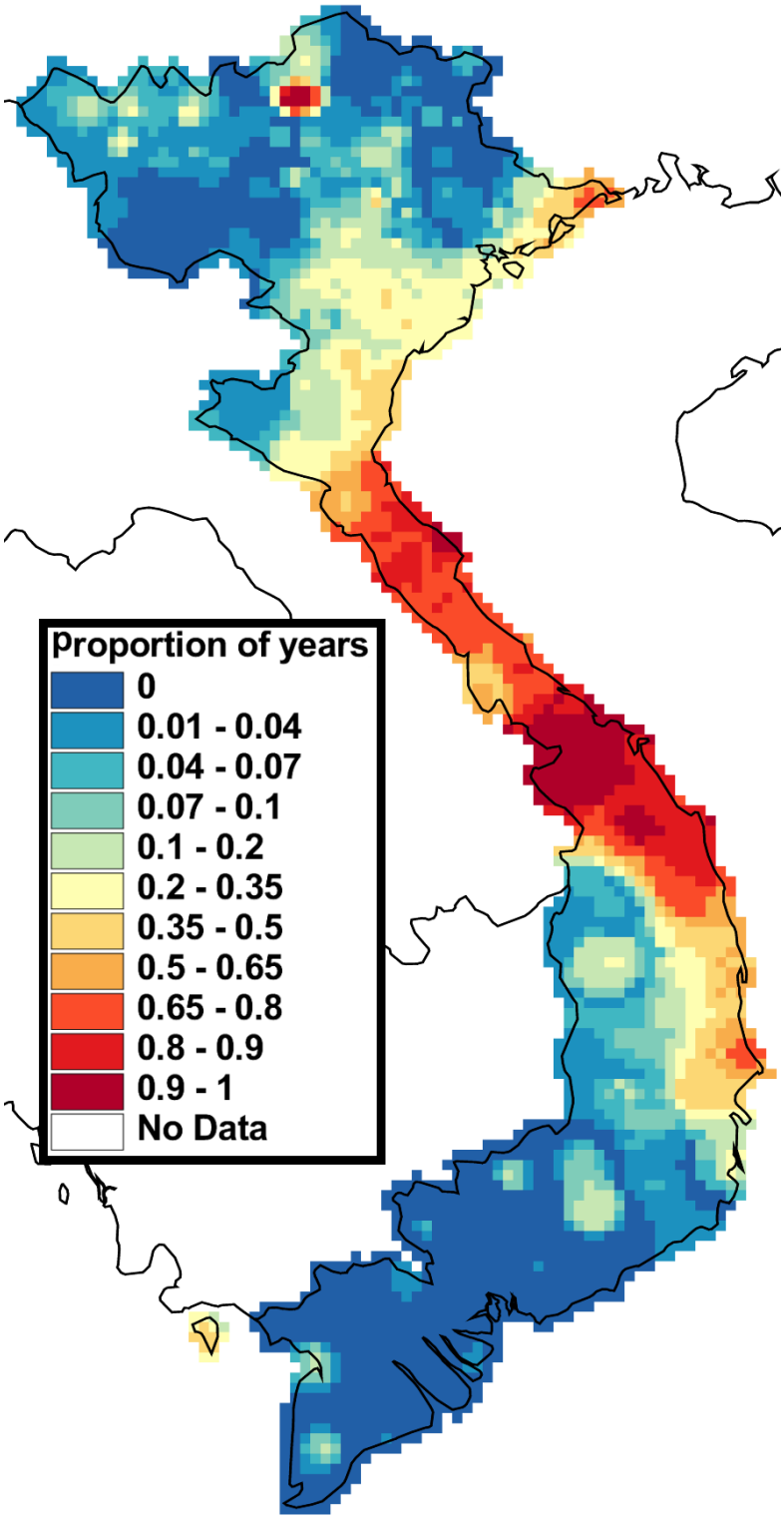
Source: Thomas et al. (2010).

Figure 4.5 Localized flooding for each year 2001 to 2006.



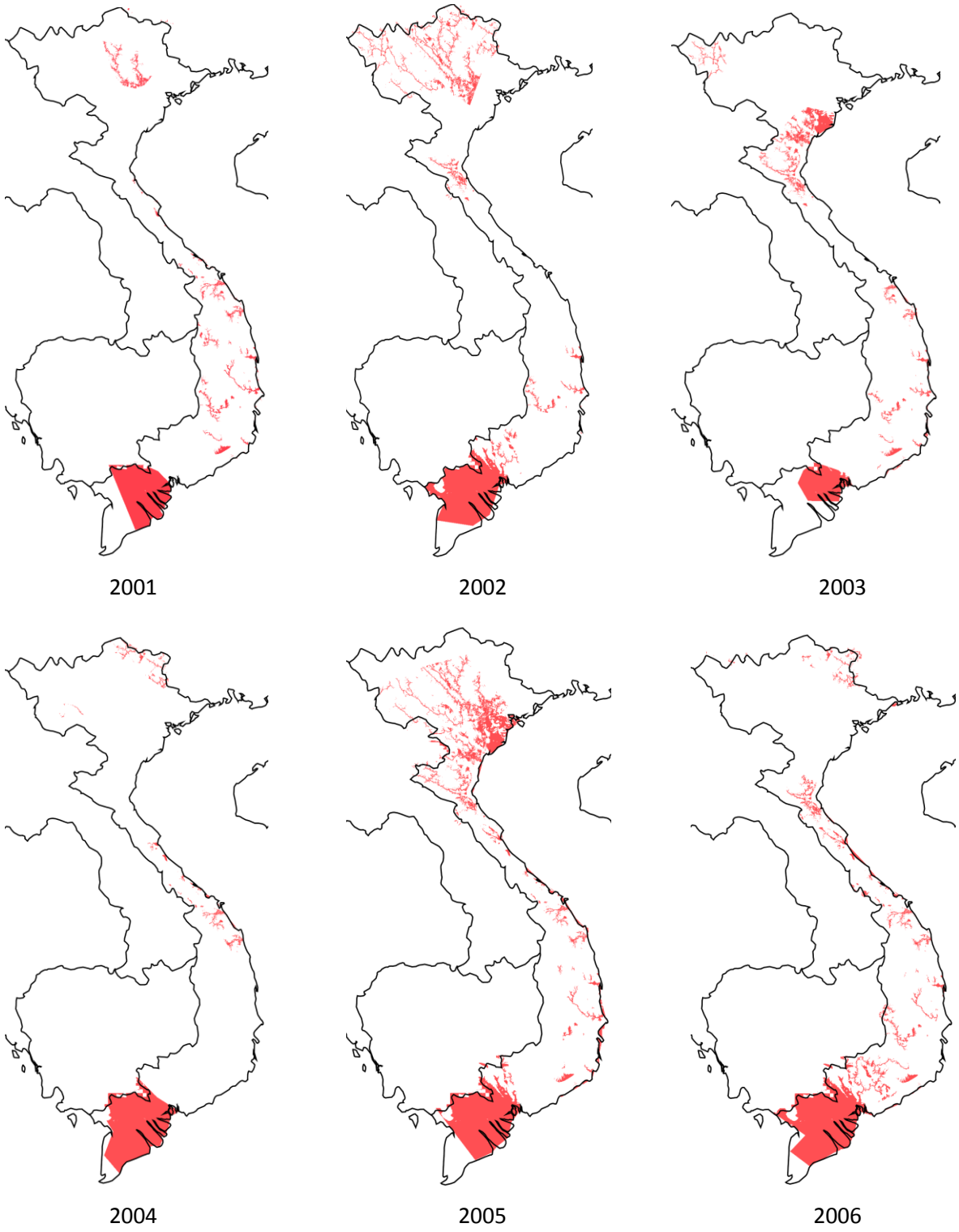
Source: Thomas et al. (2010)

Figure 4.6 Proportion of years in which 300 mm of rain fell in a consecutive 5-day period



Source: Thomas et al. (2010)

Figure 4.7 Riverine and coastal flooding for each year 2001 to 2006.



Source: Dartmouth Flood Observatory (2008) and author's calculations using Hydrosheds and GLOBE.

Figure 4.8 Proportion of riverine and coastal flooding 1985-2007.

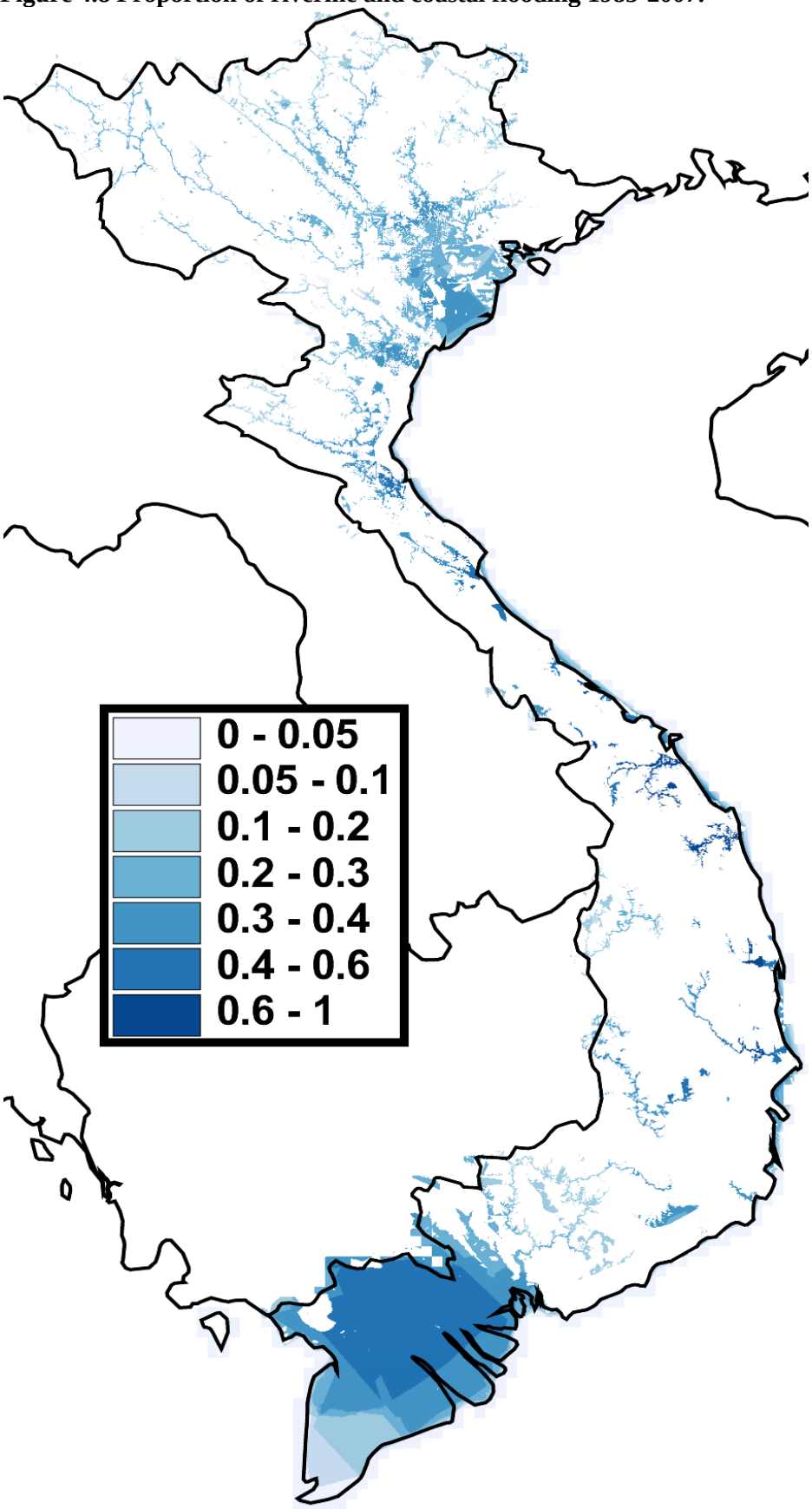
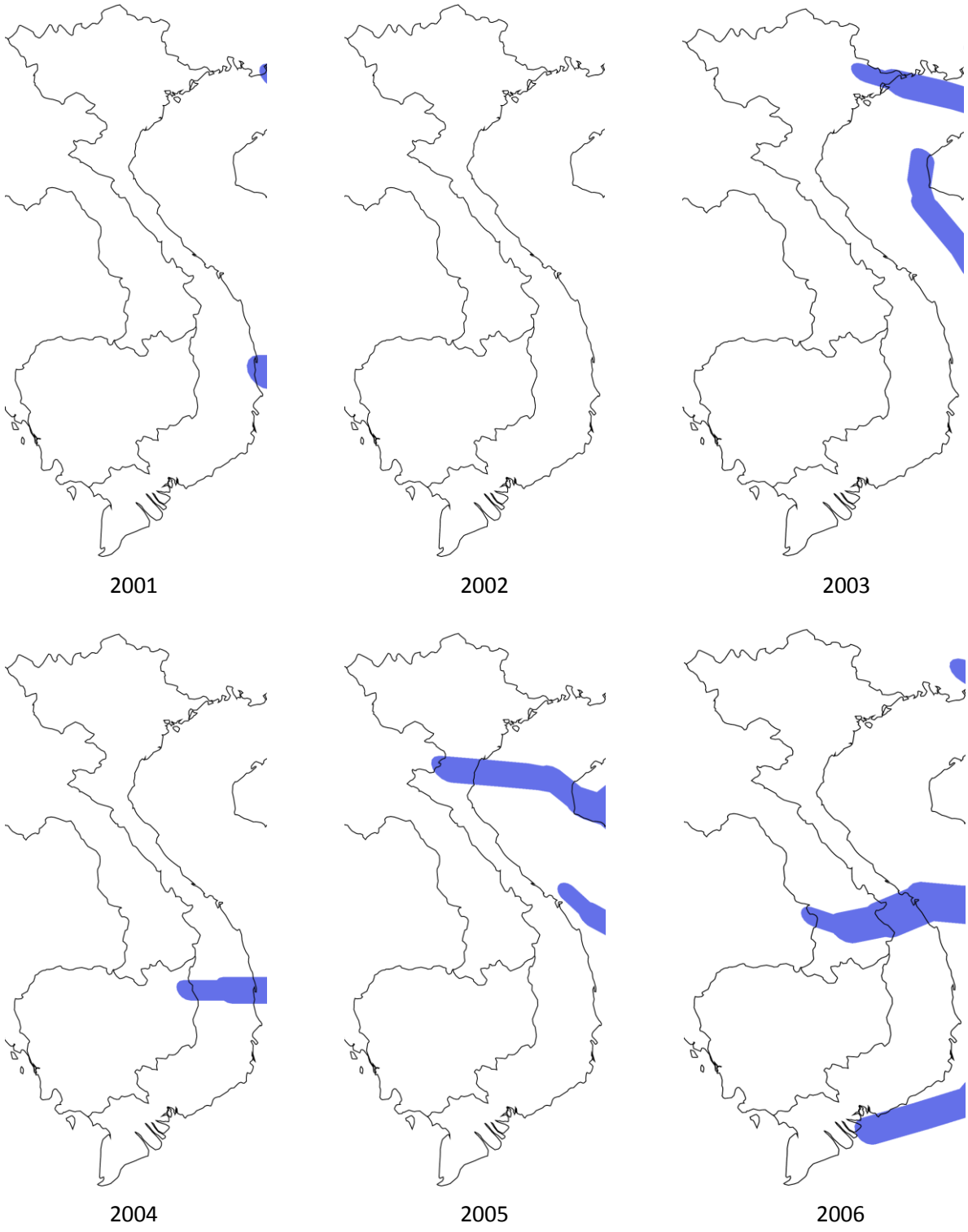
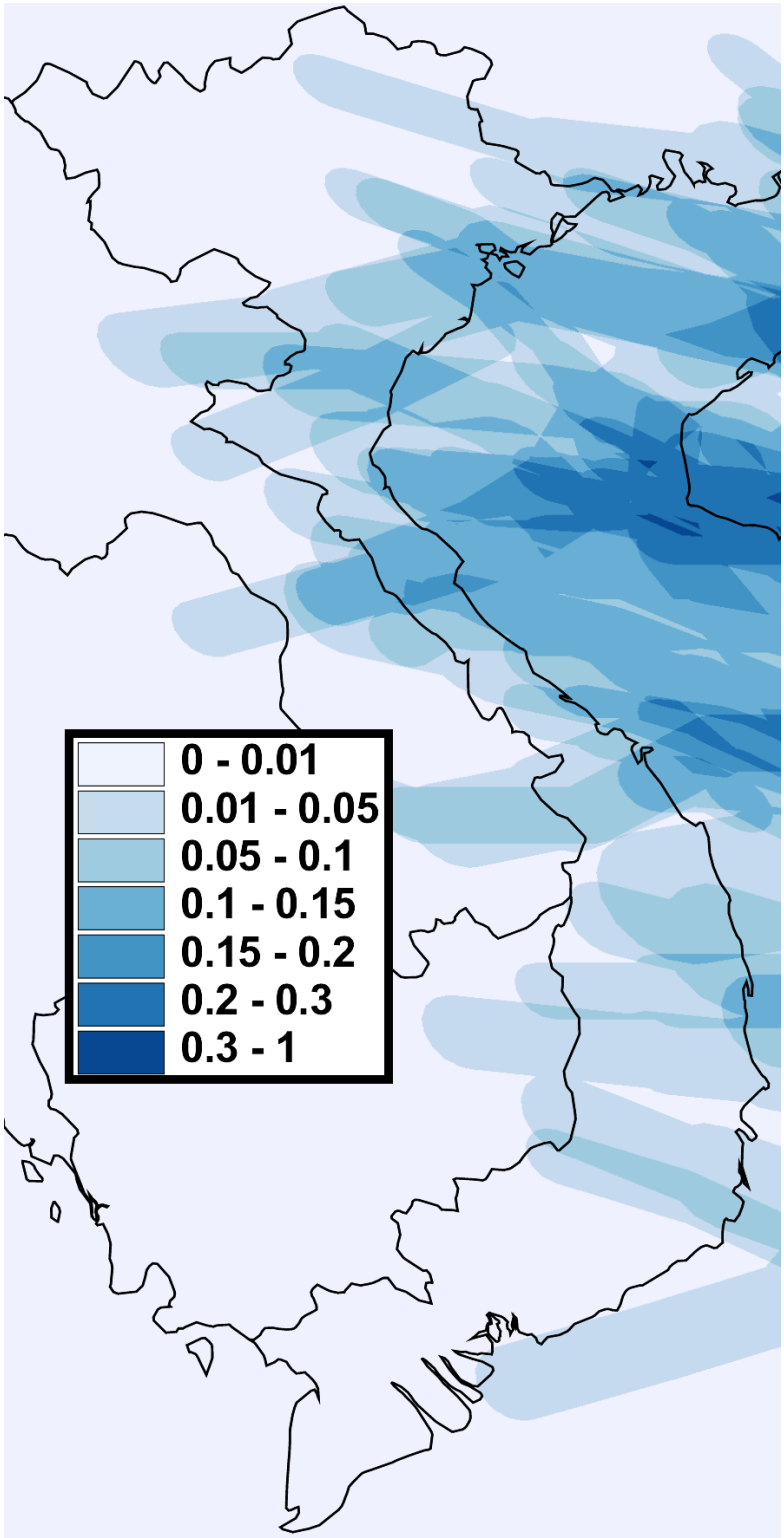


Figure 4.9 Hurricane force winds associated with tropical cyclones for 2001 to 2006.



Source: UNEP / GRID (2007) and author's calculations.

Figure 4.10 Proportion of years with hurricane force winds



Source: Thomas et al. (2010), based on GNV199 (UNEP/GRID-Europe, 2007a).

Figure 4.11 Most people are exposed to droughts, but infrequently; floods affect a sizeable population often, and a large population never; hurricanes pass by most and infrequently affect others.

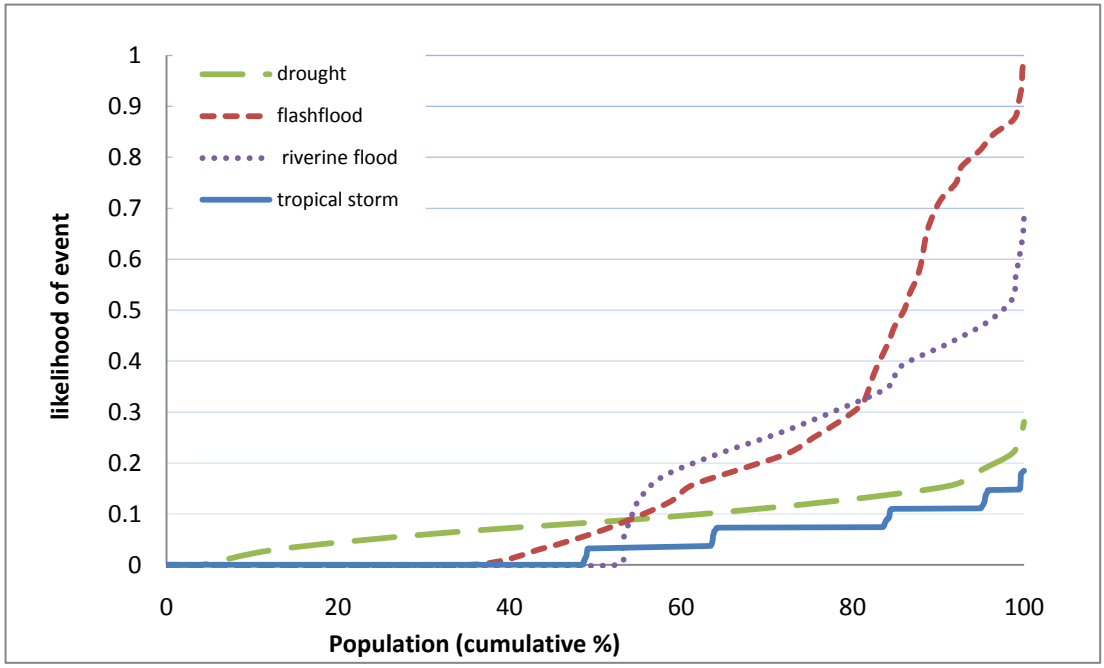


Table 4. 1 Extreme weather events can have substantial negative effects on household welfare, immediately and through adaptation over time, with adaptation and disaster relief often mitigating the immediate losses

Dependent variable: log expenditure/capita (excl. health expenditure)	OLS with Hubert-White heteroskedasticity and cluster design correction			ML corrected for spatial correlation, cluster design and heteroskedasticity
	(1)	(2)	(3)	(4)
	parameter/ t-value	parameter/ t-value	parameter/ t-value	parameter/ t-value
Extreme weather event in community				
Droughts				
Drought this year	0.0309***	0.0016	-0.0671	0.0245
	2.92	0.06	-1.04	0.58
Drought this year*drought frequency		0.3023	0.2918	0.0704
		1.48	1.39	0.46
Drought this year*ln(hours) from 500k city			0.0177	-0.0006
			1.23	-0.06
Drought last year	0.0118	0.004	0.1159	-0.0008
	0.44	0.06	0.45	-0.01
Drought last year*drought frequency		0.1253	0.0179	-0.1257
		0.35	0.05	-0.45
Drought last year*ln(hours) from 500k city			-0.0212	0.0111
			-0.39	0.31
Drought frequency (proportion)		-0.5241***	-2.5466***	-1.2609***
		-4.74	-5.54	-4.25
Drought frequency*ln(hours) from 500k city			0.5486***	0.2845***
			4.54	3.72
Excess rain				
Excess rain this year	0.0529***	-0.0658***	-0.1552***	-0.0768**
	4.14	-2.76	-2.92	-2.21
Excess rain this year*Excess rain frequency		0.1998***	0.0798	0.0685*
		4.24	1.28	1.90
Excess rain this year*ln(hours) from 500k city			0.0377**	0.0159
			2.2	1.49
Excess rain last year	0.0521***	0.0836***	0.1657**	0.1337***

Dependent variable: log expenditure/capita (excl. health expenditure)	OLS with Hubert-White heteroskedasticity and cluster design correction			ML corrected for spatial correlation, cluster design and heteroskedasticity
	(1)	(2)	(3)	(4)
	parameter/ t-value	parameter/ t-value	parameter/ t-value	parameter/ t-value
	3.58	2.88	2.56	4.14
Excess rain last year*Excess rain frequency		-0.1104**	-0.1451**	-0.0852**
		-2.09	-2.26	-2.17
Excess rain last year*ln(hours) from 500k city			-0.0166	-0.0182*
			-0.9	-1.95
Excess rain frequency (proportion)		0.0980**	-0.3440*	-0.2828**
		1.97	-1.87	-2.26
Excess rain frequency*ln(hours) from 500k city			0.0894**	0.0798**
			2.11	2.77
Riverine flood				
Riverine flood this year	0.0649***	0.0133	-0.0536	-0.0575*
	4.4	0.37	-1.05	-1.87
Riverine flood this year*Riverine flood frequency		0.1418	0.1299	0.1440**
		1.29	1.22	2.20
Riverine flood this year*ln(hours) from 500k city			0.0129	0.0091
			1.02	1.17
Riverine flood last year	-0.0615***	-0.0132	-0.1961***	-0.1723***
	-5.44	-0.38	-4.22	-5.417
Riverine flood last year*Riverine flood frequency		-0.1263	-0.0521	-0.0051
		-1.22	-0.48	-0.07
Riverine flood last year*ln(hours) from 500k city			0.0488***	0.3397***
			3.71	3.66
Riverine flood frequency (proportion)		-0.032	0.5082***	0.0407***
		-0.65	3.39	4.87
Riverine flood frequency*ln(hours) from 500k city			-0.1513***	-0.1041***
			-3.88	-4.24

Dependent variable: log expenditure/capita (excl. health expenditure)	OLS with Hubert-White heteroskedasticity and cluster design correction			ML corrected for spatial correlation, cluster design and heteroskedasticity
	(1)	(2)	(3)	(4)
	parameter/ t-value	parameter/ t-value	parameter/ t-value	parameter/ t-value
Hurricane force wind				
Hurricane force wind this year	0.0185	-0.0726	-0.4159	-0.7309***
	0.79	-1.16	-1.14	-2.93
Hurricane force wind this year*Hurricane force wind frequency		1.3281**	0.0739	-0.9634
		2.08	0.09	-1.41
Hurricane force wind this year*ln(hours) from 500k city			0.0886	0.1737***
			1.07	2.99
Hurricane force wind last year	0.0384	0.1967*	0.0658	-0.1642
	1.29	1.95	0.29	-0.96
Hurricane force wind last year*Hurricane force wind frequency		-1.1792	-1.197	-1.4028**
		-1.23	-1.28	-2.06
Hurricane force wind last year*ln(hours) from 500k city			0.0281	0.0762**
			0.54	1.97
Hurricane force wind frequency (proportion)		-0.5151***	-2.0504***	-2.1608***
		-3.42	-4.83	-7.45
Hurricane force wind frequency*ln(hours) from 500k city			0.4566***	0.4584***
			3.68	5.79
Household characteristics				
log of household size	-0.2419***	-0.2447***	-0.2474***	-0.2832***
	-36.06	-36.83	-37.38	-56.634
dependency ratio	-0.0046***	-0.0046***	-0.0046***	-0.0047***
	-28.82	-28.96	-28.92	-36.03
1 if ethnic minority; 0 otherwise	-0.2388***	-0.2411***	-0.2396***	-0.2422***
	-16.32	-16.49	-16.66	-29.05
1 if household head is female	0.0123*	0.0104*	0.0081	0.0005
	1.93	1.65	1.3	0.10
log of age of household head	0.1233***	0.1236***	0.1217***	0.1317***
	13.44	13.54	13.47	18.71

Dependent variable: log expenditure/capita (excl. health expenditure)	OLS with Hubert-White heteroskedasticity and cluster design correction			ML corrected for spatial correlation, cluster design and heteroskedasticity
	(1)	(2)	(3)	(4)
	parameter/ t-value	parameter/ t-value	parameter/ t-value	parameter/ t-value
education household head = 1 if				
primary school	0.1556***	0.1564***	0.1553***	0.14073***
	22.64	22.91	22.96	26.99
Lower secondary school	0.2618***	0.2659***	0.2659***	0.2524***
	33.02	33.83	34.16	44.32
Higher secondary school	0.4159***	0.4187***	0.4186***	0.39063***
	37.96	38.45	39	47.55
Short-term technical worker	0.4881***	0.4993***	0.5066***	0.47005***
	32.19	33.25	33.84	37.51
Long-term technical worker	0.5566***	0.5626***	0.5668***	0.5312***
	38.19	38.83	39.74	44.43
Professional secondary school	0.5787***	0.5832***	0.5833***	0.55974***
	37.36	37.69	37.8	42.96
College diploma and above	0.8133***	0.8130***	0.8099***	0.76219***
	51.35	52.7	54.59	65.25
Days ill in bed, senior household members	0.0001	0.0001	0.0001	0.0000
	0.71	0.67	0.6	0.47
Days ill in bed, adult household members	-0.0002	-0.0002	-0.0002	-0.0002***
	-1.42	-1.45	-1.57	-2.07
Days ill in bed, children	0.0001	0.0002	0.0002	0.0002
	0.74	0.84	0.84	0.94
Own a house (1=yes; 0=no)	0.1393***	0.1415***	0.1493***	0.1592***
	9.01	9.28	10.31	15.40
Own land (1=yes;0=no)	-0.7036***	-0.6848***	-0.6848***	-0.7334***
	-21.83	-21.67	-21.77	-37.63
Areas of land owned (squared metres)	0.0782***	0.0763***	0.0769***	0.0883***
	19.81	19.68	19.85	38.29
Community characteristics				
1 if sanitary drinking water in enumeration area	-0.0704	-0.0754	-0.0694	-0.0723*
	-1.5	-1.54	-1.52	-1.74
1 if sanitary living water in enumeration	0.0853**	0.0881*	0.0854**	0.1014***

Dependent variable: log expenditure/capita (excl. health expenditure)	OLS with Hubert-White heteroskedasticity and cluster design correction			ML corrected for spatial correlation, cluster design and heteroskedasticity
	(1)	(2)	(3)	(4)
	parameter/ t-value	parameter/ t-value	parameter/ t-value	parameter/ t-value
area				
	1.97	1.92	2.03	2.51
1 if electricity in enumeration area	0.0047	0.0145	0.0057	0.0018
	0.15	0.46	0.18	0.12
1 if sanitary latrine in enumeration area	0.1062***	0.1087***	0.1124***	0.1002***
	7.33	7.51	7.79	12.88
1 if living on primary or secondary road	0.1199**	0.1011**	0.0856*	0.1080***
	2.43	2.07	1.79	4.26
Log of distance (km) to closest primary or secondary road	0.0234***	0.0210***	0.0182***	0.0194***
	3.45	3.13	2.77	5.53
Log (1+ elevation in meters)	0.0130**	0.0066	0.0066	0.0008
	2.15	1.04	1.05	0.22
Log (1+diff bw highest & lowest elevation in 1 km2)	-0.0072	-0.0089	-0.0096	-0.0172***
	-1.05	-1.33	-1.46	-4.62
Log (1+tenths hours to urban area of > 25,000 people)	-0.0353***	-0.0366***	-0.0404***	-0.0530***
	-3.43	-3.5	-3.85	-8.10
Log (1+tenths of hours to urban area of > 100,000 people)	-0.0565***	-0.0555***	-0.0531***	-0.0426***
	-5.39	-5.23	-4.94	-6.03
Log (1+tenths of hours (6 minute periods) to urban area of > 500,000 people)	-0.0958***	-0.0947***	-0.1442***	-0.1190***
	-9.85	-9.57	-9.81	-11.73
Regional characteristics				
1 if urban; 0 otherwise	0.3176***	0.3128***	0.3045***	0.27923***
	21.81	21.79	21.22	34.94
Region 2: Northeast	0.0824***	0.0819***	0.0628***	0.0860***
	4.14	4.01	3.03	5.25
Region 3: Northwest	0.044	0.0505	0.0436	0.0335
	1.28	1.51	1.35	1.31
Region 4: Northcentral Coast	-0.0347	-0.0254	-0.0727***	-0.0504**

Dependent variable: log expenditure/capita (excl. health expenditure)	OLS with Hubert-White heteroskedasticity and cluster design correction			ML corrected for spatial correlation, cluster design and heteroskedasticity
	(1)	(2)	(3)	(4)
	parameter/ t-value	parameter/ t-value	parameter/ t-value	parameter/ t-value
	-1.56	-1.04	-2.89	-2.41
Region 5: Southcentral Coast	0.2475***	0.2438***	0.1464***	0.1409***
	8.97	8.36	4.32	5.55
Region 6: Central Highlands	0.0664**	0.0900***	0.0411	0.0687***
	2.08	2.8	1.28	2.75
Region 7: Southeast	0.2904***	0.2881***	0.2367***	0.2347***
	15.97	13.07	9.76	12.07
Region 8: Mekong Delta	0.2757***	0.2701***	0.2518***	0.2157***
	11.24	8.42	7.8	9.86
1 if year 2004; 0 otherwise	0.3368***	0.3367***	0.3385***	0.33537***
	36.4	35.88	35.18	44.92
1 if year 2006; 0 otherwise	0.6360***	0.6387***	0.6458***	0.64451***
	69.34	67.54	67.28	88.39
Constant	7.5505***	7.6402***	7.8854***	7.0465***
	95.01	94.78	86.6	67.38
r2/ln L	0.57	0.57	0.58	-23,761.1
F	481.45	404.4	359.8	
N	46985	46985	46985	47,167

Note: Pooled VHLSS data from 2002, 2004 and 2006. Drought if 20% below annual median rainfall; excess rainfall if > 300 mm in 5 consecutive days at least once in a year; flooding recorded in Darthmouth Flood Observatory and within 2 m elevation difference from river or coast; hurricane force winds if wind 65 knots (118 km/hour) or more.

ln(hours) from 500k city are in effect the ln(1+ tenths of hours) from 500k city with tenths of hours being 6 minute periods

Source: Thomas et al. (2010)

Table 4. 2 Extreme weather events can have substantial negative effects on household welfare, immediately and through adaptation over time, with adaptation and disaster relief often mitigating the immediate losses

Dependent variable	Log exp/capita (excl. health expenditu-re)	Log (asset and consumer durable value)	Disaster relief	Domestic remittan-ces	Remittances from outside VN	Herfindahl index
	ML	OLS		Tobit		OLS
	(1)	(2)	(3)	(4)	(5)	(6)
	parameter/ t-value	parameter/ t-value	Paramet-er/ t-value	Paramet-er/ t-value	Paramet-er/ t-value	parameter/ t-value
Extreme weather event in community Droughts						
Drought this year	0.0245	0.193	-667	423	-13387*	-0.0232
	0.58	0.95	-0.5	0.91	-1.91	-0.92
Drought this year*drought frequency	0.0704	0.9981				0.029
	0.46	1.22				0.36
Drought this year*ln(hours) from 500k city	-0.0006	-0.0923*	549	-128	4192**	0.0058
	-0.06	-1.95	1.56	-1.07	2.28	1.03
Drought last year	-0.0008	-1.2525*	-288	-2208	17699	0.0538
	-0.01	-1.68	-0.05	-1.49E+00	0.75	0.67
Drought last year*drought frequency	-0.1257	-1.0411				-0.1084
	-0.45	-0.85				-0.94
Drought last year*ln(hours) from 500k city	0.0111	0.3263**	-388	313	-4247	-0.0053
	0.31	2.24	-0.28	0.87	-0.72	-0.3
Drought frequency (proportion)	-1.2609***	-3.4800**	11703	10822***	64532	-0.3115**
	-4.25	-2.26	1.11	2.98	1.18	-2.15
Drought frequency*ln(hours) from 500k city	0.2845***	1.0100**	-3830	-2761***	-19709	0.0738*
	3.72	2.36	-1.43	-2.93	-1.35	1.96
Excess rain						
Excess rain this year	-0.0768**	-0.3798**	-8908***	707	12524**	-0.0214
	-2.21	-2.51	-2.92	1.52	2.07E+0	-1.34

Dependent variable	Log exp/capita (excl. health expenditu-re)	Log (asset and consumer durable value)	Disaster relief	Domestic remittan-ces	Remittances from outside VN	Herfindahl index
	ML	OLS		Tobit		OLS
	(1)	(2)	(3)	(4)	(5)	(6)
	parameter/ t-value	parameter/ t-value	Paramet-er/ t-value	Paramet-er/ t-value	Paramet-er/ t-value	parameter/ t-value
					0	
Excess rain this year*Excess rain frequency	0.0685*	-0.1213				-0.0265
	1.90	-0.51				-1.34
Excess rain this year*ln(hours) from 500k city	0.0159	0.1455***	2280***	-277**	-1759	0.0101*
	1.49	2.96	3.17	-2.34	-1.14	1.95
Excess rain last year	0.1337***	0.3661**	2005	1201**	-13616**	-0.016
	4.14	2.51	1.31	1.99	-2.25	-1.01
Excess rain last year*Excess rain frequency	-0.0852**	-0.5361**				-0.0191
	-2.17	-2.39				-0.86
Excess rain last year*ln(hours) from 500k city	-0.0182*	-0.0327	-310	-303**	3492**	0.0068
	-1.95	-0.74	-0.84	-2.05	2.3	1.47
Excess rain frequency (proportion)	-0.2828**	-0.8208	14364**	1237	-54117**	0.057
	-2.26	-1.49	2.52	0.85	-2.41	0.91
Excess rain frequency*ln(hours) from 500k city	0.0798**	0.1031	-3694***	-129	12517**	-0.0151
	2.77	0.73	-2.79	-0.39	2.53	-1.05
Riverine flood						
Riverine flood this year	-0.0575*	0.3427*	-1729	-826*	-6324	0.0267
	-1.87	1.93	-1.21	-1.87	-1.48	1.58
Riverine flood this year*Riverine flood frequency	0.1440**	-0.1806				-0.0531
	2.20	-0.48				-1.32
Riverine flood this year*ln(hours) from 500k city	0.0091	-0.0955**	538	259**	1857	-0.006
	1.17	-2.24	1.43	2.14	1.41E+0 0	-1.4

Dependent variable	Log exp/capita (excl. health expenditu-re)	Log (asset and consumer durable value)	Disaster relief	Domestic remittan-ces	Remittances from outside VN	Herfindahl index
	ML	OLS		Tobit		OLS
	(1)	(2)	(3)	(4)	(5)	(6)
	parameter/ t-value	parameter/ t-value	Paramet-er/ t-value	Paramet-er/ t-value	Paramet-er/ t-value	parameter/ t-value
Riverine flood last year	-0.1723***	-0.8076***	-2582**	-331	-2185	-0.0546***
	-5.417	-5.42	-2.04	-0.74	-0.42	-3.02
Riverine flood last year*Riverine flood frequency	-0.0051	1.2278***				-0.0018
	-0.07	2.91				-0.04
Riverine flood last year*ln(hours) from 500k city	0.3397***	0.1197***	612*	74	1222	0.0134***
	3.66	2.99	1.75	5.60E-01	7.90E-01	2.96
Riverine flood frequency (proportion)	0.0407***	0.6768	7506*	1177	11479	0.0434
	4.87	1.58	1.7	0.82	0.64	0.86
Riverine flood frequency*ln(hours) from 500k city	-0.1041***	-0.3161**	-1828*	-212	-4749	-0.0088
	-4.24	-2.49	-1.66	-0.56	-0.99	-0.66
Hurricane force wind						
Hurricane force wind this year	-0.7309***	0.0771	-40831	-2183	-22448	-0.0999
	-2.93	0.08	-1.32	-1.17	-0.58	-0.96
Hurricane force wind this year*Hurricane force wind frequency	-0.9634	1.1605				-0.2275
	-1.41	0.41				-0.71
Hurricane force wind this year*ln(hours) from 500k city	0.1737***	-0.0017	8208	626	3153	0.0188
	2.99	-0.01	1.33	1.54	0.39	0.75
Hurricane force wind last year	-0.1642	-1.7442***	-4902	-963	-79326*	0.0122
	-0.96	-2.86	-0.76	-0.45	-1.7	0.19
Hurricane force wind last year*Hurricane force wind frequency	-1.4028**	-3.0042				-0.4922*
	-2.06	-1.32				-1.8
Hurricane force wind last	0.0762**	0.4991***	1038	248	19613*	0.0105

Dependent variable	Log exp/capita (excl. health expenditu-re)	Log (asset and consumer durable value)	Disaster relief	Domestic remittan-ces	Remittances from outside VN	Herfindahl index
	ML	OLS		Tobit		OLS
	(1)	(2)	(3)	(4)	(5)	(6)
	parameter/ t-value	parameter/ t-value	Paramet-er/ t-value	Paramet-er/ t-value	Paramet-er/ t-value	parameter/ t-value
year*ln(hours) from 500k city						
	1.97	3.77	0.72	0.49	1.85E+00	0.74
Hurricane force wind frequency (proportion)	-2.1608***	-1.3598	-5555	-834	-9578	0.0226
	-7.45	-1	-0.46	-0.24	-0.22	0.18
Hurricane force wind frequency*ln(hours) from 500k city	0.4584***	-0.0417	1891	400	-8326	-0.0282
	5.79	-0.09	0.6	0.41	-0.65	-0.76
Household characteristics						
log of household size	-0.2832***	0.9004***	268**	-380***	1996**	-0.0772***
	-56.634	36.13	2.1	-6.2	2.01	-29.53
dependency ratio	-0.0047***	-0.0073***	25***	6***	49*	0.0010***
	-36.03	-14.26	4.07	3.27	1.78	15.03
1 if ethnic minority; 0 otherwise	-0.2422***	-0.9442***	482	-371***	3368	-0.0237***
	-29.05	-14.54	1.54	-3.11	1.49	-4.62
1 if household head is female	0.0005	-0.0971***	75	235***	4958***	-0.0037
	0.10	-4.56	0.53	3.6	4.5	-1.48
log of age of household head	0.1317***	0.1358***	269	1502***	11890***	-0.0019
	18.71	4.02	1.51	15.21	6	-0.49
education household head = 1 if						
primary school	0.14073***	0.4720***	-68	130**	2851**	-0.0044
	26.99	17.65	-0.47	1.97	2.16	-1.55
Lower secondary school	0.2524***	0.7603***	13	106	5739***	-0.0112***
	44.32	28.11	0.07	1.5	3.78	-3.55
Higher secondary school	0.39063***	1.0970***	-469*	261**	11165***	-0.0018

Dependent variable	Log exp/capita (excl. health expenditu-re)	Log (asset and consumer durable value)	Disaster relief	Domestic remittan-ces	Remittances from outside VN	Herfindahl index
	ML	OLS		Tobit		OLS
	(1)	(2)	(3)	(4)	(5)	(6)
	parameter/ t-value	parameter/ t-value	Paramet-er/ t-value	Paramet-er/ t-value	Paramet-er/ t-value	parameter/ t-value
	47.55	32.37	-1.96	1.99	5.68	-0.42
Short-term technical worker	0.47005***	1.2881***	-528	340**	10008***	0.0191***
	37.51	26.95	-1.48	2	3.66	2.83
Long-term technical worker	0.5312***	1.3951***	-359	635***	5688**	0.0218***
	44.43	31.19	-1.14	3.7	2.08	3.5
Professional secondary school	0.55974***	1.3057***	-1704***	345*	3299	0.0360***
	42.96	30.58	-3.06	1.79	1.14	5.56
College diploma and above	0.76219***	1.7775***	-654	1177***	378	0.0488***
	65.25	43.09	-1.44	5.19	0.16	7.32
Days ill in bed, senior household members	0.0000	0	2	3***	13	0
	0.47	0.09	0.77	2.86	0.89	0.76
Days ill in bed, adult household members	-0.0002***	-0.0017***	11***	3**	25*	0
	-2.07	-3.9	3.72	1.97	1.68	0.92
Days ill in bed, children	0.0002	-0.0004	7	3	-8	-0.0001
	0.94		1.49	1.29	-0.25	-0.91
Own a house (1=yes; 0=no)	0.1592***	0.8281***	-36	157	3892**	-0.0132**
	15.40	13.75	-0.13	0.79	2	-2.25
Own land (1=yes;0=no)	-0.7334***	-2.5031***	746	-306	-16968***	-0.1328***
	-37.63	-23.52	1.26	-1.33	-3.51	-10.36
Areas of land owned (squared metres)	0.0883***	0.3802***	-138*	40	1265**	-0.0038**
	38.29	28.21	-1.93	1.4	2.2	-2.38
Community characteristics						
1 if sanitary drinking water in enumeration area	-0.0723*	0.1658	-949**	-124	-2687	0.0011

Dependent variable	Log exp/capita (excl. health expenditu-re)	Log (asset and consumer durable value)	Disaster relief	Domestic remittan-ces	Remittances from outside VN	Herfindahl index
	ML	OLS		Tobit		OLS
	(1)	(2)	(3)	(4)	(5)	(6)
	parameter/ t-value	parameter/ t-value	Paramet-er/ t-value	Paramet-er/ t-value	Paramet-er/ t-value	parameter/ t-value
	-1.74	0.47	-2.09	-0.84	-1.02	0.04
1 if sanitary living water in enumeration area	0.1014***	-0.1143	18	96	8013***	0.014
	2.51	-0.34	0.04	0.6	2.67	0.58
1 if electricity in enumeration area	0.0018	0.18	76	333***	2023	-0.0324**
	0.12	0.96	0.31	3.36	0.87	-2.09
1 if sanitary latrine in enumeration area	0.1002***	0.4157***	-179	403***	13758***	0.0176***
	12.88	6.65	-1.1	6.47	9.02	3.22
1 if living on primary or secondary road	0.1080***	-0.2622	1127	216	-4525	-0.0018
	4.26	-1.54	1.13	0.57	-0.79	-0.11
Log of distance (km) to closest primary or secondary road	0.0194***	-0.0373	117	56	-432	-0.0012
	5.53	-1.55	0.88	1.11	-0.53	-0.52
Log (1+ elevation in meters)	0.0008	0.003	94	61	2879**	-0.0035
	0.22	0.1	0.44	0.69	2.21	-1.03
Log (1+diff bw highest & lowest elevation in 1 km2)	-0.0172***	-0.0773**	-359	-161*	-4553***	-0.0004
	-4.62	-2.51	-1.56	-1.84	-3.98	-0.11
Log (1+tenths hours to urban area of > 25,000 people)	-0.0530***	-0.1523***	626*	-199*	-1339	0
	-8.10	-3.58	1.72	-1.67	-0.83	-0.01
Log (1+tenths of hours to urban area of > 100,000 people)	-0.0426***	0.0482**	46	43	-1286	0.0023
	-6.03	2.22	0.35	0.91	-1.45	1.1
Log (1+tenths of hours to urban area of > 500,000 people)	-0.1190***	-0.0751***	276*	-62	-152	-0.0022
	-11.73	-3.28	1.74	-1.15	-0.15	-0.99

Dependent variable	Log exp/capita (excl. health expenditu-re)	Log (asset and consumer durable value)	Disaster relief	Domestic remittan-ces	Remittances from outside VN	Herfindahl index
	ML	OLS		Tobit		OLS
	(1)	(2)	(3)	(4)	(5)	(6)
	parameter/ t-value	parameter/ t-value	Paramet-er/ t-value	Paramet-er/ t-value	Paramet-er/ t-value	parameter/ t-value
Regional characteristics						
1 if urban; 0 otherwise	0.27923***	0.4571***	-469	30	2260	0.0247***
	34.94	10.56	-1.52	0.25	1.44	5.48
Region 2: Northeast	0.0860***	0.1445**	1004*	304*	1642	-0.0226***
	5.25	2.46	1.67	1.93	6.20E-01	-3.49
Region 3: Northwest	0.0335	0.0545	1637**	-454	9462*	0.017
	1.31	0.43	2.14	-1.29	1.87	1.45
Region 4: Northcentral Coast	-0.0504**	0.0366	1516**	613***	7550**	-0.0072
	-2.41	0.48	2.32	3.51	2.46	-0.91
Region 5: Southcentral Coast	0.1409***	0.2884***	5111***	515**	8506**	0.0254**
	5.55	2.8	4.44	2.15	2.08	2.49
Region 6: Central Highlands	0.0687***	0.1144	1936**	811***	5428	0.0605***
	2.75	0.87	2.32	3.24	1.18	5.24
Region 7: Southeast	0.2347***	0.2871***	3449***	835***	12333***	0.0825***
	12.07	3.88	4.2	4.32	3.87	10.37
Region 8: Mekong Delta	0.2157***	0.2418**	2840***	686***	13412***	0.0927***
	9.86	2.29	3.6	2.91	3.64	8.84
1 if year 2004; 0 otherwise	0.33537***	0.7683***	-5885***	729***	-304	-0.0395***
	44.92	23.52	-5.23	6.33	-0.2	-10.53
1 if year 2006; 0 otherwise	0.64451***	1.0031***	-4341***	1050***	249	-0.0246***
	88.39	30.59	-5.08	9.79	0.16	-6.59
Constant	7.0465***	5.7400***	-12589***	-5697***	-121334***	0.7821***
	67.38	14.06	-4.1	-8.86	-8.12	22.73
r2/ln L		0.3				0.29

Dependent variable	Log exp/capita (excl. health expenditu-re)	Log (asset and consumer durable value)	Disaster relief	Domestic remittan-ces	Remittances from outside VN	Herfindahl index
	ML	OLS		Tobit		OLS
	(1)	(2)	(3)	(4)	(5)	(6)
	parameter/ t-value	parameter/ t-value	Paramet-er/ t-value	Paramet-er/ t-value	Paramet-er/ t-value	parameter/ t-value
F		135.18	0.77	16.14	3.56	127.76
N	47,167	46985	46985	46985	46985	46916

Note: Pooled VHLSS data from 2002, 2004 and 2006. ML corrected for spatial correlation, cluster design and heteroskedasticity. OLS and Tobit estimators corrected for cluster design and heteroskedasiticy using Hubert-White correction. Drought if 20% below annual median rainfall; excess rainfall if > 300 mm in 5 consecutive days at least once in a year; flooding recorded in Darthmouth Flood Observatory and within 2 m elevation difference from river or coast; hurricane force winds if wind 65 knots (118 km/hour) or more. ln(hours) from 500k city are in effect the ln(1+ tenths of hours) from 500k city with tenths of hours being 6 minute periods.
Source: Thomas et al. (2010)

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APPENDIX A

Appendix A1. Correlations between weather shock variables (in rural MxFLS municipalities) and average (1951 to 1985) weather

	Annual rainfall: Standard deviations from1951-1985 average	Wet season rainfall: Standard deviations from1951-1985 average	Pre-*canícula* rainfall: Standard deviations from1951-1985 average	Annual GDD Standard deviations from1951-1985 average	Wet season GDD: Standard deviations from1951-1985 average	Pre-*canícula* GDD: Standard deviations from1951-1985 average
Wet season rainfall: Standard deviations from1951-1985 average	0.928					
Pre-*canícula* rainfall: Standard deviations from1951-1985 average	0.569	0.645				
Annual GDD Standard deviations from1951-1985 average	-0.206	-0.172	-0.164			
Wet season GDD: Standard deviations from1951-1985 average	-0.198	-0.176	-0.171	0.896		
Pre-*canícula* GDD: Standard deviations from1951-1985 average	-0.118	-0.093	-0.168	0.812	0.912	
Average annual rainfall (1951-1985)	-0.162	-0.154	0.142	-0.033	0.009	-0.074
Average wet season rainfall (1951-1985)	-0.176	-0.171	0.135	-0.050	-0.001	-0.088
Average pre-*canícula* rainfall (1951-1985)	-0.127	-0.114	0.131	-0.057	-0.056	-0.139
Average annual GDD (1951-1985)	0.024	0.032	0.001	0.008	0.022	0.053
Average wet season GDD (1951-1985)	0.052	0.051	-0.046	0.057	0.034	0.071
Average pre-*canícula* GDD (1951-1985)	0.034	0.031	-0.016	0.010	-0.021	-0.004

Appendix A2: Characteristics of MxFLS households

	All households		1992 households		1995 households	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Number of children in the household	1.679	1.655	1.785	1.711	1.552	1.575
Number of adult males (over 16) in the household	1.335	0.881	1.238	0.811	1.452	0.945
Number of adult females (over 16) in the household	1.468	0.887	1.361	0.769	1.595	0.996
Household head has not completed primary school	0.581		0.595		0.564	
Gender of household head (1=female)	0.196		0.195		0.198	
Age of household head	50.59	16.26	49.71	16.06	51.66	16.45
No separate kitchen	0.085		0.092		0.076	
No tap water	0.236		0.300		0.158	
No toilet	0.457		0.541		0.358	
No sewage	0.490		0.584		0.378	
No electricity	0.025		0.027		0.021	
Dirt floor	0.182		0.205		0.155	
Asset Index	0.078	0.810	0.120	0.810	0.026	0.807
Observation from 2005 survey	0.455					
Surveyed in the wet season	0.958		1		0.908	
Number of observations	4929		2687		2242	

Source: Skoufias et al. (2011b)

Appendix A3: Full results of weather on expenditures

Table A3.1: Weather shocks and per capita expenditures on non-health items

	Year		Wet Season		Pre-*canícula*	
Fixed effects	State FE	Locality FE	State FE	Locality FE	State FE	Locality FE
Negative rainfall shock	0.004 (0.076)	**0.141*** **(0.082)**	-0.070 (0.079)	0.065 (0.096)	-0.110 (0.089)	-0.000 (0.080)
Positive rainfall shock	0.002 (0.079)	0.068 (0.087)	-0.031 (0.073)	-0.008 (0.072)	0.039 (0.085)	-0.014 (0.086)
Negative GDD shock	-0.066 (0.080)	-0.023 (0.093)	0.006 (0.082)	0.022 (0.131)	0.004 (0.077)	-0.013 (0.129)
Positive GDD shock	0.022 (0.056)	0.027 (0.092)	**0.120*** **(0.062)**	**0.183**** **(0.082)**	0.089 (0.086)	0.081 (0.115)
Number of children in the household	-0.140*** (0.010)	-0.136*** (0.009)	-0.140*** (0.010)	-0.137*** (0.009)	-0.141*** (0.009)	-0.137*** (0.009)
Number of adult males (over 16) in the household	-0.131*** (0.029)	-0.130*** (0.029)	-0.131*** (0.029)	-0.129*** (0.029)	-0.130*** (0.028)	-0.129*** (0.028)
Number of adult females (over 16) in the household	-0.108*** (0.018)	-0.104*** (0.018)	-0.108*** (0.019)	-0.104*** (0.018)	-0.108*** (0.018)	-0.105*** (0.018)
Household head has not completed primary school	-0.199*** (0.037)	-0.184*** (0.040)	-0.202*** (0.037)	-0.184*** (0.040)	-0.202*** (0.037)	-0.186*** (0.040)
Gender of household head (1=female)	-0.035 (0.053)	-0.033 (0.054)	-0.035 (0.052)	-0.033 (0.054)	-0.035 (0.052)	-0.034 (0.054)
Age of household head	-0.004** (0.002)	-0.004** (0.002)	-0.004** (0.002)	-0.004** (0.002)	-0.004** (0.002)	-0.004** (0.002)
No separate kitchen	-0.018 (0.054)	-0.025 (0.053)	-0.018 (0.054)	-0.024 (0.052)	-0.023 (0.053)	-0.026 (0.053)
No tap water	-0.040 (0.052)	-0.053 (0.056)	-0.038 (0.051)	-0.052 (0.055)	-0.037 (0.051)	-0.052 (0.055)
No toilet	-0.187*** (0.047)	-0.164*** (0.048)	-0.185*** (0.047)	-0.166*** (0.048)	-0.183*** (0.046)	-0.163*** (0.048)
No sewage	0.039 (0.049)	0.042 (0.054)	0.038 (0.047)	0.035 (0.053)	0.040 (0.048)	0.042 (0.053)
No electricity	-0.038 (0.137)	-0.011 (0.128)	-0.043 (0.136)	-0.018 (0.127)	-0.042 (0.138)	-0.015 (0.127)
Dirt floor	-0.235*** (0.045)	-0.238*** (0.047)	-0.230*** (0.045)	-0.233*** (0.047)	-0.234*** (0.046)	-0.238*** (0.047)
Asset Index	0.276*** (0.027)	0.267*** (0.027)	0.279*** (0.026)	0.267*** (0.027)	0.278*** (0.026)	0.267*** (0.027)
Observation from 2005 survey	-0.118** (0.046)	-0.119** (0.045)	-0.102** (0.047)	-0.097** (0.045)	-0.118** (0.046)	-0.109** (0.045)
Surveyed in the wet season	-0.208 (0.149)	-0.268* (0.152)	-0.213 (0.140)	-0.234 (0.145)	-0.232 (0.145)	-0.248* (0.145)
Annual rainfall (dm)	0.001 (0.009)		0.004 (0.009)		0.003 (0.008)	
Annual gdd / 1000 days	0.012 (0.038)		0.007 (0.038)		0.019 (0.038)	
Constant	7.393*** (0.249)	7.450*** (0.164)	7.366*** (0.236)	7.400*** (0.167)	7.346*** (0.253)	7.457*** (0.186)
Observations	4,929	4,929	4,950	4,950	4,951	4,951
R-squared	0.178	0.209	0.179	0.210	0.179	0.210

Source: Skoufias et al. (2011b)

Table A3.2: Weather shocks and per capita expenditures on food

	Year		Wet Season		Pre-*canícula*	
Fixed effects	State FE	Locality FE	State FE	Locality FE	State FE	Locality FE
Negative rainfall shock	-0.049	-0.085	-0.007	0.057	-0.076	-0.028
	(0.088)	(0.109)	(0.090)	(0.111)	(0.093)	(0.148)
Positive rainfall shock	**0.150***	**0.179***	0.097	0.131	0.046	0.036
	(0.086)	**(0.107)**	(0.087)	(0.119)	(0.107)	(0.119)
Negative GDD shock	-0.101	-0.249	-0.029	-0.041	0.038	0.221
	(0.096)	(0.162)	(0.094)	(0.184)	(0.088)	(0.159)
Positive GDD shock	-0.045	0.150	-0.096	-0.062	-0.082	-0.110
	(0.083)	(0.099)	(0.088)	(0.140)	(0.108)	(0.154)
Number of children in the household	-0.131***	-0.126***	-0.128***	-0.122***	-0.127***	-0.123***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Number of adult males (over 16) in the household	-0.171***	-0.165***	-0.172***	-0.167***	-0.170***	-0.166***
	(0.036)	(0.037)	(0.036)	(0.037)	(0.036)	(0.037)
Number of adult females (over 16) in the household	-0.055**	-0.056**	-0.053**	-0.051*	-0.052*	-0.050*
	(0.026)	(0.027)	(0.026)	(0.027)	(0.026)	(0.027)
Household head has not completed primary school	-0.022	-0.011	-0.027	-0.010	-0.029	-0.007
	(0.049)	(0.052)	(0.049)	(0.052)	(0.049)	(0.052)
Gender of household head (1=female)	0.010	0.008	0.008	0.009	0.008	0.009
	(0.061)	(0.059)	(0.060)	(0.059)	(0.060)	(0.059)
Age of household head	-0.007***	-0.008***	-0.007***	-0.007***	-0.007***	-0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
No separate kitchen	-0.257**	-0.246**	-0.248**	-0.245**	-0.248**	-0.240*
	(0.121)	(0.121)	(0.122)	(0.122)	(0.120)	(0.121)
No tap water	-0.076	-0.080	-0.088	-0.087	-0.094	-0.087
	(0.074)	(0.078)	(0.072)	(0.078)	(0.074)	(0.079)
No toilet	-0.200***	-0.210***	-0.188***	-0.203***	-0.178***	-0.203***
	(0.062)	(0.068)	(0.062)	(0.067)	(0.062)	(0.067)
No sewage	-0.066	-0.064	-0.050	-0.046	-0.048	-0.047
	(0.055)	(0.060)	(0.055)	(0.060)	(0.054)	(0.060)
No electricity	0.112	0.148	0.119	0.154	0.120	0.153
	(0.198)	(0.196)	(0.196)	(0.194)	(0.195)	(0.194)
Dirt floor	-0.105	-0.125	-0.106	-0.115	-0.104	-0.112
	(0.077)	(0.080)	(0.078)	(0.081)	(0.077)	(0.081)
Asset Index	0.215***	0.208***	0.221***	0.213***	0.221***	0.214***
	(0.042)	(0.043)	(0.043)	(0.044)	(0.043)	(0.044)
Observation from 2005 survey	0.087	0.066	0.078	0.056	0.074	0.044
	(0.057)	(0.055)	(0.059)	(0.062)	(0.059)	(0.059)
Surveyed in the wet season	-0.249*	-0.401***	-0.225	-0.371**	-0.214*	-0.330**
	(0.141)	(0.149)	(0.137)	(0.144)	(0.128)	(0.133)
Annual rainfall (dm)	-0.004		0.000		-0.000	
	(0.013)		(0.012)		(0.011)	
Annual gdd / 1000 days	0.046		0.036		0.031	
	(0.047)		(0.047)		(0.047)	
Constant	6.151***	6.503***	6.096***	6.395***	6.091***	6.333***
	(0.259)	(0.170)	(0.264)	(0.177)	(0.261)	(0.175)
Observations	4,929	4,929	4,950	4,950	4,951	4,951
R-squared	0.078	0.098	0.076	0.094	0.075	0.095

Source: Skoufias et al. (2011b)

Appendix A4: Full results of weather on child's height-for-age

VARIABLES	All			Centre/South			North		
	Annual	Wet season	Pre-*canícula*	Annual	Wet season	Pre-*canícula*	Annual	Wet season	Pre-*canícula*
Negative rainfall shock	0.185	0.246	-0.025	**0.384***	**0.479****	0.127	-0.265	**-0.294****	**-0.371***
	(0.150)	(0.166)	(0.128)	**(0.204)**	**(0.228)**	(0.149)	(0.174)	**(0.142)**	**(0.199)**
Positive rainfall shock	**-0.526*****	**-0.513*****	0.960^	**-0.518*****	**-0.478*****	5.143***^	**-0.524*****	**-0.701***	-0.401^
	(0.111)	**(0.132)**	(1.040)	**(0.134)**	**(0.142)**	(1.023)	**(0.143)**	**(0.367)**	(0.257)
Negative GDD shock	0.004	0.032	0.008	0.045	-0.081	-0.062	-0.075	0.113	-0.034
	(0.152)	(0.167)	(0.178)	(0.177)	(0.189)	(0.217)	(0.256)	(0.369)	(0.211)
Positive GDD shock	-0.100	-0.084	-0.152	-0.062	-0.048	-0.121	**-0.343***	-0.251	-0.313
	(0.090)	(0.092)	(0.105)	(0.105)	(0.110)	(0.127)	**(0.176)**	(0.157)	(0.189)
Number of adult males in hh	-0.021	-0.019	-0.023	-0.010	-0.010	-0.021	-0.036	-0.028	-0.039
	(0.052)	(0.051)	(0.051)	(0.068)	(0.069)	(0.070)	(0.065)	(0.063)	(0.064)
Number of adult females in hh	-0.022	-0.028	-0.026	-0.059	-0.061	-0.053	0.004	-0.000	-0.001
	(0.060)	(0.060)	(0.059)	(0.078)	(0.078)	(0.077)	(0.088)	(0.088)	(0.089)
Number of children (16 yrs or younger) in hh	-0.044	-0.044	-0.043	-0.062	-0.060	-0.056	0.047	0.053	0.041
	(0.035)	(0.035)	(0.035)	(0.038)	(0.038)	(0.038)	(0.088)	(0.087)	(0.089)
Mother's height	-0.000	-0.000	-0.000	-0.002	-0.002	-0.003	0.005	0.005	0.005
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)
Mother speaks an indigenous language	-0.172	-0.170	-0.114	-0.181	-0.192	-0.101	-0.137	-0.169	-0.245
	(0.135)	(0.135)	(0.144)	(0.152)	(0.150)	(0.170)	(0.228)	(0.238)	(0.228)
Education mother: primary	-0.174**	-0.191**	-0.190**	-0.196**	-0.211**	-0.166*	-0.059	-0.105	-0.067
	(0.075)	(0.075)	(0.075)	(0.087)	(0.087)	(0.084)	(0.165)	(0.162)	(0.165)
Sex	-0.039	-0.040	-0.065	-0.021	-0.024	-0.072	-0.075	-0.061	-0.063
	(0.084)	(0.085)	(0.085)	(0.107)	(0.109)	(0.109)	(0.139)	(0.142)	(0.139)
Birth order	-0.003	-0.004	-0.004	0.012	0.009	0.007	-0.066	-0.063	-0.068
	(0.023)	(0.023)	(0.024)	(0.026)	(0.026)	(0.026)	(0.054)	(0.054)	(0.055)
Multiple birth	-0.663***	-0.700***	-0.732***	-0.660***	-0.709***	-0.697***	-0.910	-0.933	-0.916*
	(0.215)	(0.223)	(0.208)	(0.234)	(0.257)	(0.233)	(0.632)	(0.670)	(0.482)

	Annual	Wet season	Pre-*canícula*	Annual	Wet season	Pre-*canícula*	Annual	Wet season	Pre-*canícula*
Categorized as very small at birth	-0.466***	-0.475***	-0.449***	-0.492**	-0.502**	-0.509**	-0.355	-0.327	-0.349
	(0.168)	(0.168)	(0.169)	(0.208)	(0.208)	(0.214)	(0.301)	(0.301)	(0.295)
Has an older sibling less than 2 years apart	-0.230**	-0.235**	-0.206**	-0.240**	-0.249**	-0.240**	-0.276*	-0.247	-0.234
	(0.096)	(0.097)	(0.096)	(0.120)	(0.120)	(0.117)	(0.163)	(0.160)	(0.153)
Age: 6 months to 12 months	-0.306**	-0.301**	-0.295**	-0.493***	-0.472***	-0.480***	0.103	0.090	0.072
	(0.139)	(0.139)	(0.139)	(0.162)	(0.161)	(0.165)	(0.257)	(0.259)	(0.248)
Age: 12 months to 24 months	-0.869***	-0.860***	-0.851***	-1.078***	-1.062***	-1.087***	-0.422*	-0.402	-0.412
	(0.136)	(0.136)	(0.136)	(0.161)	(0.159)	(0.159)	(0.248)	(0.252)	(0.249)
Age: 24 months to 36 months	-1.070***	-1.065***	-1.056***	-1.202***	-1.193***	-1.218***	-0.764***	-0.755***	-0.791***
	(0.131)	(0.129)	(0.131)	(0.158)	(0.156)	(0.158)	(0.219)	(0.220)	(0.215)
Altitude of locality (in km)	-0.307***	-0.312***	-0.353***	-0.320***	-0.318***	-0.367***	-0.133	-0.180	-0.269
	(0.093)	(0.091)	(0.094)	(0.116)	(0.110)	(0.108)	(0.184)	(0.155)	(0.197)
Household asset score	0.316***	0.312***	0.331***	0.312***	0.284***	0.309***	0.328***	0.339***	0.360***
	(0.075)	(0.077)	(0.078)	(0.100)	(0.102)	(0.104)	(0.121)	(0.119)	(0.114)
Floor of dirt	-0.044	-0.044	-0.026	0.027	0.020	0.037	-0.165	-0.134	-0.155
	(0.103)	(0.104)	(0.106)	(0.119)	(0.121)	(0.121)	(0.213)	(0.220)	(0.225)
No tap water to kitchen or bath	0.092	0.076	0.084	0.075	0.029	0.093	0.081	0.106	0.122
	(0.150)	(0.152)	(0.149)	(0.209)	(0.212)	(0.201)	(0.221)	(0.217)	(0.215)
No proper indoor toilet	-0.045	-0.051	-0.039	-0.081	-0.085	-0.074	-0.055	-0.042	-0.040
	(0.108)	(0.109)	(0.108)	(0.136)	(0.141)	(0.140)	(0.199)	(0.196)	(0.201)
Constant	0.547	0.553	0.638*	0.956**	0.980**	0.979**	-0.481	-0.509	-0.199
	(0.376)	(0.373)	(0.381)	(0.438)	(0.438)	(0.431)	(0.846)	(0.844)	(0.840)
Observations	1,536	1,536	1,540	1,079	1,079	1,079	457	457	461
R-squared	0.249	0.248	0.245	0.230	0.231	0.238	0.207	0.206	0.207

Source: Skoufias et al . (2011b)

Note: Robust standard errors in parentheses, clustered by locality and *** p<0.01, ** p<0.05, * p<0.1.

^ Less than 2% of the sample experienced a positive rainfall shock in the pre-*canícula* period. Calculated using ENN with state fixed effects. A negative weather shock identifies those municipalities which in the previous agricultural year (or wet season or pre-*canícula* period) had at least 1 standard deviation less rain (or GDD) than in an average year. A positive weather shock identifies those municipalities which in the previous agricultural year (or wet season or pre-*canícula* period (had at least 1 standard deviation more rain (or GDD) than in an average year.

Appendix A5. Interpolation of weather data

IMTA's dataset contains daily information on several meteorological variables for more than 5,000 stations across Mexico, since the 1920s to 2007. These data were used to interpolate an observation of those three variables at the centroid of each of the 2,451 municipalities in the country, on a day-by-day basis. Municipality centroids were determined as the simple average of the latitude and longitude coordinates of all the localities listed within each municipality in INEGI's catalogue of localities.

The approach used to interpolate the weather data is the two-dimensional, weighted average method proposed by Shepard (1968). He summarizes it as follows:

"In essence, an operational solution to the problem of two-dimensional interpolation from irregularly-spaced data points is desired. It is assumed that a finite number of N triplets (x_i,y_i,z_i) are given, where x_i, y_i are the locational coordinates of the data point D_i, and z_i is the corresponding data value. Data point locations may not be coincident. An interpolation function $z=f(x,y)$ to assign a value to any location $P(x,y)$ in the plane is sought. This two-dimensional interpolation function is to be "smooth" (continuous and once-differentiable), to pass through the specified points (i.e., $f(x_i,y_i)=z_i$), and to meet the user's intuitive expectations about the phenomenon under investigation." (p. 517)

The interpolation function is simply a weighted average of the observed values from a certain number of data points (weather stations). Shepard chooses this number to be variable (ranging from 4 to 10, with an average of 7) by defining a radius around the interpolation point which, on average, will include 7 data points. Since in IMTA's dataset the weather stations are much more sparse in some areas of the country than others, choosing Shepard's number would have yielded a radius to small in some areas or too large in others. In addition, weather stations reported data intermittently, which implied that having a small number of stations to interpolate from ran the risk of not having any data values with which to do the interpolation.

Instead, for every municipality centroid, we first chose the 20 stations that were closest to it[88]. We then kept only those stations that reported information on the day to be interpolated. The result was that less than 6% of the interpolations were based on only one weather station, around 8% (the highest proportion) were based on 7 stations, and around 1% were based on 18 or more stations.

The weights (w_i) used in the interpolation function consider two aspects: Distance and direction. Distance is used to give a bigger weight to data points that are closer to the point of interpolation. Direction is used to take into account "shadowing" effects: A weather station B that is 'behind' another weather station A (as seen from the point of interpolation P) provides less information than another station C which is located in another direction—even if station B is closer to the point of interpolation than station C—because station B has been shadowed by station A (see Figure A.1)

[88] The number 20 was chosen because it was the smallest number of stations with which less than 1 percent of the interpolations would have to be made based on the data of only one station (the rest of the stations having failed to report data on that day).

Figure A.1. Weather station B is shadowed by station A

|--B---A---**P**----------C--|

The interpolation function for each of the 2,451 interpolation points P (for each day since January 1st, 1950 to December 31st, 2007) was the following:

$$f(P) = \begin{cases} \dfrac{\sum_N w_i z_i}{\sum_N w_i} & \text{if } d_i \neq 0 \ \forall \ i \\ z_i & \begin{array}{l} \text{if } d_i = 0 \ \text{ for some } i, \text{ or} \\ \text{if } N = 1 \end{array} \end{cases}$$

Where d_i is the distance between interpolation point P and station i (among the N stations that reported information that day, out of the 20 stations closest to P), z_i is weather station i's measure of the variable of interest (rain, maximum temperature, or minimum temperature), and w_i is station i's weight for that day's interpolation.

The weights are defined as

$$w_i = (s_i)^2 \bullet (1 + t_i),$$

where

$$s_i = \begin{cases} \dfrac{1}{d_i} & \text{if } 0 < d_i < \dfrac{D}{3} \\ \dfrac{27}{4D}\left(\dfrac{d_i}{D} - 1\right)^2 & \text{if } \dfrac{D}{3} < d_i \leq D \end{cases}$$

(with D being the distance to the farthest station), and

$$t_i = \frac{\sum_{j \neq i} s_j \left[1 - \cos\left(D_i P D_j\right)\right]}{\sum_{j \neq i} s_j}$$

(with $D_i P D_j$ being the angle between weather stations i and j with interpolation point P as vertex).

APPENDIX B

Table B1: Inverse elevation difference weighted rainfall index most important in predicting monthly rainfall in wettest months (April-November), while inverse distance squared weighted rainfall index also important for predicting rain during drier months (December-March)

Dependent variable = log (monthly rainfall)				
month	constant	inverse distance squared weighted rainfall index	inverse elevation difference weighted rainfall index	mean rainfall (mm)
1	-0.19	0.64	0.34	24.7
2	-0.27	0.49	0.52	27.5
3	-0.56	0.34	0.75	41.3
4	-0.95	0.06	1.11	78.1
5	-0.72	0.02	1.10	220.8
6	-1.05	0.07	1.10	232.1
7	-1.16	0.08	1.11	277.1
8	-0.95	0.07	1.09	314.7
9	-0.20	0.05	0.97	242.2
10	-0.51	0.16	0.91	194.8
11	-0.30	0.32	0.69	117.2
12	-0.13	0.58	0.38	65.6

Notes: OLS estimated coefficients from regressing (log) monthly rainfall in 166 rainfall stations from across in Vietnam during 1980-2006 on the logs of their respective inverse distance squared weighted and inverse elevation difference weighted indices, monthly dummies and their interaction terms; R-squared=0.768; Mean rainfall reflects averages of rainfall stations taken over 2001-2006 R-squared: 0.768

Table B2: Temporal and cross disaster correlation of extreme weather events

		drought (20%<median)			flash flood (>300mm in 5 consec days)			river flood (DFO, <2m elevation diff)			hurricane		
		this year	last year	incidence	this year	last year	incidence	this year	last year	incidence	this year	last year	incidence
drought (20%<median)	this year	1											
	last year	-0.0079	1										
	incidence	0.242	0.1474	1									
flash flood (>300mm in 5 consec days)	this year	-0.1351	0.033	0.1219	1								
	last year	-0.0322	0.0249	0.2783	0.4409	1							
	incidence	-0.1247	0.102	0.3386	0.6106	0.7001	1						
river flood (DFO, <2m elevation diff)	this year	0.3488	0.0051	0.1178	-0.1609	-0.1628	-0.3001	1					
	last year	0.4008	-0.0288	0.1916	-0.0985	-0.0693	-0.1617	0.5465	1				
	incidence	0.3723	0.0045	0.2108	-0.1331	-0.1091	-0.1954	0.7497	0.7305	1			
hurricane	this year	0.0407	0.0439	0.0451	0.0044	0.1672	0.1503	-0.0377	-0.0142	-0.0321	1		
	last year	-0.044	-0.0149	0.1372	0.013	-0.0303	0.0954	-0.0377	0.0067	-0.0283	-0.0114	1	
	incidence	-0.161	0.0623	0.2017	0.2614	0.2953	0.5501	-0.3945	-0.1772	-0.1991	0.1151	0.1327	1

Table B3: Households further away from the metropolitan centers are more engaged in agriculture, have less assets and irrigated land, are less likely to receive remittances from abroad, but as likely or more likely to receive domestic remittances and disaster relief, albeit at much smaller amounts than those closer to the metropolitan centers

Distance from 500k city (hrs)	Ratio of household employees engaged in		asset holdings		support systems					
averages	wage earner	farmer	share of land irrigated	log(value of durable and fixed assets)	Share households receiving disaster relief	average disaster relief received[1)]	share households receiving domestic remittances	average domestic remittances received[1)]	share households with remittances from abroad	average remittances received from abroad[1)]
< 1 hour	0.51	0.19	0.91	9.73	0.05	2038	0.83	3513	0.13	19303
1-5 hours	0.28	0.53	0.87	9.14	0.08	1013	0.88	2073	0.05	14284
5-10 hours	0.25	0.59	0.72	9.08	0.09	1252	0.79	1741	0.05	16729
> 10 hours	0.30	0.50	0.72	9.05	0.12	634	0.85	1626	0.06	12475
Total	0.31	0.48	0.82	9.21	0.08	1096	0.85	2172	0.07	16017

1) average amounts among those who received disaster relief or remittances